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How Urban Morphology Explains Logistics Operations:
A Spatial-Temporal Analysis of Logistics Vehicles

by

Hailey A.M. Irwin
Student ID: 2218186
Surname and initials: Irwin, H.A.M.

Graduation Supervision Committee
Prof. Dr. Soora Rasouli, Karen Valitov
Dr. Bram Kin, Finn Winkelmann

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Author: Irwin, Hailey Alicia Morgan (H.A.M.)
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Graduation Supervision Committee:

Main Supervisor and Chair: Prof. Dr. Soora Rasouli from Department of the Built Environment, TU/e
Second Supervisor: Karen Valitov, MSc from Department of the Built Environment, TU/e
Third Supervisor: Dr. Bram Kin from TNO
Fourth Supervisor: Finn Winkelmann from TNO

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Abstract

In today's urban environments, increasing logistics activity poses ever more complex challenges for urban planners seeking to balance practical operational requirements with sustainability and livability objectives. By understanding the spatial-temporal dynamics of urban logistics operations, important insights can be gained about how urban morphology, covering the built, social, and economic environments, affects these activities. This analysis uses the Dutch cities of Amsterdam, Rotterdam, and Utrecht as case studies for a data-driven examination of how urban morphology influences logistics vehicle operations and the resulting spatial-temporal patterns. This methodology utilizes correlation, spatial mapping, regression, and random forest machine learning models to identify the most relevant morphology indicators, as well as the spatial and non-linear relationships within the data. The analysis identified high cluster patterns of logistics activity, including industrial corridors, major junctions, and arterials. Conversely, it found that these patterns are absent in historic and densely populated residential areas. The temporal variations identified align with theoretical findings regarding consumer and operator preferences. The primary determinants of logistic intensity cluster patterns are indicators related to population density and the built urban environment. These insights offer actionable information for urban planners and policymakers to guide and develop targeted interventions that promote more sustainable and efficient urban logistics operations. Overall, the research presents a hybrid spatial predictive framework that can be transferred to future applications and integrated into urban logistics planning initiatives.

Keywords: Urban Logistics; Urban Morphology; Spatial-Temporal Analysis; Spatial Regression; Spatial-Lag; Random Forest Ensemble; Sustainable Urban Mobility; Hotspot Analysis; Logistics Operations; Curbside Management

Preface

This thesis marks the culmination of my academic journey in the European Union European Institute of Innovation & Technology (EIT) Urban Mobility's Master in Sustainable Urban Mobility Transitions, where I studied at KTH Royal Institute of Technology in Stockholm, Sweden, and Eindhoven University of Technology in Eindhoven, Netherlands.

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Chapter 1

Introduction

Cities worldwide are expanding and densifying, transforming the urban landscape, increasing competition for space, and challenging the livability of increasingly chaotic metropolitan areas. Urbanization gives rise to many negative externalities, with a critical one being the impact of logistics operations on city streets and traffic flow. Population growth increases demand for logistics activities. At the same time, changing consumer habits create new spatial pressures and conflicts across the urban landscape. In short, urban logistics activities are transforming the spatial dynamics of the urban realm (Büyüközkan & Ilıcak, 2022). Rather than focusing on the needs of logistics operators, urban planners have traditionally emphasized walkability, the layout of public spaces, and the reclamation of space for use by urban residents. The historical neglect has worsened these challenges associated with logistics operations. However, society's dramatic shift toward online shopping and on-demand, direct-to-home delivery has raised awareness of the challenges that urban logistics pose to urban planning (Savelsbergh & Van Woensel, 2016). Logistics vehicles have become a more visible presence on city blocks. As a result, this traditionally neglected component of the urban landscape has become a more pressing concern (Dablanc, 2011). However, while urban planners may pursue the adoption of EVs to address the negative environmental impacts of urban logistics, they have not fully considered the shift in spatial externalities of urban logistics (Dablanc, 2011; Kin & Quak, 2024). Such externalities include increased curb competition, shortages of parking, limited maneuvering space, and longer dwell times (Veld, 2024).

Critically, the spatial claims of logistics vehicles extend beyond just their physical dimensions to encompass operational and behavioral interactions across the urban environment (Stathopoulos, Valeri, & Marcucci, 2012). Unlike private vehicles, urban logistics movements are highly variable, dependent, and goal-oriented, thus causing conflicts with other urban actors (Lee & Joo, 2025). Addressing these spatial challenges is needed to find solutions that promote sustainable urban logistics, human-centric living, and efficient urban planning.

Quantifying logistics vehicles' spatial impact is even more critical, and this analysis must consider different temporal scales and diverse urban morphologies. The concept of logistics footprint was developed by Rondaij et al. as the "*[number of urban logistics vehicles, subsequently decomposed in] number of trips and kilometers per segment and vehicle type*" (Rondaij et al., 2022, p. 2943). Understanding the spatial allocation of logistics operations is

needed as (Dutch) planners aim to reduce emissions, manage traffic flow, and promote car-free development (Quak et al., 2024).

Logistics is a highly time and type-dependent activity, which makes it essential to quantify the spatial-temporal behavior of logistics vehicles. This analysis provides a baseline assessment for identifying potential misalignments between planning and the ongoing realities of urban logistics operations. Specifically, it can establish the foundation for understanding logistics vehicles' spatial and temporal claims at the city, neighborhood, and street levels. Building on Veld's work on dwell time, Barendregt's work in curbside management, and Holguin-Veras's study on freight-efficient land use, this research aims to extend these analyses to quantify logistics spatial behavioral patterns and understand how they interact with the built environment and urban morphology. The results can then inform interventions and policies to manage and minimize logistics vehicle spatial claims (Holguin-Veras et al., 2021).

1.1 Background and Problem Description

Global urbanization has accelerated over the past century, resulting in larger and densely populated urban areas. These trends have reshaped urban structures and created new demands on urban space, which leads to pressures and competing spatial claims. Additionally, demographic trends have created new pressures on urban planners, infrastructure, and services, which directly and indirectly impact logistics operations as growing populations not only increase pedestrian and private vehicle traffic but also logistics activities in dense, mixed-use urban areas. Effective urban logistics management requires systematic "*examination, planning, maintenance, and improvement of the logistics activities*" to enhance urban livability (Behrends, 2011; Büyüközkan & Ilıcak, 2022). Increased vehicle activity results in traffic congestion and other urban nuisances, including higher levels of air and noise pollution (Ewbank, Vidal Vieira, Fransoo, & Ferreira, 2020).

Within this environment, the rapid rise of e-commerce is prompting a redesign of urban logistics patterns and city planning (Allen et al., 2018). These changes concern last-mile delivery, fleet size, demand patterns, and people's expectations regarding delivery and thus will inevitably reshape the spatial dynamics and mobility patterns of cities. This place demands on both the logistics sector and urban planners seeking to balance logistics needs with other livability objectives of cities. As previously noted, the need to accommodate logistics functions in urban planning frameworks has often been overlooked, even in dense urban areas where people rely on logistics for essential services and amenities. This oversight ignores the reality that freight activities are of tremendous, if sometimes hidden, significance to efficient urban planning and smooth traffic flows (Rodrigue, Dablanc, & Giuliano, 2017).

From a street-level perspective, the reality is that today's urban infrastructure was not designed with urban logistics needs in mind, particularly in historic and established urban cores. Instead, this existing infrastructure has had to accommodate the intensifying logistics activity under highly constrained conditions (Dalla Chiara & Goodchild, 2020). As a result, delivery vehicles increasingly compete with pedestrian activity, commercial ride-hailing services, and public transit vehicles. All of this means that urban curb space is a scarce resource that is increasingly

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in demand (Dalla Chiara & Goodchild, 2020, p. 26). This competition can result in mismanagement and increased friction, making the integration of logistics demands into urban planning frameworks essential for minimizing the negative externalities of logistics vehicles. While some recent urban development and redesign projects are incorporating logistics considerations (especially in Europe and North America), in most cases planners continue to prioritize walkability, mixed-use areas, and public space aesthetics at the expense of logistics operations (Quak et al., 2024).

Logistics vehicle operations face challenges beyond just increasing demand, such as sustainability initiatives. The moves toward electrification, zero-emission zones, and electric vehicles may reduce greenhouse gas emissions; however, evidence suggests that logistic operators are simply replacing existing combustion vehicles with electric vehicles on a one-for-one basis (Barendregt, 2023). Notably, *"goods movements are largely indifferent to the internal structure of cities."* Instead, logistics operations "*adjust to the city environment and its many constraints (congestion, narrow streets, physical obstacles of all sorts, etc.)*" (Dablanc, 2007, p. 281-282). This highlights the importance of a comprehensive street network design, since, without it, growing demand will only create additional inefficiencies and further disrupt broader traffic flows.

While electric vehicles contribute to environmental goals, they fail to address the physical spatial demands associated with logistics vehicles. There are still the spatial demands of logistic vehicles' effects on urban land use and livability, from blocking traffic to occupying valuable curb space and encroaching on bike lanes and public areas. While logistics operations are increasing in downtown areas, evidence indicates less activity at traditional delivery hotspots on cities' periphery (Heijdeman, 2018). Nor is there an expectation that this situation will become more manageable in the future in terms of kilometers traveled, demand for curb space, or spatial claims in general.

Urbanization pressures have heightened focus on various aspects of the urban logistics challenge, from population and demographic changes to on-demand last-mile delivery and the establishment of zero-emission zones. While there are commonalities, cities around the world vary significantly in their physical structure, population density, and how they approach urban planning challenges. In turn, these differences affect the specific urban logistics challenges present in different types of cities. For example, compare the sprawling cities across North America to the densely populated urban environments found in Europe. In Paris, a densely populated and historic city, there is limited space, which leads to intense competition between logistics vehicles and other urban users (Dablanc & Bexiat, 2015). This contrasts with cities like Los Angeles, where a car-centric design and extensive sprawl create their own set of very different logistical challenges (Dablanc, 2011). Furthermore, cities across Asia, South America, and Africa are quite diverse in their infrastructure, in part because of rapid urbanization. The Netherlands is not only one of the most densely populated countries, but its urban structures vary from its historically compact cities to those designed in the modernist, car-centric era (Quak et al., 2024). From an analytical perspective, this diversity is useful because it highlights not only the intensity of the logistics-

related spatial frictions in densely populated cities but also in more car-centric urban areas, making the Dutch context a transferable framework to other urban areas.

Urbanization leads to more densely populated cities. This is measured using population density, which is the number of people per square mile. According to the European Union (2014), the classification of a highly dense urban area is defined by "*contiguous grid cells of 1 square kilometer with a density of at least 1,500 inhabitants per square kilometer and a minimum population of 50,000*" (p. 6). In the context of the Netherlands, more than ten cities consistently meet these criteria, with 44% of the Dutch population living in highly dense urban areas (European Union, 2014, p. 11).

Understanding how logistics operations interact in specific urban contexts is critical to aligning supply and demand. Inefficiencies currently relate to and depend on urban morphology, a field of study that involves quantifying cities' physical layouts, built environments, and social demographic patterns, among other aspects, to understand the structure of urban spaces (Biljecki & Chow, 2022). As Barendregt and Veld both argue, factors such as density, neighborhood type, and land use shape how logistics vehicles operate and how much space they claim (Barendregt, 2023; Veld, 2024). Understanding the connections between urban morphology and logistics is important to identifying the causes of logistical hotspots and spatial management challenges.

The temporal dimension is important because the effect of morphology on vehicle behavior can vary throughout the day due to the fluctuations in retail, commercial, or residential activities. These spatial-temporal dynamics directly affect the neighborhood and block spatial configurations from curb occupation and peak and off-peak delivery hours, which translate into varying spatial-temporal demands influenced by urban characteristics, land use, and operational requirements. Current evidence indicates a misalignment between the configuration of public spaces and the needs of their users, which creates friction in the urban environment (Gardrat & Serouge, 2016). And the lack of spatial integration, partly because of limited transparency in spatial governance, leads to logistics operations claiming more urban space with little accountability, thus leading to logistics operations adapting to urban configurations that were not designed with them in mind, creating ripple effects across a city's street network (Coenen et al., 2023; Holguín-Veras et al., 2021). This problem is exacerbated by urban cores' dense, mixed-use nature and intense competition for curb space, constrained operating areas, and restrictions on logistics operators. For example, in the Netherlands alone in 2019, "*more than 1250 formal complaints were made about urban logistics drivers, including dangerous driving and improper stopping*" (Barendregt, 2023, p. 2). Adding the temporal scale to analysis enables a better understanding of how spatial claims change dynamically, providing better insight into the behavior and impact of logistics vehicles. Thus, logistics considerations should be systematically incorporated into cities' spatial, temporal, and morphological frameworks rather than only being addressed retroactively, which would promote the creation of a human-centered urban environment that can accommodate rising levels of logistics activity.

It may be tempting to address these issues by restricting logistics vehicle operations, thereby reducing traffic flows. However, the fundamental problem is the traditional lack of attention to

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logistics vehicles' spatial and temporal requirements. Trying simply to reduce logistics traffic leaves the negative externalities arising from their spatial claims on the urban environment unaddressed (Dablanc, 2011; Jaller, Holguín-Veras, & Hodge, 2013). Thus, as the world becomes increasingly urbanized, observers anticipate that logistics vehicles will continue to be a significant source of traffic within cities (Bachofner, Lemardelé, Estrada, & Pagès, 2022). Thus, while policymakers may be concerned about pollution and congestion, they should place equal weight on accommodating logistics vehicle operations in urban spatial planning and governance. Without such a study, the negative externalities will persist and grow, disrupting the urban fabric and creating additional inefficiencies.

1.2 Research Objectives and Questions

In dense urban areas, spatial-temporal friction occurs lead to congestion, delays, and spatial conflicts (ITF, 2022). To address these problems, the objective is to study the spatial-temporal footprint of logistics activity and use analytical results to support research on how logistics operations interact with the built environment. While the environmental performance of urban logistics has improved substantially thanks to EVs and the low-emission zones popular in Dutch cities, there remains a limited understanding of the spatial-temporal dimensions of freight operations, particularly in urban planning frameworks (Quak et al., 2024; Holguin-Veras et al., 2021; Kin & Quak, 2024).

The research objective is to leverage spatial analysis and urban morphological data to quantify the impact of logistics vehicles on the urban realm, providing a baseline for future efforts to not only decrease logistics vehicle impacts but also improve the livability of urban spaces. A critical challenge is the fact that the interaction of logistics vehicles with the urban environment is highly dynamic and influenced by many aspects of street design, from width requirements to land use (Girón-Valderrama, Machado-León, & Goodchild, 2019). And these interactions thus affect the street-level urban life through the spatial conflicts they generate.

Understanding the spatial-temporal footprint of logistics vehicle operations involves multiple variables beyond just population density. While most research leans on population as a primary predictor of logistic activity, the importance of urban morphology as a predictive tool is growing in awareness to address such limitations (Alho & Silva, 2015; Jaller, Holguín-Veras, & Hodge, 2013). This research will examine current urban environmental conditions and their connection to the spatial claims of logistics vehicles. Using a geographically-based analytical framework, the study will quantify the logistics footprint across space and time and relate it to morphological indicators. Through modeling, it will also explore how morphology can explain logistic patterns in Dutch cities by comparing three cities. The research aims to develop strategies and guide targeted interventions and potential policy innovations by analyzing the spatial-temporal claims of logistic vehicles across different urban morphologies. Urban morphology is the study of the physical form of urban environments and how these interact with the socio-demographic features that shape urban life. Although focused on the Dutch urban context, the research critically examines the broader applicability of the methodology beyond the Netherlands.

Thus, the main research question to be addressed is as follows:

> *How does urban morphology, through its physical and socio-spatial indicators, explain the spatial-temporal claims of urban logistics vehicles?*

To answer this overarching question, we will address three subordinate questions, including:

- HOW DO SPATIAL AND TEMPORAL HOTSPOTS OF LOGISTICS VEHICLES INTERACT WITH URBAN MORPHOLOGICAL INDICATORS ACROSS TIME FRAMES?

- WHICH URBAN MORPHOLOGICAL INDICATORS (E.G., ROAD WIDTH, LAND USE, BUILDING DENSITY) CORRELATE MOST SIGNIFICANTLY WITH LOGISTICS VEHICLES' SPATIAL-TEMPORAL CLAIMS?

- WHAT CAN A PREDICTIVE MACHINE LEARNING MODEL SHOW ABOUT THE RELATIONSHIP BETWEEN URBAN MORPHOLOGY AND THE SPATIAL–TEMPORAL LOGISTICS INTENSITY?

The structured approach will improve the field of urban logistics research related to land use, urban land management, and spatial planning frameworks, along with other innovative methods such as curbside digitalization, sustainability regulations, and electrification. It provides a robust spatial methodology for context-specific urban logistics planning.

1.3 Scope of Study

The research examines how urban morphology influences the spatial-temporal claims of logistics vehicles. Its goal is to develop and apply spatial analytical tools to reduce the burdens of logistics vehicle operations, thereby promoting human-centric urban planning and logistic operational efficiency. The analysis will focus on the contemporary Dutch urban context, where compact historical spatial patterns, mixed-use development areas, urban densification, and zero-emission zones generate increasing challenges for logistics vehicle operations (Quak et al., 2024; Kin & Quak, 2024).

This research employs an empirical quantitative spatial analysis approach driven by the research question to explore how urban morphology explains logistics vehicle operational patterns. The analysis concentrates on three Dutch urban environments, Amsterdam, Utrecht, and Rotterdam, which were chosen due to their contrasting morphological conditions, their close geographic proximity within the Netherlands, and the availability of datasets covering both urban morphology and logistics operational activities. Each area is examined using a multi-spatial scales approach, from the macro urban level down to the neighborhood and street block levels. The multi-level framework allows for the identification of urban morphology influences that operate at different spatial scales, which in turn supports the development of targeted interventions to reduce the externalities caused by logistics traffic.

Amsterdam, the largest city in the Netherlands, serves as the primary case study to develop a detailed data-driven understanding of the relationship between urban morphology and logistics patterns, including aggregated traffic flows and intensity over space and time, as well as individual vehicle stopping behavior related to dwell time and curb usage at specific spatial and temporal points. As the training diagnostic study, the results from Amsterdam provide the framework for understanding why certain areas experience higher logistic intensity than others. This quantified correlation between urban morphology and logistic intensity provides evidence-based insight. The Amsterdam analysis is used to evaluate how urban morphology explains operational dynamics across different Dutch cities (e.g., Utrecht and Rotterdam). However, variations in Amsterdam alone can surpass the differences observed with other cities. The unique Dutch postcode 6's classification enables detailed street-level analysis, providing a deeper understanding of patterns across an entire city. Integrating this data with morphological indicators and operational datasets allows for the quantification of urban morphology and the related spatial-temporal claims of logistics vehicles.

Understanding logistics behavior within the context of urban morphology advances spatial planning. It informs solutions to develop livable urban environments, especially with the rapid urbanization and increasing last-mile delivery traffic flows. This effort aims to raise awareness of how urban morphology analysis can serve as a tool to understand the current state of urban dynamics and logistics frictions, as well as serve as a predictive instrument for urban logistics planning and space allocation decision-making.

1.4 Academic and Societal Relevance

As cities experience growing urbanization, densification, and logistics activities, they must update their spatial planning tools and frameworks to align with human-centered design goals. This research addresses academic and societal needs by bridging the gap between the spatial-temporal dynamics of logistics vehicles and the use of urban morphology.

1.4.1 Academic Relevance

From an academic perspective, the research aims to address the gap in the literature by integrating urban morphology into the spatial and temporal analytical framework of logistics operations. Existing research often prioritizes mitigating environmental externalities, such as emissions, while overlooking spatial impacts. Some studies seek to address this gap, such as those aimed at quantifying logistics vehicles' spatial-temporal claims through research on dwell time reduction (Dablanc, 2011; Kin & Quak, 2023; Veld, 2024). In an academic field primarily focused on environmental concerns and population density, this research advances the discussion of how best to integrate spatial analysis of urban morphological indicators to better understand the spatial-temporal footprint of logistics vehicles. Spatial-based modeling enables the systematic identification of logistics points of friction and offers granular spatial insights into vehicle behavior, addressing the research gap in logistics frameworks and providing a predictive model for policy and interventions (Kin & Quak, 2024).

Building on research about dwell-time analysis, curbside management, and efficient land use for logistics, this study examines the relationship between morphological indicators and logistics behavior. It employs a framework of morphological analysis as an evidence-based predictive tool that can support policy decisions (Veld, 2024; Barendregt, 2023). As technological innovation and logistics demands grow, methodological advancements provide a stronger basis for incorporating spatial modeling into urban planning.

1.4.2 Societal Relevance

From a societal perspective, this research examines key challenges impacting urban livability and logistic efficiency. Today, global commodity flows touch every dimension of urban life, making it an issue of significant importance that impacts livability, safety, and equity in urban environments. The logistics-related challenges are driven by increasing congestion, traffic, greenhouse gas emissions, and spatial conflicts (Dalla Chiara & Goodchild, 2020).

Furthermore, the ongoing frictions affect multiple stakeholders, from private vehicles to public transportation systems, pedestrians, cyclists, and businesses. This highlights the importance of reducing the negative externalities of urban logistics. Public concern is growing regarding the pressure urban logistics places on the environment. With urban logistics *responsible for 25% of urban transport-related CO2 emissions and 30 to 50% of other related pollutants,* there are significant challenges in the public domain (ERTRAC, 2020, p. 5). Additionally, 60% of EU citizens view urban congestion and air quality as major issues (European Court of Auditors, 2019). Therefore, from a public perspective, the growing impact of urban logistics is becoming a key topic of debate.

The research objective is to provide recommendations to transform urban logistics practices and effectively reduce the spatial competition caused by logistics vehicles' activity. By quantifying the impact of the urban environment, we can inform targeted interventions and policies that promote more human-centric and sustainable designs aligned with overall societal objectives, both within the Netherlands and globally (Kin & Quak, 2024).

1.5 Essay Outline

This research project comprises seven sections: introduction, literature review, concept and methods, data, results, and discussion and conclusions.

The Introduction addresses the spatial challenges of urban logistics operations within densifying cities and examines the increasing spatial conflicts caused by logistics activities. It highlights the main research gaps related to the spatial-temporal claims of logistics.

The Literature Review (chapter two) establishes the theoretical foundation for the study by examining previous conceptual and empirical work related to urban logistics operations, morphology, and spatial-temporal dynamics. It also highlights critical research gaps and situates the study within the broader academic landscape.

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The Concept and Methods section (chapter three) outline the research's methodological and analytical framework and explains how spatial analysis, predictive modeling, and spatial regression tools contribute to the research objectives.

The Data section (chapter four) details the empirical foundation of the research by introducing the spatial, morphological, and logistics datasets used in the study. It describes the case study selection, data sources, and the standardization procedures applied to ensure comparability across variables.

The Results section (chapter five) presents the empirical findings of spatial-temporal analysis and case study. The chapter includes a baseline analysis, geospatial hot spot mapping of logistics activities, regression modeling, and machine learning simulations to compare the diverse urban morphologies of different cities and their predicted logistics flows.

Finally, the Discussion and Conclusions section (chapter six) explores the theoretical and practical implications of the research findings. It highlights the predictive value of urban morphology as an analytical tool and outlines the study's contribution to urban logistics research, acknowledges its limitations, and suggests directions for future research.

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Chapter 2

Literature Review

2.1 Interactions between Urban Planning and Urban Logistics

Urban planning and urban logistics are inherently intertwined with logistics operations, influencing a city's spatial and social dynamics (Buijs & Rauws, 2024). However, traditionally, urban planning and logistics management have not been well aligned and have led to inefficiencies and friction between logistics operations and the urban environment. And this occurs despite the growing significance of logistics in the fabric of urban life. Nevertheless, considering urban logistics movements is essential for minimizing their negative externalities. Therefore, addressing this disconnect is especially important as cities continue to densify and grow, requiring a deeper understanding to develop a more sustainable, human-centered urban environment.

Urban logistics is a complex and inherently multidisciplinary field that considers environmental, societal, and economic factors. Contemporary urban logistics focuses on "*optimizing the logistics and transport activities by private companies with the support of advanced information systems in urban areas considering the traffic environment, the traffic congestion, the traffic safety, and the energy savings within the framework of a market economy*" (Taniguchi, 2014, p. 311). This contrasts with the more narrowly defined field of urban freight, which focuses specifically on "*all movements of goods into, out from, through, or within the urban area made by light or heavy vehicles, also including service transport*" (Alice, 2021). While urban freight focuses on the actual movement of goods, logistics encompasses the overall system and the complex strategies that surround it. Critically, it is about understanding the complexities of urban logistics and its role in a city's economic and planning framework (Dablanc, 2011).

2.1.1 Historical Context of Urban Logistics in Planning

Urban logistics systems are the backbone of cities, managing the movement of goods and services within specific geographic areas to sustain urban life (Coenen et al., 2023). At its core, every economic activity has a related freight generation profile since cities are "places of consumption, production, and distribution of material goods" (Rodrigue & Behrends, 2018, p. 3). At the same time, urban logistics is part of the global transport distribution network that satisfies consumers' material and service demands through suppliers and intermediaries. This urban supply chain influences all aspects of urban life, from consumer-driven retail, food deliveries, parcel services, home services, and city management to everything in between (Rodrigue & Behrends, 2018; Andruetto, Stenemo, & Pernestål, 2024).

Furthermore, logistics behavioral patterns depend on their functional type, which, in turn, determines their spatial-temporal impact. These are categorized as consumer-related, such as home delivery (e.g., food and material goods), in contrast to producer-related activities, including industrial and terminal haulage (Rodrigue & Dablanc, 2014). There is an interactive relationship between logistics and urban development, as logistics operations both reflect society's economic and technological advancements while also influencing the shape of the urban form.

Traditionally, cities have been connected through critical trade routes, an early form of urban logistics (Rodrigue, 2024). Nevertheless, despite their long history and importance, urban logistics "remains an afterthought in general urban planning" (Shrestha, Haarstad, & Rosales, 2024, p. 1). Traditional urban planning has prioritized accommodating other transportation users: private vehicles, pedestrians, cyclists, and public transport systems and as such, conventional design priorities often focus on "*streets as thoroughfares for traffic and measure their performance in terms of speed, delay, throughput, and congestion*" (NACTO, 2012, p. 6). The emphasis is on movement flow rather than on how space is occupied. This is significant because it forces urban logistics to adapt to urban spaces not designed to accommodate such activity, leading to negative externalities, and exists as a secondary concern for many urban planners (Dablanc, 2007). When logistics operations are considered, they tend to be managed primarily through traffic regulatory measures, such as time windows and low emission zones. As a result, the knowledge of how to effectively (re)integrat[e] logistics within urban planning remains "hardly available" (Kin & Quak, 2024, pp. 130-131; Kin, Buldeo Rai, Dablanc, & Quak, 2024, p. 24). This disconnect stems from the fragmentation between logistics and urban planning domains, governance structures, and competing priorities within urban planning.

As urban development progresses, the importance and role of urban logistics have changed substantially, shaped by broader socio-economic and planning factors. The shift from the industrial revolution's point-to-point services to the post-industrial era's hub-and-spoke networks resulted in logistics sprawl. This sprawl conflicts with the principle of proximity logistics. It both increases travel distances and triggers the need for more complex spatial and operational coordination, which introduces complexity, emissions, and congestion (Rodrigue, 2024; Dablanc, Ogilvie, & Goodchild, 2014; Aljohani & Thompson, 2016; Kin, Buldeo Rai, Dablanc, & Quak, 2023). Such challenges highlight the importance of integrating logistics considerations into urban planning frameworks in the post-industrial automotive age, a field that continues to be neglected in planning processes (Dalla Chiara & Goodchild, 2020).

Efforts to integrate logistics into urban planning have emerged in response to increasing spatial and temporal frictions. However, common solutions like electrification or low-emission zones are unlikely to significantly reduce the spatial footprint of logistics operations (Kin & Quak, 2024; Holguín-Veras et al., 2021; Barendregt, 2023). Freight-efficient land use serves as a starting point for rethinking urban logistics strategies, since they aim to "*minimize the social costs (private plus external costs) associated with both the supply chains and the economic activities that consume and produce goods, at all stages of production and consumption*," thus streamlining the flow of goods (Holguín-Veras et al., 2021, p. 6). This approach is valuable, but it requires a deeper understanding of logistics patterns within the spatial context.

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At the European level, policies and frameworks for integrating sustainable logistics into urban planning are gaining more attention. For instance, a 2011 White Paper proposes a strategy for "near zero emission urban logistics by 2030," along with the subsequent "*Urban Mobility Package, the Low Emission Strategy of 2016, and the three Mobility Packages of 2017 and 2018,*" all of which encourage greater awareness of urban logistics in future urban planning processes (EGUM, 2024, p. 6). Historically, urban logistics management has been approached from an "exclusively historical or engineering" perspective. However, there is a growing understanding that studying urban logistics necessitates a "holistic-complete approach…multi-scientific and multidisciplinary" approach in today's urban context to effectively manage the ever-growing urban logistics sector (Andreea-Eva & Ioan, 2020, p. 1).

2.2 Urbanization Impact on Urban Logistics

Urbanization is causing significant challenges, affecting transportation systems, logistics, and the built environment. The 17 Sustainable Development Goals adopted by United Nations member states in 2015 offer critical tools for measuring and tracking population changes and their impact (U.N. Secretary-General, 2024). The goal of the framework is to address global population and environmental problems while creating cities that are environmentally and resource-aware. As of 2007, urban migration has resulted in over 57% of the global population residing in metropolitan regions (Ritchie, Samborska & Roser, 2024; McKinsey Global Institute, 2011). The definition of urban areas varies by population density. For Europe, the focus of this study, these groupings include "*1) cities, 2) towns and semi-dense areas, and 3) rural areas.*" In Western Europe, approximately 35% of the population currently lives in cities, 33% in towns and semi-dense areas, and 33% in rural areas (Dijkstra et al., 2020, p. 5). With 68% of its population currently living in cities or towns, Western Europe has one of the highest urbanization rates in the world. This figure is expected to reach 83.7% by 2050 (European Commission, 2020), creating economic opportunities but also posing challenges for urban planning given the physical limitations of urban spaces.

Rapid urbanization alters the landscape of cities and creates challenges for urban logistics. As populations expand and become more concentrated, they generate ever-increasing demand for goods and services within constrained physical spaces (World Bank, 2021). While urbanization can positively affect logistics (e.g., by reducing "per capita energy consumption"), it also places pressure on constrained spatial resources, producing congestion and inefficiencies (World Bank, 2021, p. 7). Furthermore, these changes also bring heightened spatial competition, environmental sustainability concerns, and service efficiency issues in mixed-use and public spaces (Quak et al., 2024; Allen et. al., 2018). Cities serve as epicenters for consumption and distribution, as well as centers of production for goods, services, and innovation (Hatuka & Ben-Joseph, 2022). Such activities create different logistical spatial-temporal claims for service and goods delivery, distribution operations, or the starting point for production (Sander et al., 2019). Logistics operations must contend with and adapt to the ever-changing urban environment while facing the physical constraints of the street's infrastructure.

Previous research has noted that increased logistic activity contributes to congestion, negative environmental externalities, and the degradation of urban quality of life (Rodrigue & Dablanc,

2014). Thus, spatial competition increases with logistics activity, which is often displaced to prioritize residential and commercial development within the competitive urban environment (Pritchard & Martinez, 2024). The rapid growth of e-commerce and on-demand services has only exacerbated the already challenging logistics environment, with estimates suggesting that business-to-consumer deliveries now account for most shipments and deliveries (Holguín-Veras et al., 2021). The spatial constraints of densely populated urban areas further exacerbate the challenges, given the footprints of delivery vehicles, dwell times, and limited space for logistics facilities (Quak et al., 2024). Moreover, varied land use patterns highlight the need for context-sensitive urban planning to accommodate essential logistics activities within the urban environment effectively. Thus, the effects of urbanization are twofold, as it boosts logistics demand while also imposing constraints on the physical environment. These twin forces accentuate the need to incorporate logistics into spatial and policy frameworks.

2.3 Spatial-Temporal Dynamics of Logistics Vehicles

In establishing a foundational understanding for this study, it is necessary to grasp the theoretical concepts of the spatial and temporal dynamics of urban logistics within the built environment. Maneuvering patterns, stop planning, loading and unloading activities, and varying delivery windows create distinct spatial-temporal demands that lead to conflicts in the urban environment. Logistics vehicles operate in highly dynamic, constrained environments, and their spatial-temporal activities create external effects on the urban fabric of cities.

2.3.1 Logistics Patterns

The urban context drives the behavior of logistics vehicles, with operating efficiency influenced by factors such as delivery scheduling, vehicle types, and parking/staging availability, along with a variety of unpredictable elements. Moreover, logistics stopping practices drive the intensity of vehicles' spatial claims and offer metrics for measuring operational efficiency. The behavior of logistics vehicles is also affected by the larger urban environment, from regional driving patterns to stop light timing and urban density. As such, common driving behaviors, including acceleration patterns, speed, and unpredictable maneuvers, pose additional spatial-temporal risks for logistics operators (Tselentis & Papadimitriou, 2023). Importantly, these spatial-temporal issues will persist even with the introduction of electric vehicles.

The study by Tselentis & Papadimitriou (2023) reviewed Artificial Intelligence and Machine Learning approaches used in understanding driving patterns. For data analysis, 20 driver profiles and 26 driving patterns were utilized. Using clustering and neural networks, this study identifies driving patterns in relation to internal and external measurements, including the urban environment. This process creates a traffic model specific to the driver. The study not only provides a macro-micro machine learning framework to inspire this research but also builds on traffic analysis and its modeling.

The form of the built environment further shapes logistics operational patterns. Factors such as the location of building entrances, retail store types, availability of loading areas, and local populations dictate where operations can occur (e.g., on or off street, in public spaces, etc.)

(Butrina et al., 2017). Moreover, urban morphology should consider more than just a space's outward design; it can include factors such as floor count, average building density, building type, and building age, all of which significantly influence logistics operations. In street designs, particularly in mixed-use areas, elements such as cafés, terraces, benches, and planters should be incorporated, as they can also influence where legal logistics activities can occur (Escand, Chen, & Conway, 2018). It is also important to remember that urban morphology influences dynamics temporally, as adjacent land use can shift throughout the day and is therefore a dynamic and flexible approach for understanding urban logistics in a spatial and temporal sense.

Likewise, delivery frequency also influences spatial-temporal dimensions, as each vehicle creates a new spatial claim. Thus, the higher the drop density, number of deliveries completed in a specific area, the more clustered the deliveries, enabling drivers to make more stops in less time. However, this may also indicate that failing to effectively reduce inter-drop distances between delivery points, along with higher volumes of delivery requests and frequent short stops, can lead to additional disruptions (Veld, 2024). Note the research finding that "*deliveries that were delivered to multiple…destinations within a building had longer dwell times*" compared to single destination deliveries (Kim, Goodchild, & Boyle, 2021, p. 329). However, fewer physical vehicle stops will occur within given timeframes and areas. Similarly, urban landscape characteristics influence spatial claims: "*Shopping centers had a higher percentage of off-street parking facilities, whereas local shops tended to have more on-street parking*" (Kim, Goodchild, & Boyle, 2021, p. 329).

The research by Kim, Goodchild, & Boyle (2021) examined vehicle behavior and the challenges of optimization related to parking and dwell time in Seattle, Washington. The study used field data from five different building types to perform an empirical analysis of 157 delivery operations cases. Additionally, it developed a generalized linear regression to understand the factors influencing dwell time. Moreover, Veld (2024) studied spatial interventions as they relate to reducing dwell time in logistics operations. The goal was to enhance sustainability and livability within urban spaces. A case study analysis was conducted in Amsterdam and Utrecht through three district logistics operators. Using the collected data, geospatial analysis and regression analysis were performed to examine potential scenario impacts. Critically identified were the key determinants of dwell time, scenario insights, and proposals for operational efficiency. These studies serve as a framework for understanding how logistics operate in urban environments and for developing the geospatial-centric framework for this research.

From a sustainability perspective, spatial analytics can map environmental impacts and help to optimize logistics activities to minimize adverse effects. Thus, spatial-enabled environmental management efforts can be used to identify problem areas and help target interventions. For example, the case of Lisbon's spatial-based routing initiative, conducted by Schröder & Cabral (2019), illustrates how spatial-driven analysis of data on the built environment can reduce vehicle fuel consumption. They found that "*eco-friendly routes [it] can yield significant fuel and emission saving potentials of up to 20%*" (p. 1). Beyond vehicles, spatial optimization can also be applied to facility location for micro-hubs and distribution centers, which is exemplified by the H2020 SENATOR project's Urban Living Lab in Dublin. This effort employed spatial

analysis to identify potential optimal logistics locations based on proximity to demand clusters and potential environmental impacts (Urban Living Labs, 2020).

2.3.2 Logistics Temporal Fluctuation and Mismatch

Urban logistics operations fluctuate over time, often creating mismatches as these activities interact with urban spaces throughout the day. These fluctuations reflect the demands of logistical efficiency, operator preferences, and regulatory frameworks. When analyzing curb space demands, variations in spatial claims across a 24-hour cycle highlight the importance of adaptive planning. For example, logistics activity typically peaks during specific periods, such as early morning, corresponding with pre-business hours and municipal delivery windows. However, these periods often create additional conflicts in urban centers due to concentrated activity levels (Gemeente Amsterdam, 2025; Gemeente Rotterdam, 2025; Gemeente Utrecht, 2025). While these times may represent peak hours, not all operations fall within these designated time windows, and even if they do, the available physical space often cannot fully accommodate peak period demand (Jaller, Holguín-Veras, & Hodge, 2013). As Jaller, Holguín-Veras, & Hodge note, with an assumed average "truck parking space length of 33 ft," research shows that "demand is more than two times the capacity" (p. 49). Allocating space for every vehicle during peak hours would create a severe temporal allocation mismatch during off-peak times, when far less curb space is required (Jaller, Holguín-Veras, & Hodge, 2013). The rise of e-commerce has only intensified these challenges as catering to consumer preferences creates additional sources of temporal variations.

Jaller, Holguín-Veras, & Hodge (2013) expand their analysis of these spatial-temporal mismatches in urban space. The objective of their research is to address the demand for parking and the supply of space. This is achieved through modeling methodologies that encompass trip generation, spatial-temporal and scenario analysis, and the use of surveys as an explanatory resource. Modeling-based research and the development of a spatial-temporal evaluation further support operational research, which informs the integrated approach to morphological analysis used in this paper.

Local streets are critical for last-mile deliveries, but their limited capacity and restricted parking often force delivery vehicles to park illegally, thus blocking traffic and causing tension with local users. These conflicts are unavoidable for efficiency-focused operators because road classification frameworks and spatial-temporal allocation systems, such as those on local streets, force a trade-off between mobility, accessibility, and efficiency. In these hierarchical systems, freeways and arterials facilitate logistics movement, while collectors and local streets focus on actual delivery and service operations with direct curb access. (SUDAS, 2014).

The spatial footprint of logistics vehicles, influenced by the urban environment, changes throughout the day and varies by area, indicating that there is no one-size-fits-all solution. This leads to logistics activities occurring in areas not designed for them, creating overlapping and conflicting claims with urban life. The resulting temporal misalignments generate external impacts, contributing to congestion, scheduling inefficiencies, and adverse stopping behaviors. All of these generate spatial spillover effects. Approaching logistics operations through an

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integrated planning framework that considers spatial-temporal dimensions can promote more effective allocation of urban spaces.

2.4 The Externalities of Urban Logistics

Efficient urban logistics systems are critical for cities' functioning and economic prosperity; however, complex and often unintended consequences arise from logistics operations. These externalities depend on a city's urban form, levels of demand, and existing infrastructure, making it critical to understand points of contention when designing suitable interventions.

2.4.1 Spatial Externalities

Urban logistics operations are projected to increase significantly within dense, mixed-use, high-demand areas where physical space is highly constrained. Within this context, the spatial claims of logistics vehicles encompass multiple dimensions, including location, routes, and stop frequency. Previous research reveals that logistics vehicles make "37 stops on average" each day, with "95% being on-street" space, highlighting the critical dependence of these operations on this limited resource (Allen et al., 2018). As the presence of logistics vehicles grows, so too will their spatial demands.

Research by Allen et al. (2018) aimed to understand the impacts of e-commerce-driven, last-mile vehicle activity within the urban realm of London. The objective of the study was to understand the pressures on last-mile logistics operators and optimization strategies needed to reduce their negative externalities. The study used a road traffic trend analysis with a case study of parcel delivery operations, utilizing GPS tracking and surveys. The data collected was used to model the impacts of logistics vehicles on congestion, emissions, and delivery operations. The researchers found that, in the UK, e-commerce is becoming a major driver of logistics activity, now accounting for 80% of goods movement in London. Building on research by Allen et al. (2018) on mixed-use and high-demand areas in central London, spatial analytics was used as a key tool to understand the complex spatial and temporal dynamics of urban logistics.

Spatial analytics has been used to analyze land use patterns, traffic data, transportation networks, and route optimization, processing geospatial information from various sources. Research shows that spatial analytics used in transportation logistics has led to a 30% reduction in delivery times, a 15-20% decrease in fuel costs, and improved vehicle maintenance and customer satisfaction (Wu, 2025). Thus, integrating spatial analytics into Allen et al. (2018) traffic analysis enables the development of traffic models that identify congestion points and generate alternative routes to minimize emissions and dwell times. By visualizing such traffic flows, spatial analytics helps identify congestion hot spots, infrastructure challenges, and traffic dynamics.

Logistics operations utilize a broad spectrum of vehicle types depending on cargo characteristics, delivery context, and operating constraints. Barendregt (2023) categorizes various vehicles for general and fresh cargo deliveries, ranging from tractor-trailers and box trucks to cargo bikes, with home deliveries typically employing "box trucks and delivery vans or cargo bikes" (Barendregt, 2023, p. 10). Smaller vehicles are standard in the parcel and express sector,

particularly for online shopping fulfillment. Service and facility logistics, meanwhile, have their own specific requirements, with delivery vans being most common. However, they also have their own heterogeneous profiles, which comprise anywhere from "10% to 41% of all urban freight transportation" (Barendregt, 2023, p. 11). This variation in vehicle usage impacts spatial-temporal behavioral patterns in urban areas, thus affecting space demand throughout the day.

The research by Barendregt (2023) aimed to understand the intersection of urban planning and logistics by studying the possible mitigation of curbside externalities through a stakeholder focus framework. The framework employed a mixed methods approach, focusing on stakeholder interviews and surveys to understand real-world practices. Crucially, it was found that typology is important in the spatial and temporal activities of logistics. Inspired by Barendregt's thesis work, the understanding of the typology of the spatial and temporal aspects of logistic vehicles is being extended.

As Kropf & Malfroy (2013) define it, the analysis of typology and urban morphology is traditionally defined as "*the study of the built form of cities, and it seeks to explain the layout and spatial composition of urban structures and open spaces, their material character and symbolic meaning, in light of the forces that have created, expanded, diversified, and transformed them*" (p. 128). However, over time, the concept of urban morphology has evolved, with studies increasingly characterizing urban morphology as the analysis of a city's physical form and human life, shaped by social, demographic, and economic dynamics (Benini, de Godoy, & da Silva 2024; Biljecki & Chow, 2022). From a logistics perspective, urban morphology influences the spatial and temporal patterns that impact urban logistical operations. This research aims to develop a framework that links urban morphology with urban logistics operations. Since morphological features directly influence the competing spatial-temporal claims, including these considerations is essential to explaining urban logistics patterns.

The impact of logistics vehicles extends beyond their physical dimensions to include broader spatial externalities. These externalities arise as vehicle staging areas relocate to suburban zones and vehicles travel longer distances between their start and end points, further contributing to congestion and traffic spatial claims (Kin, Buldeo, Rai, Dablanc, & Quak, 2024). Logistics vehicles require space for movement and stationary activities, such as stopping, maneuvering, loading and unloading, parking, and other curbside operations. In fact, research indicating that logistics vehicles spend more time stopped than in motion (Gardrat & Serouge, 2016). Furthermore, stationary activities, whether temporary or extended, occupy curb at loading zones, while often have a spatial spillover effect onto sidewalks or bike lanes, etc. when adequate curb space is unavailable.

Kin, Buldeo Rai, Dablanc, & Quak (2024) research focused on integrating logistics facilities to improve efficiency and livability through proximity logistics, which involves logistics activities in city centers. The study uses theoretical sampling and a multiple case design to explore spatial initiatives through logistics dualism, focusing on studies of Rotterdam and Paris. Furthermore, Gardrat & Serouge (2016) research concentrated on spatial dynamics needed for logistics operations and used modeling-based quantification and scenario analysis in understanding spatial

allocation and optimization. The case study uses a supply coefficient to model movements and movement durations and stop type to understand vehicle footprint and thus spatial-temporal element. Combined, these cases provide validation for typology-based analysis and explore the complex spatial-temporal dynamics of logistics.

Beyond descriptive analysis, spatial analytics offers a range of optimization capabilities to assist logistics and urban planning decision-makers. Spatial-temporal analysis tools such as spatial clustering and hot spot analysis can be used to identify the mismatch of space availability over time. Spatial clustering involves understanding spatial distributions and identifying point features, such as vehicle intensity, that are densely distributed relative to the surrounding context (ESRI, n.d). Hot spot analysis identifies statistically significant spatial clusters, including hot and cold spots, as they relate to a specific area of focus using the Getis-Ord Gi* statistic, which determines whether the hot or cold spots are statistically significant (ESRI, n.d.). Proximity analysis enables insights into conflicting and overlapping zones to explore the relationship between one or more feature classes (ESRI, n.d.). Moreover, predictive modeling tools within spatial analytical systems also enable forecasting future conditions under different policies. This can support targeted interventions to minimize the disruptive spatial claims of logistics vehicles. More generally, visualizing trade-offs in land use and space allocation can facilitate the integration of urban logistics into the broader planning field.

Overlapping demands for curb space create competing spatial claims and conflict zones. This is true even when dedicated parking spaces exist, given that they often are insufficient during peak demand periods (Dablanc & Beziat, 2015). Surveys indicate that approximately 50% of delivery vehicle operators report double parking in urban environments, while 60% acknowledge parking illegally (Dablanc & Beziat, 2015, p. 2). Safety conflicts and spatial inefficiencies are created and can vary depending on the urban context, with mixed-use, commercial, shopping, and residential areas presenting different challenges. Managing logistics spatial externalities is also challenging due to the under-regulation of many urban environments. Urban logistics operations frequently exist in a 'gray zone' where carriers use space informally or opportunistically due to insufficient designated delivery infrastructure.

Dablanc and Beziat (2015) studied Paris's parking behaviors and spatial spillover effects through the use of a supply and demand assessment model to analyze logistics areas against estimated daily operations. It mapped these operations by combining spatial and temporal analysis. Overall, the study provided an understanding of spatial and temporal analysis practices, like the morphology-driven approach used in this paper. It demonstrated the spatial and temporal distribution and mismatches that contribute to negative externalities in the urban environment. They found that these spatial misalignments can extend beyond the parking supply to affect the broader network.

Furthermore, spatial misalignments between network classifications and the needs of logistics operations only go to create operational inefficiencies. Through hierarchical network classifications, it can guide traffic flows, prioritize infrastructure investments, and shape urban policy. They organize streets based on geometric features, function, capacity, and connectivity

within the urban built environment (SUDAS, 2014). The widely adopted hierarchical classification system breaks down street networks into highways, arterials (major and minor), collectors (major and minor), local streets, and private streets (SUDAS, 2014). These street classification's structure logistics networks and often create constraints on logistics system operations. Theoretically, the framework of hierarchical street classifications should promote efficiency and clarity regarding the network's function, however, this is not always the case. This is due to a "*complex relationship between the spatial and functional structure of city logistics*," especially regarding the "organization and density of land use" (Rodrigue, 2024). This exacerbates spatial conflicts and generates additional spatial disruption.

2.4.1.1 Hierarchical Street Classification

Hierarchical street classification systems segment the transportation infrastructure and dictate how streets are used. This, in turn, defines the system accessibility and permissible behavioral patterns, particularly concerning vehicle maneuvering activities, access, speed, and curbside use. For example, highways are used for high-speed and long-distance travel, have limited access points, and serve as regional mobility routes between cities. In terms of logistics, these routes offer long-distance travel between hubs and regional distribution centers (SUDAS, 2014; Rodrigue, 2024). Arterial roads enable movement across urban areas that have high traffic capacity. Moreover, major arterial roads facilitate movement in urban areas by bypassing central locations. In contrast, minor arterial roads connect the major arterial road network for intra-community travel without entering neighborhood levels (SUDAS, 2014).

For logistics operations, arterial roads serve as the backbone of urban logistics routes, with their design enabling connections across different zones and thus linking distribution centers and major commercial nodes (Rodrigue, 2024). However, because they are designed for high-volume traffic flows with limited stopping, they offer limited curb access. Collector streets serve as intermediary routes between arterial roads and local streets (SUDAS, 2014). Major collectors serve as transition routes between arterials and minor collectors, facilitating movement between residential and commercial areas with moderate access. Minor collectors connect to local streets within residential, commercial, or other zones (SUDAS, 2014). From a logistics perspective, collector streets facilitate through-traffic travel *and* serve as endpoints for logistics activities. This dual role generates conflicts between traffic circulation and access to addresses (i.e. stopping). Local streets form the foundation of urban street networks, providing direct access to residences and businesses. However, these have their own challenges from narrow widths, on-street parking, and diverse traffic patterns (SUDAS, 2014).

2.4.2 Temporal Externalities

Beyond their spatial dynamics, logistics operations produce temporal inefficiencies relating to the timing and frequency of stops, dwell time, and travel time throughout the week. Temporal externalities are the result of the dynamic nature of logistics operations and the misalignment of delivery schedules with broader urban demands. These stem from the concentration of peak delivery windows, which often coincide with commuting hours, thus intensifying traffic

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congestion (Rodrigue & Dablanc, 2014). Studies have shown that, in some areas, logistics-related traffic can contribute to up to 30% of traffic congestion (Brandy-Philips & Holmes, 2024).

The research by Rodrigue & Dablanc (2014) looks to understand the complexity of city logistics in terms of global typology through the frameworks of economic factors, infrastructure, and sustainability. Employed is a comparative analysis by using city categorization to identify logistics challenges and tailored solutions based on urban contexts of such categorization. These results highlight that a one-size-fits-all approach is not always the best. Furthermore, Brandy-Philips & Holmes (2024) studied targeted interventions and how they should be used to develop recommendations for more efficient and sustainable urban logistics. It utilized a city archetype modeling tool to understand the impacts of interventions. These context-based analyses provide insight into how urban contexts influence urban logistics. Such classification systems enable one to go beyond traditional traffic flow-centric methods by incorporating logistics operational rates to address curbside and spatial load demands based on street activity.

Improved classification systems can lead to a more dynamic understanding of movement beyond that offered by fixed, hierarchical street-defined traffic flow models. Quak et al. (2024) extends the hierarchical street classifications by introducing neighborhood classifications of historical city centers, old city districts, high-rise neighborhoods, car-free districts, and suburban areas, each associated with different delivery challenges. This analysis focuses on urban historical districts characterized by their spatial constraints, complex and overlapping spatial claims, and increasing traffic volumes (Quak et al., 2024). Research shows that historical urban areas often have a "street layout that is not suitable for goods transport" due to "narrow and sinuous streets," leading to negative "*externalities such as high energy consumption, noise and emission of pollutants*" (UN-Habitat, 2013, p. 63). While permitting shorter freight routes, this dense urban network exacerbates congestion and conflict at intersections. The historic morphology of these areas thus necessitates adaptive freight strategies to meet demand.

Delivery operations are heavily influenced by the type of goods and services involved, as well as the operational hours. In Dutch urban centers like Rotterdam and Amsterdam, authorized delivery windows in city cores are restricted to 6:00-12:00 (Gemeente Amsterdam, 2025; Gemeente Rotterdam, 2025; Gemeente Utrecht, 2025). Retail establishments and restaurants prefer these time blocks to minimize disruption for their customers, whereas for food service and accommodations businesses, receiving perishable goods late at night or early in the morning is preferable (Chowdhury et al., 2022, p. 419). However, Cherrett et al. (2012) found that "*26% of businesses did not have a set delivery time arranged, with goods potentially arriving at any time during the working day*" (p. 26). Off-peak delivery scheduling can provide significant benefits, including reduced service times, decreased competition for curb space, and lower emissions given congestion levels (Chowdhury et al., 2022). However, for parcel deliveries, consumer preferences drive timing considerations, with those who work traditional office hours typically preferring evening deliveries, while those with flexible schedules can accommodate more daytime deliveries. Moreover, consumer expectations for on-time and quick service only increase activity concentration, especially in mixed-use and residential areas. These challenges are further magnified in dense urban environments where space is highly constrained.

Chowdhury et al. (2022) focused on quantifying the impacts of travel time and congestion on off-peak delivery. The study, which focused on Toronto and Hamilton, used a GTHA commercial vehicle model to measure trip generation and distribution as well as scenario analysis to perform spatial-temporal evaluation that highlighted the importance of off-peak delivery in terms of efficiency and suitability. Additionally, Cherrett et al. (2012) studied how urban form affects transport activity, using a meta-analysis of 30 United Kingdom freight surveys to understand delivery frequency, vehicle types, and services. A comparative analysis of urban environments was conducted to understand freight movements in different urban contexts. The trip generation models and geospatial mapping were used to analyze vehicle movements through a comparative study, revealing how activity intensifies across the city and temporal periods, underscoring the complex dynamics of spatial-temporal variations that go beyond route optimization.

These spatial-driven approaches seek to balance accessibility and efficiency while addressing the increasing concern for sustainability in urban logistics and the impact on urban livability. With its planning-centric and data-driven framework, spatial technology is a powerful tool for integrating urban and logistics planning activities. These tools integrate multiple data sources to analyze locational information along with socio-demographic and urban environmental data, supporting complex spatial analysis. From real-time monitoring systems to multi-agent and traffic simulations, spatial tools can serve as the foundation for predictive management systems to optimize urban logistic networks (Rietdorf et al., 2024). In short, spatial analytics can enable dynamic temporal analysis through visual representations of changes over time and the quantification spatial claims of logistics vehicles within urban blocks.

Trip attraction, the number of trips a location draws, is another key factor influencing the temporal externalities as they relate to logistics (Alkaissi, 2021). For example, Barendregt (2023) notes that larger stores attracted 83.94 movements per week, wholesalers attracted 21.67, and bookstores and stationery shops attracted 13.8 per week. E-commerce logistics presents even more complexity and variability. A study conducted in Lyon, France, found that "*home deliveries account for approximately 130,000 weekly movements,*" or 17% of business-to-business goods movement (Gardrat, Toilier, Patier, & Routhier, 2016, p. 9). Despite regulatory efforts, the competition for limited curb space, varied time windows, and operational constraints pose significant challenges for urban logistics systems.

Alkaissi (2021) aimed to understand trip generation and baseline transport demand forecasts. The study used a Four-Step Transportation Planning Process (FSTP) and demand modeling to connect land use and socio-economic variables to overall trip production. The study identified classification and demonstration trips, thus emphasizing the importance of land use attraction in forecasting abilities. Furthermore, Gardrat, Toilier, Patier, & Routhier (2016) researched consumer practices and their impact on urban logistics in Lyon. With support from a survey, the study focused on movement patterns based on socio-demographic factors and consumer habits. These two studies directly relate to this effort as they address trip generation distribution and their connection to socio-demographic factors.

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Beyond street classification, the physical design, usage, and context of urban environments critically influence the spatial behavior of logistics vehicles, as do area economic and social demographics. Sadeghi and Li (2019) observe that urban morphology reflects the "tangible effects of social and economic tensions," with multiple elements of the built environment working together to drive logistics demand and vehicle behavior. These elements influence the chosen physical routes and operational challenges within specific urban contexts.

The persistent temporal mismatch in urban logistics operations creates external effects that exacerbate the negative impact on environmental, spatial, and livability conditions, as well as the flow and function of urban space. These interconnected externalities increase inefficiencies across multiple dimensions, highlighting the need for a comprehensive to manage these effects effectively.

2.5 Logistics Models

Within urban logistics, models are critical tools for understanding current movements and forecasting future logistics flows. These vary greatly in terms of their spatial, geographic, and analytical scope, including morphology, spatial, and temporal characteristics. While they seek to capture the complexity inherent in logistics operations, they inevitably fail to address all the relevant dimensions.

Models differ in type and are often classified as either explanatory or predictive. As Sainani (2014) explains, explanatory models, like spatial regression, aim to interpret the underlying cause-and-effect relationships related to the outcome. This contrasts with predictive models, like machine learning, which use a combination of factors to forecast or best predict a current diagnosis or a possible future one (Sainani, 2014). Together, the explanatory models facilitate hypothesis testing and provide insight into the fundamental mechanisms underlying urban logistics. In contrast, the predictive models support analysis of current, future, and new scenarios for policy and intervention initiatives. In more modern works, researchers advocate for more hybrid modeling approaches, thus enabling the combination of interpretability with predictive performance (Hagenauer & Helbich, 2017). Each modeling tool, however, targets different research objectives in terms of understanding why, where, and when.

Within the reviewed research, explanatory and predictive models are generally categorized into four types, which include general regression, spatial regression, simulation-based models, and machine learning models. A regression model, as seen in Alkaissi (2021)'s Four-Step Transportation Planning Process (FSTP), is a framework in urban mobility studies that models trip generation, distribution, modal splits, and traffic assignment. Within Alkaissi's work, the connection between socio-economic and land use indicators is used to analyze freight demand in an urban setting. The indicators highlighted in the model included the importance of how space is used and population density in relation to urban logistics. In terms of spatial regression, Reda, Tavasszy, Gebresenbet, and Ljungberg (2023) research integrates a geographically weighted spatial autoregression model (MGWR-SAR) to study the relationship between freight patterns and built form. The study focused on the ability to demonstrate that a spatial regression model,

which accounts for spatial autocorrelation, can improve the accuracy of predicting freight activity and trip attraction compared to non-spatial regression models.

Gardrat, Toilier, Patier, & Routhier (2016) use a hybrid approach combining empirically informed and simulation-based models to study logistic trip generation and distribution within Lyon, France. Incorporated were survey data and socio-demographic variables to simulate freight movements through the city, which aimed to quantify the number of trips generated based on commercial habits and use the simulations to inform the spatial-temporal allocation of space (Gardrat, Toilier, Patier, & Routhier, 2016). The strength of simulation models, such as agent-based models, lies in their ability to simulate logistics behavior at an operational and granular level. Finally, machine learning models are used primarily for their predictive powers, as they can capture non-linear interactions. The study by Hagenauer & Helbich (2017) shows how ensemble machine learning methods, specifically random forest, can be used to predict travel behavior in urban areas based on population, city network, weather, and temporal attributes. It highlights the strength of random forest algorithms in predicting trips.

These models each have their strengths and tell different stories. While the models are all shown to provide clarification on the field of trip generation, there remains a lack of systematic incorporation of urban morphology into the field. Furthermore, the often-high macro-level forecasting overlooks detailed micro-level perspectives, which enable more precise spatial understanding and insights into logistics behavior. Overall, these gaps contribute to the ongoing research challenges.

2.6 Research Gap

There is an increasing recognition that mounting pressure is being placed on constrained urban areas, such as sidewalks, curbs, and traffic lanes, especially in dense urban environments. This situation requires innovative strategies for spatial interventions that optimally allocate space based on the spatial-temporal claims of logistics vehicles. Completely removing logistics vehicles from public streets is not feasible given their critical role in supporting urban life. However, if planners do nothing to improve the current approach to urban design, urban logistics will inevitably compete more intensely for the already limited urban space. Addressing the inefficiencies caused by urban logistics thus requires new approaches to guide context-targeted interventions in the future.

This research lies at the intersection of spatial and temporal studies. While urban logistics has gained attention in recent years, there are still critical gaps that remain in integrating spatial-temporal analysis with urban morphology. Current research lacks a context-specific understanding of the spatial and temporal nuances of logistics vehicles. Some studies acknowledge the spatial and temporal complexity of logistics; however, there is a lack of analysis connecting vehicle behaviors to specific urban morphological indicators at a detailed urban block level. Despite advancements in the analysis of logistics dynamics related to environmental, economic, and efficiency externalities, there is still a lack of focus on the spatial-temporal patterns, a void this research aims to fill.

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Current research recognizes that urban logistics has often been overlooked, which has caused significant problems, as the generalized planning approach fails to address logistics needs. Rather than employing a one-size-fits-all approach to interventions, one must consider the complexities of urban form, given that logistics pressure varies based on urban morphology. Additionally, the lack of rigorous, comprehensive data in such studies compounds these issues. This study aims to overcome these obstacles by examining the behavior of logistics vehicles in relation to urban morphology using rigorous, quantitative spatial tools.

Previous studies also lack a thorough understanding of the dynamics of logistics operations, treating them as a static phenomenon rather than one that experiences temporal fluctuations within spatial constraints. With increasing digitalization, spatial analytics and other tools enable the evaluation of logistics vehicle behaviors and their spatial-temporal interactions within the urban realm throughout the day. The underutilization of spatial technology and context-sensitive interventions has led to a fragmented baseline understanding of logistic dynamics and poses a challenge for evidence-based policymaking, resulting in the current state of reactive interventions rather than those designed by leveraging predictive analysis. This is also driven by the failure to capture complex, non-linear relationships, instead of focusing only on linear and spatial models. The use of machine learning models in this context of urban form and logistics vehicle behavior enables more complex spatial-temporal relationships to be captured, which can improve predictive capabilities and enhance the generalization and transferability of findings across urban settings.

From these gaps, the following four theory-driven hypotheses emerge, guiding the methodological design.

- MORPHOLOGICAL: URBAN MORPHOLOGY SIGNIFICANTLY EXPLAINS THE SPATIAL-TEMPORAL CLAIMS OF LOGISTICS VEHICLES.

- MORPHOLOGICAL: THE SPATIAL AND TEMPORAL CLUSTERS OF LOGISTICS ACTIVITY ARE DRIVEN BY URBAN MORPHOLOGY INDICATORS.

- CONTEXTUAL: URBAN MORPHOLOGICAL INDICATORS HAVE VARYING LEVELS OF INFLUENCE ON LOGISTICS INTENSITY ACROSS AND WITHIN URBAN CONTEXTS, WITH THEIR EFFECTS EXTENDING ACROSS ZONES AND INTO PERIPHERAL AREAS.

- PREDICTIVE: URBAN MORPHOLOGY INDICATORS ARE SIGNIFICANT PREDICTORS OF SPATIAL-TEMPORAL VARIATION IN URBAN LOGISTICS ACTIVITY.

In addressing the research gaps, this study aims to contribute to the study of urban logistics and urban planning by providing a theoretical and data-driven framework for the consideration of how urban morphology explains the spatial-temporal claims of logistics vehicles.

Chapter 3

Concept and Methods

This section dives into the research methodology, beginning with the conceptual framework guiding the work, which is supported by previous theoretical investigations. The methodological framework and analytical process is targeted to address the study's main research question:

How does urban morphology, through its physical and socio-spatial indicators, explain the spatial-temporal claims of urban logistics vehicles?

3.1 Conceptual Framework

The conceptual framework is based on theories regarding efficient land use, spatial-temporal logistics dynamics, and the effects of urban morphology (Holguín-Veras et al., 2021; Dalla Chiara & Goodchild, 2020; Rodrigue & Dablanc, 2014; Kin & Quak, 2024; Barendregt, 2023; Veld, 2024; Kropf & Malfroy, 2013; Rodrigue, 2024). This work builds upon this prior research to develop a data-driven, analytical, and spatial-based assessment.

Figure 1 provides a visual overview of the conceptual framework and the factors that shape the interactions between urban morphology and logistics operations. The framework is premised on the hypothesis that specific morphological characteristics, urban context, and logistical operational factors directly shape spatial-temporal claims and generate predictable frictions in urban spaces.

This multidimensional approach incorporates a range of variables identified in the academic literature to inform and structure the spatial-temporal analysis. It hypothesizes that urban morphology is a dynamic rather than static feature of the urban environment and is closely correlated with logistics vehicles' impact on urban spaces.
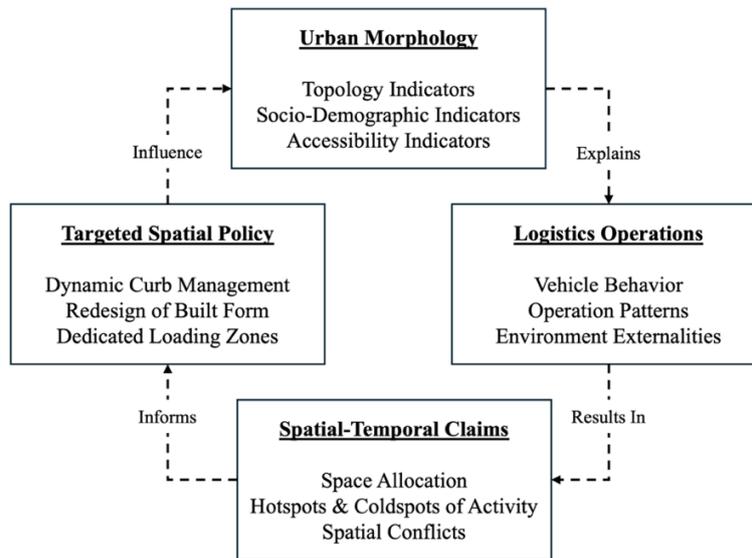
Figure 1: Conceptual Model

Figure 1 presents the theoretical framework that underpins the study. The model highlights the correlative and causal relationships among four key components: urban morphology, logistics operations, the spatial-temporal claims, and targeted spatial policy. Urban morphology, the central element of the study, includes topology, socio-demographic factors (including economic factors), and accessibility indicators. Together, these indicators characterize the urban space's physical layout and lived experience, which directly and indirectly influence logistics operations. They do so by shaping the structural and behavioral constraints within which logistics vehicles operate. Logistics operations refer to the behaviors, patterns, and environmental externalities associated with urban logistics. These operations, in turn, generate specific spatial-temporal claims. Measurable data arises from traffic and activity concentrations, clustering, street space allocation, and spatial conflicts involving other users during peak activity periods.

Furthermore, these observed effects of logistics operations, influenced by interactions with urban morphology, further inform targeted spatial policies and interventions aimed at reducing the negative externalities of logistics activities and optimizing such operations. Critically, these spatial interventions in turn influence the urban environment and urban morphology, thus over time creating a loop cycle of the redesign of physical space and socio-spatial dynamics. This cycle changes how urban life and logistic operations interact with space, highlighting potential future developments within the urban environment. The conceptual model not only emphasizes the causal relationship influencing logistics operations but also illustrates the dynamic system of urban planning, supporting both explanatory and predictive modeling by showing how features generate behavioral influences and how these outputs guide responses.

3.2 Descriptive Statistics

These core concepts that structure the study are further broken down into variables identified in the research literature (see Table 1 and 2). Using these variables to analyze the morphological and logistical vehicle operational conditions provides the means to deconstruct the contributors

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to the spatial-temporal claims of logistics vehicles. These variables were selected based on their perceived importance, as established in prior research, in shaping the spatial-temporal claims of logistics vehicles. The tables summarize each core concept captured in the variables.

Table 1 categorizes the independent indicators by type and provides definitions and references. The specific calculations for each indicator, along with an explanation of their relevance to to logistics activity is described below.

Topology Indicators

Urban typology indicators relate to the physical form and structure of urban spaces, including the built environment, street layouts, and land use.

- *Building Volume:* Calculated as building footprint multiplied by building height, the three-dimensional size of a building, measured in cubic meters, supports logistic intensity classification based on size and required logistics activity.

- *Building Height:* Measured as the highest point of the building minus ground elevation, the vertical distance in meters influences logistics complexity and dwell time because of the number of floors and building layout.

- *Minimum Bounding Rectangle (MBR):* Calculated by multiplying the building length by the building width, it is the simplified building footprint measured in square meters that indicates building size and potential impacts on access and maneuvering space for logistics operations.

- *Complexity:* Calculated by building vertex count, building shape complexity measured through a scale score influences accessibility and maneuvering behavior for logistic operations.

- *Party Wall Area:* Calculated by multiplying shared wall length by shared wall height, the proportion of adjacent properties measured in square meters of shared wall area affects logistics operations by reducing side-loading options and thereby increasing the concentration of stops at the front curb.

- *Gross Floor Area (Office, Retail, Industrial, Residential, and Meeting):* Calculated as the sum of the Basisregistratie Adressen en Gebouwen (BAG) floor area by attribute, the usable floor area, measured in square meters, and broken down by function, influences the overall land-use function and logistic activity within an area. Office floor area reflects office-related logistics generation and business district zones. Retail floor area is correlated with higher delivery frequency (see Table 1 for references). Industrial areas often attract extensive and specialized logistics activity. Residential gross floor area correlates with parcel delivery and service demands. The HORECA (hotels, restaurants, cafés) area, designated for bars, cafés, and other meeting functions, highlights where people attraction competes with logistics activity for space.

- *Open Space Ratio (OSR):* The metric ratio on a scale from 0 to 1 measures open space by using the formula one minus building area divided by land area. The share of open space affects the urban fabric and the availability of space for logistics operations.

- *Mixed Use Index (MXI):* The ratio of types of urban development, derived from the equation of residential plus lodging divided by gross area minus other uses plus secondary area, overall influences delivery frequency and demand, based on the belief that higher mixed-use diversity requires more logistic activity (see Table 1 for references).

- *Simpson Diversity Index (SDI):* A ratio that measures land-use heterogeneity within an area quantifies the balance between living, working, and services, thereby affecting curb space availability. It is calculated by one minus the sum of the gross floor area of each land use class divided by the square of the total gross floor area.

- *Ratio of Neighbor Footprint Sum to Buffer Area (50m):* Measured by summing the local built building footprints within a 50-meter radius, divided by pi and then multiplied by 2500. The ratio of built surface reflects spatial congestion and delivery curb pressure.

- *Standard deviation of Footprint Area within Buffer (50m):* The variability of building footprints, measured in square meters, is determined by the standard deviation of all building footprints within 50 meters of a subject building. This indicator influences the spatial heterogeneity within the postcode and determines whether the urban built environment is fragmented or uniform.

- *Street Width:* The distance, measured in meters, is the horizontal space between buildings. The street width impacts how easily logistics vehicles can maneuver and stop, which in turn affects the overall spatial allocation of the streetscape. Additionally, the variation in curb-to-building distance is shown by the range in street width, calculated as the difference between the maximum and median estimated street widths per postcode.

- *Year Built:* Construction year indicates the era of urban form, design standards, and street access.

Socio-Demographic and Accessibility Indicators

Beyond the physical form, socio-demographic and accessibility indicators are critical for shaping logistics operations because these features can significantly influence the demand for and behavior of logistics operations.

- *Population Density:* The number of people in an area influences delivery volume, freight demand, and thus logistics spatial claims.

- *Household Size:* The number of people at each address influences consumption and the volume of logistics demands.

- *Urbanity:* Based on address density per square kilometer. The level of urbanization influences demand, delivery patterns, and overall logistics operations. The levels of urbanization are: Very Highly Urban ≥ 2,500, Highly Urban ≥ 1500 to 2500, Moderately Urban ≥ 1000 to 1500, Little Urban ≥ 500 to 1000, and Non-Urban < 500.

- *Property Value:* The price of land, expressed in euros, affects expected buying power and delivery options.

- *Address Density:* The number of addresses, counted by address in the postcode, within an area correlates with logistic stop density and demand intensity.

- *Age:* A population's age distribution, broken down by age groups within each geographic area (0 to 15 years, 15 to 25 years, 25 to 45 years, 46 to 65 years, and 65+ years), influences consumer behavior and demand preferences.

- *Immigrate & Native Population (Socio-Cultural):* The socio-cultural variation of an area affects consumption habits and thus logistics activity. The socio-cultural composition for each postcode was determined by the majority population, broken down into Dutch, Other European, Non-European Dutch, European Abroad, and Non-European Abroad.

- *Public Transit Stops:* The count of public transportation stops per postcode, a measure of a location's accessibility, has a dual effect on logistics by indicating a person's ability to access the system and a broader network of shops. It also influences street space demand and availability.

As noted in Table 1, this research will focus on a specific set of contextual factors that can be readily measured and generally have a consistent effect on logistics services. Factors like weather or labor actions, which are less predictable, will not be included in this study. Importantly, although there were many potential urban morphological characteristics, the selection was narrowed based on the importance of urban morphology to the research question. The study does include a significant number of indicators chosen for their predictive value as shown in previous academic research.

Table 1: Operationalization of Independent Variables

Indicator	Description	Calculations	Reference
		Topography	
Building Volume	Total three-dimensional space occupied by a building	Cubic Meter; Building Footprint * Building Height	Biljecki & Chow, 2022; Fehr & Peers, 2023
Building Height	Vertical distance from the ground to the highest point of the building	Meter; Max Building Height - Ground Elevation (Estimated from Building Volume / Building Footprint Area)	Veld, 2024; Allen et al., 2018;
Minimum Bounding Rectangle (MBR)	Simplified building footprint	Square Meter; Building Length * Building Width	Biljecki & Chow, 2022
Complexity	Measure of polynomials representing the building shape complexity	Building Vertex Count	Sadeghi & Li, 2019
Party Wall Area	Shared structural element between two or more adjacent properties	Square Meter; Shared Wall Length * Shared Wall Height	UN-Habitat, 2013; Biljecki & Chow, 2022
Gross Floor Area; Office Function	Total area within the perimeter - Office	Square Meter; Sum of BAG floor-area by attribute	Urban Freight Lab, 2020; Quak et al., 2024
Gross Floor Area; Retail Function	Total area within the perimeter - Retail	Square Meter; Sum of BAG floor-area by attribute	Allen et al., 2018; Urban Freight Lab, 2020
Gross Floor Area; Industrial Function	Total area within the perimeter – Industrial	Square Meter; Sum of BAG floor-area by attribute	Fehr & Peers, 2023
Gross Floor Area; Residential Function	Total area within the perimeter - Residential	Square Meter; Sum of BAG floor-area by attribute	Tanco & Escuder, 2021
Gross Floor Area; Meeting Function	Total area within the perimeter - Bar, café, etc.	Square Meter; Sum of BAG floor-area by attribute	Urban Freight Lab, 2020; Kin & Quak, 2024
Open Space Ratio (OSR)	Measure of open space	Ratio; (1 - Building Area / Shape Area) / (Gross Area / Shape Area)	Biljecki & Chow, 2022; Quak et al., 2024
Mixed Use Index (MXI)	Measure of different types of urban development	Ratio; (Residential Gross Floor Area + Lodging Gross Floor Area) / (Gross Floor Area - (Other Use Gross Floor Area + Secondary Gross Floor Area))	Kin & Quak, 2024; Urban Freight Lab, 2020
Simpson Diversity Index (SDI)	Measure of community diversity	Ratio; 1 - Sum of (Gross Floor Area of Each Land Use Class / Sum of Total Gross Floor Area) ^ Squared	Kin & Quak, 2024; Urban Freight Lab, 2020
Ratio of Neighbor Footprint Sum to Buffer Area (50m)	Built-surface density within a 50-meter buffer	Ratio; Sum of Buildings Footprint within 50 meters / Pi * 2500	Campbell et. al, 2018
Standard Deviation of Footprint Area within Buffer (50m)	Variability in building size around	Standard Deviation of All Building Footprints within 50 Meter of Subject Building	Yang et. al, 2023; Biljecki & Chow, 2022
Street Width	Horizontal distance across a street	Meter; Distances Between Building Façades	UN-Habitat, 2013; Dablanc, 2011; ITF, 2022
Street Width Spread	Variation in curb-to-building distance	Meter; Max Estimated Street Width - Median Estimated Street Width per Postcode	UN-Habitat, 2013; Dablanc, 2011; ITF, 2022
Year Built	Year of building construction	Year of Construction	UN-Habitat, 2013; Quak et al., 2024
		Demographic	
Population Density	Measure of individuals within a geographic area	Count of People in Postcode	Barendregt, 2023; Ritchie, Samborska & Roser, 2024
Household Size	Number of individuals living together in a single housing unit	Number of Inhabitants per Address	Savelsbergh & Van Woensel, 2016
Urbanity	Measure of human activity concentration	Address per square kilometer; Very Highly Urban ≥ 2,500, Highly Urban ≥ 1500 to 2500 <, Moderately Urban ≥ 1000 to 1500 <, Little Urban ≥ 500 to 1000 <, and Non-Urban < 500	Büyüközkan & Ilıcak, 2022; World Bank, 2021
Property Value	Price of a piece of real estate	Property Value in Euros.	Urban Freight Lab, 2020; Allen et al., 2018
Address Density	Number of addresses within a geographical location	Count of Addresses in Postcode	Allen et al., 2018; Plomp, 2024
Age	Population age bins	Count of People in Postcode per Age Bin; 0 - 15 Year Old, 15 - 25 Year Old, 25 - 45 Year Old, 46 - 65 Year Old, and 65+ Year Old	Mishra, Golias, Kaisar, & Figliozzi, 2023
Immigrate & Native Population	Socio-cultural variation of area	Majority Share of Population in Postcode by origin categories; Dutch, Other EU, Non-EU European, EU-abroad, Non-EU abroad	Goodchild, Sanchez-Diaz, & Browne, 2024; AIC, 2025
		Accessibility	
Public Transit Stops	Number of public transportation stops	Count of Stops in Postcode	Castrellon & Sanchez-Diaz, 2024

Table 2, shown below, details the dependent variables captured. Based on data availability, the study used information on logistics vehicle behavior, including delivery times and the type of logistics operations. Additionally, since this research focuses on the spatial aspect of vehicle activity, the content of the delivery or service provided will not be considered.

Logistic Operation Indicators

To capture the spatial-temporal intensity of urban logistics operations, the dependent variables, as shown in Table 2, were disaggregated by vehicle type and time of day. The classification scheme is provided by the data source, MASS-GT (Multi-Agent Simulation System for Goods Transport), and offers a detailed analysis of how different logistics operations interact with the urban environment over time (Freight & Logistics Lab, 2017). Through this structure, dependent variables facilitate the comparisons of vehicle functions and temporal periods, allowing the study of volume intensity and spatial variation throughout the day.

The dependent variable indicators represent vehicle counts for three logistics-related flow categories: logistic trucks for freight or goods movement, service and construction vans, and parcel vans focused on last-mile deliveries to households. Additionally, these disaggregated flow types were separated into three-time bins: morning peak (AM), afternoon peak (PM), and off-peak (other) periods. Besides the detailed separation by vehicle type, an aggregated vehicle traffic indicator was also calculated for each time bin and the entire day.

Table 2: Operationalization of Dependent Variables

Time	Indicator	Description
Morning Peak (AM)	AM Truck	Disaggregated logistic truck traffic
Morning Peak (AM)	AM Service	Disaggregated service and construction van traffic
Morning Peak (AM)	AM Parcel	Disaggregated parcel van traffic (only last mile to household)
Morning Peak (AM)	AM Aggregated	Aggregated logistics vehicle traffic
Afternoon Peak (PM)	PM Truck	Disaggregated logistic truck traffic
Afternoon Peak (PM)	PM Service	Disaggregated service and construction van traffic
Afternoon Peak (PM)	PM Parcel	Disaggregated parcel van traffic (only last mile to household)
Afternoon Peak (PM)	PM Aggregated	Aggregated logistics vehicle traffic
Off-Peak (Other)	Other Truck	Disaggregated logistic truck traffic
Off-Peak (Other)	Other Service	Disaggregated service and construction van traffic
Off-Peak (Other)	Other Parcel	Disaggregated parcel van traffic (only last mile to household)
Off-Peak (Other)	Other Aggregated	Aggregated logistics vehicle traffic
Peak and Off-Peak (All)	All Aggregated	Total logistic traffic of the day (AM, PM, and Other)

3.3 Cluster Analysis

This research step will contribute insights to answer the following subordinate research question:

- HOW DO SPATIAL AND TEMPORAL HOTSPOTS OF LOGISTICS VEHICLES INTERACT WITH URBAN MORPHOLOGICAL INDICATORS ACROSS TIME FRAMES?

Capturing and quantifying the different factors that influence the urban logistics footprint across the built environment is critical for understanding the spatial-temporal claims of logistics vehicles. Cluster analysis enables the visualization of the dynamic nature of a variety of spatial and temporal drivers, which is needed for a comprehensive understanding of their interactions.

The goal of clustering is to visualize spatial claims through hot spot and cold spot analysis to examine how, where, and when urban logistics operations occupy space. Mapping such activity establishes a baseline of logistics operations while connecting them to specific geographic areas and morphological features. By identifying cluster patterns, the analysis enables targeted studies of the morphological conditions of the urban environment as they relate to logistics intensity.

The footprint of logistics vehicles is quantified using spatial-temporal modeling, which is a mathematical representation that combines spatial and temporal functions to analyze and predict the characteristics of parameters (He et al., 2022). It uses a space-time function to capture characteristics, as this approach modifies the traditional static occupancy model by measuring the spatial-temporal use of road space by logistics vehicles (Hall, n.d.). Tobler's First Law of Geography, that "*everything is related to everything else, but near things are more related than distant things,*" provides the rationale for cluster analysis (ESRI, n.d.). Thus, hot spot analysis over a defined temporal timeframe (e.g., one temporal block) calculates the cumulative spatial-temporal claims for an urban block using the summation theorem presented in Equation 1:

Equation 1: Summation of Spatial-Temporal Claims Across Time

$$STC_{total}(\Delta t) = \sum_{i=0}^{n} STC_i$$

Here, STC_{total} is the total spatial claim by logistics vehicles over the time frame for a postcode block, with Δt representing the change in time. In the equation, i is measured in terms of the temporal unit, n is the total number of temporal units per location, and STC_i is the measured spatial claim of logistics vehicles during a time unit. The larger the STC_{total}, the greater total logistics pressures felt by the postcode geographic unit. Using this formula, the higher the result, the greater the spatial clustering claims of logistic vehicles. This translates the static spatial claims of individual vehicles into a dynamic one through the inclusion of a temporal component.

The observed spatial-temporal claims set up the hot spot cluster analysis, which uses the Getis-Ord Gi tool to weigh points and identify clusters of urban logistics pressure. The Getis-Ord Gi* formula is presented in Equation 2:

Equation 2: Getis-Ord Gi Hot Spot Formula

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i.j} x_j - \bar{X} \sum_{j=1}^{n} w_{i.j}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i.j})^2}{n-1}}}$$

The Getis-Ord Gi* statistic identifies statistically significant clusters of logistics activity by comparing local spatial means to global means (ESRI, n.d.). This accounts for spatial autocorrelation (Ord & Getis, 1995). In Equation 2, G_i^* refers to the Getis-Ord Gi* statistic, n is the total number of spatial features within the study area, and $w_{i.j}$ denotes the spatial weight between locations i and j respectively. Furthermore, x_j is the observed spatial-temporal claim

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value at location j, and $\bar{X}$ and S is the mean and standard deviation of the STC value across all n locations.

When applying it to STC at a postcode 6 level, X is the variable into which this would be inserted. Additionally, the Space Time Cube tool conceptualizes space and time through a 3D cube using longitude, latitude, and time, which, when applied to an urban block, allows for the comparison of spatial-temporal data to visualize both 2D and 3D patterns (ESRI, n.d.). One application of this technique is for 2D hot spot analyses. The tool identifies clusters of spatial units where high values of the dependent variable, such as logistics traffic type counts, are significantly concentrated or not - i.e., hot spots or cold spots. Within the scope of this study, hot spots are postal codes that consistently attract high levels of logistics traffic. These hotspots form spatial clusters, indicating problem areas within the urban transport network. The hotspot analysis was conducted separately for different times of day (morning, afternoon, and other times), as well as for all periods combined. It was also performed for various types of logistics traffic. Results are categorized as significant hot spots or cold spots based on their z-scores at the 99%, 95%, and 90% confidence levels. Hot spots are marked in red, while cold spots are shown in blue.

Torsten Hägerstrand's time geography involves understanding the how and why of the spatial-temporal dynamics within transportation geography (Ellegård & Svedin, 2012). This tool enables the quantification of urban logistics vehicles' spatial-temporal claims.

Furthermore, these spatial–temporal claim values, corresponding Gi* z-scores, and hot spot analysis are used further within the context of the predictive framework for Utrecht and Rotterdam and for all three cities' independent variable mapping. Using a trained non-linear machine learning model to map the logistics intensity based on urban morphological indicators, hot spot analysis was used to evaluate generalizability across diverse urban contexts.

3.4 Statistical Modeling

This research step provides insights into the following subordinate research questions:

- WHICH URBAN MORPHOLOGICAL INDICATORS (E.G., ROAD WIDTH, LAND USE, BUILDING DENSITY) CORRELATE MOST SIGNIFICANTLY WITH LOGISTICS VEHICLES' SPATIAL-TEMPORAL CLAIMS?
- WHAT CAN A PREDICTIVE MACHINE LEARNING MODEL SHOW ABOUT THE RELATIONSHIP BETWEEN URBAN MORPHOLOGY AND THE SPATIAL–TEMPORAL LOGISTICS INTENSITY?

Building on the baseline logistics and morphology spatial analyses, this step connects the three through a statistical analysis to gain insight into their interaction. This analysis employs multiple forms of statistical analysis to correlate behavioral patterns and the urban landscape, establishing statistically significant relationships, along with machine learning models.

3.4.1 Multicollinearity

Multicollinearity is when two or more independent variables in a multiple regression model are highly correlated, which violates a key assumption of the 'absence of multicollinearity' necessary

for any multiple regression analysis. Variance inflation factors (VIFs) are a statistical tool that measure how much the variance of a regression coefficient increases due to multicollinearity. Variables with VIFs above five were flagged for either full removal or consolidation with other variables, as some variables could be represented multiple times due to the nature of their attributes. An example of such an occurrence is with MBRA, or minimum bounding rectangle, measured by length multiplied by width. MBRA overlaps with the singular attributes of length and width, as well as footprint and perimeter. VIFs above five (and especially ten) indicate that the variable is problematic in terms of multicollinearity, given its high correlation with other variables. In contrast, those with lower VIF are more acceptable given the evidence of low collinearity.

3.4.2 Correlation

A correlation matrix was prepared to understand the complex dynamic relation between the two segments of the analysis. The correlation matrix is used to show the correlation coefficients between two or more sets of variables. In the current study, these are urban logistics and morphology (Ferré, 2009). A result near +1 suggests a strong positive relationship, and -1 a strong negative correlation. We must use Spearman's rank correlation coefficients, given that urban morphology (and urban logistics operations, for that matter) is nonlinear and ordinal. This leads to the mathematical formula, Equation 3 (Lund Research, 2018):

Equation 3: Spearman's Rank Correlation Coefficient

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

The correlation matrix is employed to Spearman rank the relationship between the identified morphology indicators and urban logistics vehicle intensity. In the equation, equation 3, ρ represents Spearman's rank correlation coefficient, or rho, n the number of paired observations, and d_i is the difference between the ranks of each pair of observations with i representing the observations. Furthermore, for selected variables informed by prior research, morphological indicators and logistics behavior factors were compared to further build an initial correlation. Specifically, this applies to areas where existing spatial-temporal interventions focus on regulating urban logistics operations. The variables that were statistically significant were selected as the morphological indicators.

3.4.3 Regression

A baseline ordinary least squares (OLS) model is performed after data alignment. OSL is a linear regression model to generate "*dependent variable in terms of its relationships to a set of explanatory variables*" (ESRI, n.d.). This accounts for the linear effect of urban morphology on the dependent variablesof logistics vehicle traffic count at the postcode 6 level. The general OSL equation is defined as (Equation 4):

Equation 4: Ordinary Least Squares Regression Model

$$y_i = \beta_0 + \beta_{1i} X_{1i} + \beta_{2i} X_{2i} + \cdots + \varepsilon_i$$

In this equation, the dependent variable y for postcode 6 at location i is regressed on a set of independent variables x at the exact location. Moreover, in equation 4, β_0 is the intercept of the expected value when all independent variables are zero, $\beta_{1i}, \beta_{2i}\ldots$ and the independent variable regression coefficients, $X_{1i}, X_{2i}\ldots$ are the value of the independent variable at location i, and ε_i is the error term for location i, thus enabling the capturing of variation not explained by the model. Furthermore, OLS residuals or Moran's I, a statistical value that quantifies the level of spatial autocorrelation in a dataset (ESRI, n.d.), Equation 5.

Equation 5: Moran's I Statistic for Measuring Spatial Autocorrelation

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i{}^2}$$

In the equation for Moran's I, n is the number of postcode 6 units, z_i is the deviation of the attributes for feature i, and w_{ij} is the spatial weight (ESRI, n.d.). Furthermore, z_j is the deviation of the logistics vehicle spatial-temporal claim in the neighboring postcode, thus accounting for spatial autocorrelation and S_0 is the aggregate of all spatial weights. The interpretation of the results is that if the value is above 0, there is positive spatial autocorrelation; if below 0, there is negative spatial autocorrelation; and if close to 0, it indicates spatial randomness. The Moran's I statistic informs spatial autocorrelation and model adjustment given the results.

Employed is a Lagrange Multiplier diagnostic, which is a test tool that examines the model's misspecification (Engle, 1982). Applied to the baseline OSL residuals, for each dependent variable, the goal is to correct for spatial misspecification. The test's LM–error and LM–lag were run on the residuals. The LM error tests for spatial autocorrelation specifically within the error terms (i.e., λ), compared to LM lag, which examines the spillover effect (i.e., spatial autocorrelation within the dependent variable) (Rüttenauer, 2019). The diagnostic results indicate which spatial regression model to develop.

To account for the spatial spillover effect within the observations, a spatial lag regression model was developed for each dependent variable using the statistically significant predictors as informed by the previous correlation analysis. It is important to remember that spatial lag regression models are used as explanatory tools to demonstrate the extent to which the selected independent variables explain the variation in the dependent variable observations. With the general spatial lag model, or SAR, the aim is to estimate each dependent variable y, similar to a linear regression model. The general equation for the SAR model is provided in the concept and method section above. The spatial lag (SAR) model, or spatial autoregression model, is a type of regression that accounts for spatial weights and dependence in the dependent variable (Rüttenauer, 2019). It incorporates the values of neighboring postcodes, known as the spatial weights, into the model. The equation shown below includes the spatial lag coefficient, which measures the influence of neighboring areas; W represents the spatial-weights matrix or queen-contiguity for standardization; X is the matrix of explanatory variables; and the coefficients β (Stakhovych & Bijmolt, 2009). From an observational perspective, this equation is applied with different specifications depending on the dependent variable, as outlined in Equation 6.

$$y_i = \alpha + \rho \sum_j w_{ij} y_j + \sum_{k=1}^{K} \beta_k x_{ik} + \varepsilon$$

The intercept, ρ, is the spatial autoregression coefficient, or spatial rho, while the constant, α, is the regression intercept. Furthermore, w_{ij} is the spatial weight between locations i and neighboring location j, y_j is the dependent variable for postcode 6 at location j, K is the number of independent variables, β_k is the coefficient of the kth independent variable, x_{ik} is the value of the associated independent variable, and ε is the residual error. Equation 7 presents the compact formula for spatial lag as applied. In this formula, w is the spatial weights matrix, y is the vector of dependent variables for all spatial units, beta is the vector of regression coefficients, x is the matrix of independent variables, and is the residual error. Importantly, the SAR models were standardized through log-likelihood, which was carried out using a spatial weights matrix with a row-standardized method (Stakhovych & Bijmolt, 2009). This was constructed based on contiguity, considering the adjacency of the postal code units, as shown in Equation 7.

Equation 7: Compact Form of the Spatial Lag Model

$$y = \alpha + \rho w y + \beta x + \varepsilon$$

3.4.4 Machine Learning

To capture the complex, non-linear interactions of urban morphological predictors in an out-of-sample case study, a random forest regression model was selected and trained on the Amsterdam data. The random forest regression model is a simple machine learning model. Overall, the model necessitates a few assumptions, with the main assumption being that the training data are representative of the population, in this case, Amsterdam's logistics activity intensity (Singh, 2024). Furthermore, the model assumes no multicollinearity, non-linearity, independence of data. The data can be either normally distributed or skewed (Singh, 2024). Random forest models provide high accuracy, robustness, and versatile data results. However, the optimistic in-fold random forest model provides only a baseline understanding of exploratory performance patterns, as external validation datasets are unavailable. There is an understanding that a more selective and specialized machine learning model would be required to fully capture the relationship between urban morphology and logistics activity (Lee, 2025). However, this is beyond the scope of the study.

The random forest model is an ensemble method that averages the predictions from many decision trees built using the training data (Lee, 2025). It employs the concept of bagging decision trees to improve predictive accuracy. The equation for the random forest model, shown below, is used for making predictions. In the equation, T represents the number of decision trees in the forest with prediction of the t decision tree for the postcode unit, $\hat{y}_{RF}$ and $\hat{y}_t$ is the predicted value for the data point from decision tree t (Andrade et. al., 2023). See Equation 8.

$$\hat{y}_{RF} = \frac{1}{T} \sum_{t=1}^{T} \hat{y}_t$$

The method used in random forest is referred to as bootstrap aggregation, where each tree in the model is built using a random sample with replacement from the data with the final prediction being the average of all individual trees (see Figure 2) (Andrade et al., 2023. The figure illustrates the structure of a random forest regression model, highlighting the individual decision trees and how they are combined to produce the final prediction. Figure 2 shows the dataset used to train the model, and it also illustrates how the model uses bootstrap aggregation to make each tree work with slightly different data sets. In doing so, the model aims to reduce overfitting. The final output is the average value of all tree predictions.
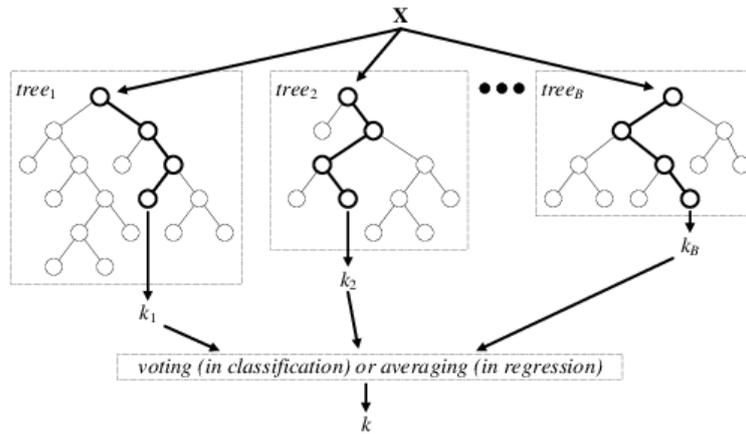
Figure 2: Architecture of the Random Forest Model (Vaiciukynas et. al., 2016)

This analysis offers empirical support for linking urban layout with logistics activities. However, it should also be combined with an outlier detection analysis to identify postcodes that do not fit the observed relationships. Residual analysis identifies outliers by comparing observed with predicted variables. In this study, these would be spatial-temporal claims with significant positive or negative residuals compared to others (Newcastle, n.d.). The mathematical equation for this is presented in Equation 9:

Equation 9: Residual Between Observed and Predicted Spatial-Temporal Claims

$$Residual = ActualSTC - PredictedSTC$$

Analyzing these relationships offers insight into how the independent variables of urban morphology affect the dependent variables of logistics behavior and whether they are statistically significant. It also lays the groundwork for a deeper understanding of these relationships.

A Spatial-Temporal Analysis of Logistics Vehicles

Chapter 4

Data

4.1 Case Studies

The study employs a multi-city case study approach to analyze how urban morphology influences the spatial-temporal patterns of logistics vehicles. It includes three cities in the Netherlands—Amsterdam, Utrecht, and Rotterdam—and relies on high-quality, readily available datasets on logistics behavior and urban form. The case study analysis is structured into two analytical steps: a macro-level focus on Amsterdam to identify trends and then applying these insights to Utrecht and Rotterdam to validate how urban morphology affects logistics vehicle behavior. For reference, Figure 3 illustrates the geographical scope of the case studies.
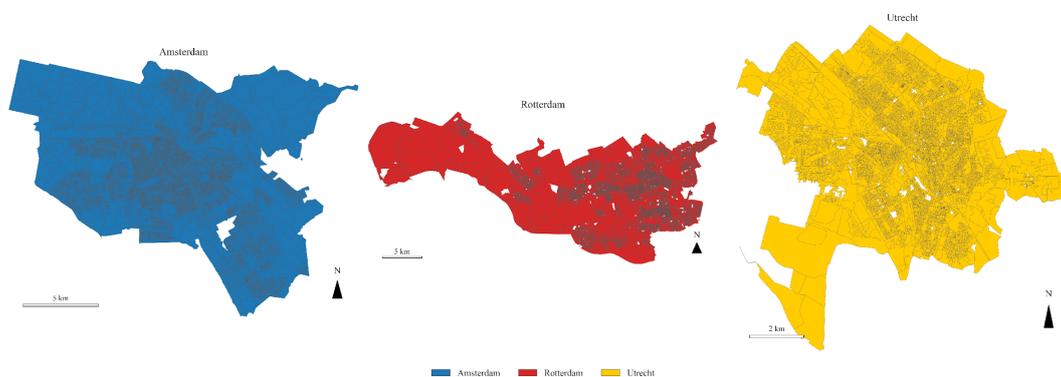
Figure 3: Comparative Visualization of Postcode 6 Boundaries in Amsterdam, Rotterdam, and Utrecht

The three scenarios are each explained in detail below. At a high level, the three case studies are based on postcode 6 data cells, with Utrecht including 7,185 cells, Amsterdam containing 10,062 cells, and Rotterdam comprising 18,148 cells.

Amsterdam, the largest city in the Netherlands, serves as the macro-scale training data for the case study in this research. The city's historic center features high density, mixed-use development, and popularity, making it an example of a complex urban environment for logistics operations. Due to the variety of data available from both spatial and logistical perspectives, the city provides a dynamic empirical example of how Dutch cities operate. Analyzing data at the postal code six-level (PC6) allows for the identification of spatial patterns related to the spatial and temporal behavior of logistics across different morphological clusters. The context of

Amsterdam and its various morphological clusters helps us identify spatial-temporal logistics patterns, allowing these findings to be applied in other urban environments later.

The Multi-Agent Simulation System for Goods Transport (MASS-GT) establishes the analytical baseline for modeling Amsterdam's logistics operations (Freight & Logistics Lab, 2017). While the MASS-GT only offers a model to predict logistics flow, these estimates provide a highly detailed understanding of logistics traffic patterns. Figure 3 shows the selected case study area where spatial-temporal mapping analysis was performed. Amsterdam, used as training data for the case study, offers foundational insights into morphological indicators, which in turn inform logistics operation patterns.

Utrecht and Rotterdam both serve as micro-scale case studies at the urban postcode 6 level. Table 3 compares the urban and social demographic contexts of Amsterdam, Utrecht, and Rotterdam.

Table 3: Demographic, Spatial, and Economic Profiles of Case Study Cities

City	Population	Size (sq km)	Population Density (per sq km)	Number of Postcode 6	GDP (€ Billion)	Sectors
Amsterdam	933680	215.09	4341	10055	201.100	Finance, Culture, Trade
Rotterdam	664311	386.65	1718	18148	188	Industry, Logistics, Sea Port
Utrecht	376435	71.13	5292	7185	71.5	Research, Education, Services

Utrecht, the fourth-largest city in the Netherlands, provides a case study and validation of targeted spatial intervention effects on spatial-temporal logistics dynamics. Utrecht features a dense historic core with medieval design (Koomen & Bação, 2005). Figure 3 highlights the focused study area at the PC6 level within Utrecht.

Rotterdam is the second-largest city in the Netherlands and serves as a second case study. Unlike Utrecht, Rotterdam was extensively bombed during World War II and was almost entirely rebuilt in the 1950s, offering a morphological contrast that makes it more relevant for other car-centric cities (Koomen & Bação, 2005). Key differences include wider streets, more modern buildings, and an environment characterized by 1950s modernist design. Figure 3 shows the study area on the PC6 level.

Overall, the comparative case study analysis facilitates the examination of spatial-temporal logistics and morphological features across diverse urban environments, aiming to provide better insights for development interventions to improve urban logistics operations.

4.2 Data Collection

The data used in the research include number of logistic vehicles in different areas and urban morphology data. The three case studies used available data from Amsterdam's multi-agent simulation system, which included traffic pattern data and expected logistics operations activity. Insights from these patterns were then applied to the Utrecht and Rotterdam case studies.

Logistics Vehicle Data

Logistics vehicle data forms the basis of the study. The data on logistics operations in the Netherlands is highly disaggregated, which limits the amount of usable data. The requirement for the training data, specifically for Amsterdam, was that it be granular data at the postcode 6 level on a macro scale. Thus, simulated multi-agent simulation system generalizations for Amsterdam served as the foundation of the study.

The MASS-GT, on which the Netherlands Organization for Applied Scientific Research works with Significance and the Technical University of Delft, functions as the main spatial-temporal engine for estimating urban logistics operations in Amsterdam (Freight & Logistics Lab, 2017). The model utilizes truck trip diary data and related logistics datasets to ensure that the categories of vehicle types, time-of-day segments, and goods flows accurately reflect the observed patterns in Dutch urban freight operations (de Bok, Tavasszy, & Thoen, 2022). The model is a framework designed to simulate the decision-making processes of key logistics actors and their patterns across transportation markets such as "*commodity, transportation services, traffic services, and infrastructure markets*" (de Bok, Tavasszy, & Thoen, 2022). Thus, it enables the reproduction of freight transportation patterns while also considering the heterogeneity among different stakeholders. The data sets, primarily based on Statistics Netherlands' (CBS), used to develop the model are sourced from private, academic, and public organizations, highlighting the complexity of logistics operations in the Netherlands.

MASS-GT offers a macro-scale model for predicting logistics flows by segment and vehicle type, overcoming the fragmented nature of logistics data in most planning models and permitting crucial estimates of mobility patterns. The classification of the data follows the MASS-GT segmentation logic, which represents demand at the aggregate level using a commodity flow matrix and is then disaggregated into individual shipments through Monte Carlo Simulation. breaking this down, the commodity flow matrix is a model that classifies the variety of "*logistic flow types for transports taking place between producer, consumer, and logistic nodes; there are 9 possible flow types between producer, consumer and logistic nodes* (de Bok, Tavasszy, & Thoen, 2022, p. 122).

The provided information covers the type, quantity, value, location, and mode of transportation, based on observed market shares for each flow type. Additionally, the Monte Carlo Simulation is a technique that uses random sampling to model the probability of different outcomes, which are difficult to predict due to the presence of random variables within the model. Since shipment sizes are very heterogeneous in distribution and type, transportation flow and logistics activities fall into this category (de Bok, Tavasszy, & Thoen, 2022). Much like random forest modeling, the Monte Carlo Simulation uses many calculations with slightly different sets of randomly generated inputs to produce a range of possible results and their associated probabilities, enabling the accounting of uncertainty. Following these steps, each logistic shipment is assigned to specific origin and destination agents, i.e., logistic nodes and end locations, based on type, size, and location to then describe the shipment's market share and mode of movement (de Bok, Tavasszy, & Thoen, 2022). Critically, MASS-GT's empirically structured model provides

validation for the study's data-driven representation of urban logistic activity and the possible connection to urban morphology.

It is important to note that because MASS-GT and its associated data source originate from a model-generated dataset, its structure and content are based on underlying assumptions that influence the model's output. These include assumed logistics demand patterns, and vehicle estimates, which are not only stable over the model period but are also derived from socio-economic, land use, and network characteristics. Additionally, the datasets reflect observed vehicle route behaviors generated within the model framework, which operates at a relatively high level of disaggregation in terms of vehicle type, logistics segment, tour composition, temporal periods, and spatial allocation. This approach simplifies potential real-world human decision influences and specific company requirements (de Bok, Tavasszy, & Thoen, 2022).

The categorization structure of the study, shown in Table 2, reflects MASS-GT's own segmentation and is based on vehicle type, logistics segment, and time periods. For example, vehicle types are grouped by capacity and configuration, aligning with the CBS MASS-GT information. The same applies to market share and time periods. The study uses the tour spatial-temporal paths derived from aggregated CBS trip diary data, specifically focusing on tour complexity and delivery spatial sequencing. However, neither the study nor the MASS-GT data includes micro-level stop behavior, which limits the ability to incorporate loading and unloading points, dwell times, parking choices, or curb occupation. Moreover, the data serves as a reliable proxy for real-world logistics activity based on typical logistics profiles and trip generation, but does not capture any unique variations. Similarly, the spatial allocation of the data is estimated at the postcode 6 level, assuming a spatial granularity that reflects urban logistics dynamics; thus, data is spatially allocated within each postcode. Additionally, the multi-agent simulation model is assumed to be periodically updated in response to changes in the urban landscape, thus providing up to date macro-scale spatial-temporal data for studies in a field that often lacks aggregated logistics information.

Furthermore, the data cleaning process, explained below, includes the postcode overlay to remove any postcodes not generated by the MASS-GT model, thus ensuring the integrity of logistical operational analysis.

Urban Morphology Data

The basis for the urban morphology data is the global building morphology indicators dataset by Biljecki and Chow (2022). The dataset is a comprehensive spatial database with over 380 fields that utilizes PostgreSQL/PostGIS and OpenStreetMap to analyze urban form across different spatial scales (Biljecki & Chow, 2022). The sources include OpenStreetMap, Global Streetscapes by NUS Singapore, and Google Earth Engine, all of which are open-source mapping tools for analyzing the urban fabric, land use, population data, and street view images. BAG (Basisregistratie Adressen en Gebouwen), BRT TOP10NL, and 3DBag provide comprehensive data on shapefiles for classifying buildings and roads, as well as overall building registration information. In addition, for physical curb space, TNO's Safe and Sustainable Urban Mobility Department and Gemeente Amsterdam both provide information on parking locations in the

Netherlands, with the latter also offering geographical data on streets that are restricted for loading and unloading activities in Amsterdam. Socioeconomic and demographic data is obtained from CBS postcode, which includes statistics at various postcode levels. See Table 4 for the sources of the urban morphology indicator data.

Table 4: Independent Variable Data Sources

Indicator	Source
Building Volume	3DBAG, tudelft3d & 3DGI
Building Height	3DBAG, tudelft3d & 3DGI
Minimum Bounding Rectangle	Global Building Morphology Indicators, Urban Analytics Lab
Complexity	Global Building Morphology Indicators, Urban Analytics Lab
Party Wall Area	3DBAG, tudelft3d & 3DGI
Gross Floor Area; Office Function	Rudifun
Gross Floor Area; Retail Function	Rudifun
Gross Floor Area; Industrial Function	Rudifun
Gross Floor Area; Residential Function	Rudifun
Gross Floor Area; Meeting Function	Rudifun
Open Space Ratio	Rudifun
Mixed Use Index	Rudifun
Simpson Diversity Index	Rudifun
Ratio of Neighbor Footprint Sum to Buffer Area	Global Building Morphology Indicators, Urban Analytics Lab
Standard deviation of Footprint Area within Buffer	Global Building Morphology Indicators, Urban Analytics Lab
Street Width	Nationaal Wegenbestand
Street Width Spread	Nationaal Wegenbestand
Year Built	Rudifun
Population Density	Centraal Bureau voor de Statistiek, Postcode 6
Household Size	Centraal Bureau voor de Statistiek, Postcode 6
Urbanity	Centraal Bureau voor de Statistiek, Postcode 6
Property Value	Centraal Bureau voor de Statistiek, Postcode 6
Address Density	Centraal Bureau voor de Statistiek, Postcode 6
Age	Centraal Bureau voor de Statistiek, Postcode 6
Immigrate & Native Population	Centraal Bureau voor de Statistiek, Postcode 6
Public Transit Stops	Open Street Map

3.3.2 Data Processing

The objective of this step of the analysis is to quantitatively relate variations in urban logistics spatial-temporal behavior to specific morphological characteristics. To accomplish this, a systematic classification of the street segments (postcodevlakken PC six) must be applied. This section of the analysis classifies the built form by morphological indicators. Each set of postcodes, PC6, is assigned a set of morphological indicators through the data preparation process. The resulting morphology categorization supports modeling morphology and urban logistics relationships, providing a foundation for structuring the predictive modeling to inform the targeting of spatial interventions.

Before modeling, each postcode 6 polygon within the geographic region (Amsterdam, Rotterdam, or Utrecht) was assigned standardized morphological indicators after data cleaning. Next, each individual indicator was visualized. This visualization used graduated symbology to display spatial patterns of the urban morphology indicators at the postcode 6 level. These maps were later combined to analyze the geographic distribution of morphological indicators in relation to logistics intensity, aiming to better understand the predictive model and identifiable patterns. The equation for the spatial graduated symbology is provided below.

The first step of data preparation was creating detailed postcode 6 entries with the morphology indicators from the databases. This involved collecting the source layers in ArcGIS from shapefiles, APIs, and Excel sheets. Once projected onto the same coordinate system, Amersfoort / RD New EPSG 28992, the data, formatted as polygons, points, and lines, were clipped to the city boundaries. See Table 5 for the independent and dependent variables with corresponding feature classes.

Table 5: Independent and Dependent Variables Corresponding Feature Classes

Independent Variables		Dependent Variables	
Indicator	*Feature Classes*	*Indicator*	*Feature Classes*
Building Volume	Poly	AM Truck	Line
Building Height	Poly	AM Service	Line
Minimum Bounding Rectangle	Poly	AM Parcel	Line
Complexity	Poly	AM Aggregated	Line
Party Wall Area	Poly	PM Truck	Line
Gross Floor Area; Office Function	Poly	PM Service	Line
Gross Floor Area; Retail Function	Poly	PM Parcel	Line
Gross Floor Area; Industrial Function	Poly	PM Aggregated	Line
Gross Floor Area; Residential Function	Poly	Other Truck	Line
Gross Floor Area; Meeting Function	Poly	Other Service	Line
Open Space Ratio	Poly	Other Parcel	Line
Mixed Use Index	Poly	Other Aggregated	Line
Simpson Diversity Index	Poly	All Aggregated	Line
Ratio of Neighbor Footprint Sum to Buffer Area (50m)	Poly		
Standard deviation of Footprint Area within Buffer (50m)	Poly		
Street Width	Line		
Year Built	Poly		
Population Density	Poly		
Household Size	Poly		
Urbanity	Poly		
Property Value	Poly		
Address Density	Poly		
Age	Poly		
Immigrate & Native Population	Poly		
Public Transit Stops	Point		

* The logistics intensity data for the city of Amsterdam was displayed in line segments. Since the study focused exclusively on urban and peri-urban areas within Amsterdam's boundaries, freeway segments were removed using the select tool because they only accommodate high-capacity vehicle traffic. The removal of this traffic alters the results for these postal codes. However, the inclusion of this traffic for postcodes containing the freeway segments would artificially inflate urban logistics activity. Thus, its removal ensures that the models are not skewed by freeway network flows.

For each postcode 6 area, the spatial join tool was used to apply the boundaries of the postcode 6 as the data collection container. A spatial join is a tool that "*joins attributes from one feature to another based on the spatial relationship*" (ESRI, n.d.). The target feature, the postcode 6 polygons, was joined to the morphological indicators based on the spatial intersection. Depending on the morphological indicators, various statistical operations were used to assign the appropriate aggregation statistic.

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Table 6 provides an overview of the morphological indicators and the applied statistical normalization methods. These operations ensured that each postcode 6 unit reflects a consistent morphological profile. The statistical operations used were sum, median, mean, and count. The sum and count of 'point features' are used for variables where totals indicate the X value in postcode 6. The mean was applied to variables where the postcode average provided the relevant insight, and the median was used for skewed variables to represent the central tendency, thus reducing the influence of outliers. Once joined, all the statistical summaries are added as new attribute fields on a central postcode 6 layer in which every postcode polygon has the complete set of morphological indicators.

Table 6: Morphological Indicators and Statistical Normalization Methods

Indicator	*Measure*	*Mathematical Modeling*
Building Volume	Sum	Normalize by postcode area in cubic meters
Building Height	Sum	Derived from volume/footprint area in meters
Minimum Bounding Rectangle	Median	In square meters; length * width
Complexity	Median	Scale, Low Value = Low Building Complexity and High Value = High Building Complexity
Party Wall Area	Median	In square meters; Length of Shared Wall * Wall Height of Building
Gross Floor Area; Office Function	Sum	Normalize by postcode area in square meters
Gross Floor Area; Retail Function	Sum	Normalize by postcode area in square meters
Gross Floor Area; Industrial Function	Sum	Normalize by postcode area in square meters
Gross Floor Area; Residential Function	Sum	Normalize by postcode area in square meters
Gross Floor Area; Meeting Function	Sum	Normalize by postcode area in square meters
Open Space Ratio	Median	Ratio, 0 to 1; Open Space Ratio = (1 - Building Area / Shape Area) / (Gross Area / Shape Area)
Mixed Use Index	Median	Ratio, 0 to 1; Mix Use Index = (Residential + Lodging) / (Gross Area - (Other Use + Secondary Area))
Simpson Diversity Index	Median	Ratio, 0 to 1; normalized and quantifies land-use heterogeneity around a building.
Ratio of Neighbor Footprint Sum to Buffer Area	Median	Ratio, 0 to 1; measures local built density around a building
Standard Deviation of Footprint Area within Buffer (50m)	Median	In square meters; variability of footprint
Street Width	Median	Median estimated street width in meters
Street Width Spread	Spread	In meters, Max Estimated Street Width - Median Estimated Street Width
Year Built	Median	Median year of construction in postcode
Population Density	Sum	Count of people in postcode
Household Size	Mean	Average people per address; count of people
Urbanity	Ordinal Category	Model based on address density, in address per kilometer squared; Very Highly Urban ≥ 2,500, Highly Urban ≥ 1500 to 2500 <, Moderately Urban ≥ 1000 to 1500 <, Little Urban ≥ 500 to 1000 <, and Non-Urban < 500.
Property Value	Mean	Average property value in euros
Address Density	Sum	Count of address in postcode
Age	Sum	Count of people in postcode per age bin; 0 to 15 Year Old, 15 to 25 Year Old, 25 to 45 Year Old, 46 to 65 Year Old, and 65+ Year Old
Immigrate & Native Population	Ordinal Category	Determined by majority of population; Dutch, Other European, Non-European Dutch, European Abroad, and Non-European Abroad
Public Transit Stops	Sum	Count of stops in postcode

Once the postcode 6 collections are created, a standardization procedure occurs to enable comparison of indicators such as years with population or gross floor area. The data was first standardized by size when applicable, such as X per hectare (hectare densities), then z-score

standardization was used to bring every morphological indicator onto the same scale, making them comparable over time and across variables. Z-score standardization is a type of data management tool that "*standardizes values in fields by converting them to values that follow a specified scale*" (ESRI, n.d.). The z-score, calculated using the equation below, measures the difference between a value and the mean of all values in the field using standard deviations (ESRI, n.d.), Equation 10.

Appendix A, Table 6 reports each independent variable chosen for aggregation by postcode, along with its resulting raw data mean, standard deviation, and the corresponding z-scores statistics.While the independent variables were normalized using z-scores, the dependent variable outcome remains in observed units, vehicle counts, to allow for direct interpretability and transferability. Therefore, the model's coefficients represent the expected change in vehicle count associated with a one standard deviation change in the predictor.

Equation 10: Standardization Formula for Converting Values to Z-Scores

$$x' = \frac{x - \bar{X}}{\sigma_x}$$

* Both median estimated street width and street width spread are reported as they are complementary aspects of street width distribution. The estimated street width statistic was calculated using the national road database, a meter buffer, and the removal of urban form overlaps to calculate the estimated street width, as the data did not exist. It was presumed to have a statistically significant impact on logistic intensity. The median indicates the typical street width but is often underestimated due to mapping errors and the inclusion of narrow alleys. The width spread is used to compensate for these effects, thereby creating a robust method to characterize the state of the street networks.

Once this mix-tool approach is completed, the results are a cleaned postcode 6 polygon shape level where the connection between urban morphology and logistics traffic counts is easily achievable.

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Chapter 5

Results

The results in the following section are reported separately for the regression and random forest models, calibrated for the city of Amsterdam and applied to the cities of Rotterdam and Utrecht. Overall, the findings provide insights into the extent of the impact of each morphological attribute on logistic vehicle counts. Moreover, through statistical and random forest modeling, the results offer valuable information on the complex relationships between independent and dependent variables, thereby generating implications for how logistics operations interact with urban morphological variables.

The analysis results are reported for three temporal segments corresponding to the city-defined operational periods, bevoorradingstijden. These are Morning peak (7:00 to 9:00), Afternoon peak (16:00 to 18:00), and off-peak (all other times) (Gemeente Amsterdam, 2025; Gemeente Rotterdam, 2025; Gemeente Utrecht, 2025).

5.1 Results of Clustering

Hot spot analysis uses the Getis-Ord GI statistic to identify clusters of spatial units with high vehicle counts. In Appendix B, Figure 6, the Getis-Ord Gi* hot spot maps illustrate this by showing that the western industrial zones (A) and postcodes along the southeast entry corridor (B), the southern edge of the city (C), and in the central city (D) all display areas of intense logistics activity across nearly every layer. Secondary hot spots can be seen in port-adjacent zones and key city corridors. This differs from the historic canal rings and residential neighborhoods, which have considerably less logistics traffic. These findings make sense considering the narrow streets, pedestrian zones, and regulations on logistics operations, as indicated by the available spatial and policy data provided by Gemeente Amsterdam (Gemeente Amsterdam, 2025). Note that the wetlands in the northeast appear as cold spots with limited populations and road networks, which is a notable anomaly in Amsterdam.

While a few morning and afternoon hot spots are scattered across the city, most traffic hot spots appear on arterial roads. During the morning peak (AM Aggregated), hot spots occur in multiple areas, including the northwest, especially in places like Sloterdijk, located in the central part of the city (E), and Westpoort in the northwest (A), as well as in the south-central areas of Amstel (F) and the southern edge of Zuid (B). This indicates high levels of overlap with commuters entering the city center. In contrast, during same period, (AM Aggregated), cold spots are seen

in residential areas in the west of the city, like Oud-West (G), where through traffic is lighter, as vehicle presence aligns more with end or origin destination traffic.

During the afternoon peak (PM Aggregated), hot spots shift slightly, with more intense areas emerging along the riverfront and on outbound feeder corridors, again indicating high interaction with commuter traffic flow. Throughout the rest of the day, hot spots become fewer and more localized to industry-specific regions, with fewer in the city center. When considering all periods of the day (All Aggregated), hot spots most consistently appear at central bottleneck points in the Central Station (D) area and major freeway exits in southern Zuid (C). These are clearly shown on the combined hot spot map (see Figure 6 in Appendix B). When examining vehicle type-specific patterns, during both AM and PM periods, service vehicles exhibit more variety of cold spots in the city center compared to trucks and parcels, suggesting that the type of logistics is not tightly linked to logistics corridors. Additionally, when :other trucks" is compared to AM and PM trucks, there are more neutral spots, indicating lower trip intensity. "PM parcels" spreads into residential areas, matching typical consumer patterns. Thus, the analysis shows that logistics vehicle traffic in Amsterdam is not evenly distributed but tends to cluster along freight routes, industrial zones, and major junctions. Meanwhile, activity in the residential areas and historic city centers remains relatively low, tending to cluster to a degree only in the afternoons.

The spatial patterns identified in the Amsterdam cluster analysis are shown in Table 7. Table 7 provides descriptive statistics related to postal code traffic counts. Notably, the significant differences between the average mean (200) and average maximum (20,000) counts reflect a heavy-tailed distribution, indicating that logistics vehicle traffic is concentrated on a small number of arterial links, as confirmed by the median count across all time frames. Of the entire table, AM Parcel has the highest skewness score, while Other Parcel has the lowest. Additionally, based on the mean and median relationship, during the evening peak, zero logistics counts in the postal code are observed only 68 times, compared to 950 in the morning (see Table 7). Thus, during the morning peak, many local streets are rarely used by logistics vehicles, in sharp contrast to the situation in the afternoon.

Table 7: Descriptive Statistics from Cluster Analysis of Postcode Logistics Vehicle Counts in Amsterdam

Dependent Variable	Mean	Median	Std. Dev.	Null Count	Min	Max	Sum	Skewness	Kurtosis
AM Truck	88.304	8.000	345.902	2772	0.000	7630.001	888518.996	10.019	137.217
AM Service	77.000	12.556	269.642	1374	0.000	8350.396	774773.541	11.618	224.068
AM Parcel	2.144	0.000	6.888	6055	0.000	249.000	21574.000	14.695	377.311
AM Aggregated	167.448	24.091	560.320	950	0.000	13241.395	1684866.537	8.759	114.190
PM Truck	93.299	9.966	348.876	1344	0.000	7462.138	938773.478	9.165	114.496
PM Service	77.000	12.556	269.642	1374	0.000	8350.398	774773.544	11.618	224.068
PM Parcel	4.023	2.114	7.502	399	0.000	224.084	40474.644	11.440	240.933
PM Aggregated	174.321	26.108	573.675	68	0.000	13593.095	1754021.666	8.567	109.477
Other Truck	581.091	60.000	2333.716	1319	0.000	54711.602	5846940.116	10.278	143.779
Other Service	93.363	12.284	381.364	1730	0.000	11459.772	939416.683	13.315	271.361
Other Parcel	19.430	10.000	33.407	879	0.000	855.000	195501.000	8.554	142.130
Other Aggregated	693.884	87.928	2625.533	541	0.000	61138.299	6981857.799	9.657	128.103
All Aggregated	1035.654	139.063	3697.772	0	0.151	83232.820	10420746.002	9.023	113.109

Overall, the hotspot analysis reveals a highly non-normal and dispersed freight traffic pattern, with a small set of corridors accounting for the majority of the traffic. Thus, Amsterdam's logistics-impacted congestion occurs and is most noticeable along its entry and exit roads, as well as around key structural intersections and infrastructure. Furthermore, secondary streets, which are adjacent to major commercial zones or arterial roads, appear as cold spots. However, when major roads are excluded, these secondary streets appear as hot spots as logistics traffic overflows into neighboring roads. This provides visual cues regarding the location of choke points and, therefore, possible points of intervention for infrastructure improvements.

Overlaying the maps of the independent variables reveals patterns that show that street geometry and network hierarchy are strong indicators of hot and cold spots. Appendix C, Figure 9 provides a spatial overview of the urban morphological indicators across Amsterdam, illustrating the heterogeneity of the built environment, socio-demographic factors, and accessibility indicators across the city. The maps contextualize the spatial attributes that influence the observed logistics activity patterns. When comparing the built form attributes to logistics operators' activity, one notes that high logistics intensity areas tend to have wider streets, less land use diversity, and fewer public transit stops. This reflects logistics operators' preference for wider thoroughfares. Likewise, logistics hot spots are often characterized by limited mixed-use development and low address density, indicating single-use zoning. As population, home values, and public transport stops increase, logistics activity generally decreases. The physical constraints of these areas, along with strict policy regulations, limit logistics drivers' willingness to operate there.

5.2 Results of Multicollinearity and Correlations

Critical to any statistical analysis and predictive modeling is the assessment of variance inflation factors (VIFs) and pairwise correlations, using Spearman correlation.

Table 8 lists the desired variables for the study. However, using the VIF diagnostic, some variables needed to be adjusted or removed entirely. First are the variables for dominate immigrate code and urbanicity level. To adjust for the VIF outliers, an assumed base case of predominantly Dutch and urban areas was created, thus removing one of each dummy variable, as they together create near-perfect linear dependencies among themselves. However, these variables were later removed due to the informed correlations and statistical significance prediction using Spearman's rho method.

Another set of high VIFs was associated with age, particularly in the age bins per geographic area, with the highest VIF of 68 in the 45 to 65 age range. The 0 to 15 age bin was highly correlated with average household size, which makes sense given the high proportion of families. Based on this, the age bins were removed from the variable list. This decision was made because including the 25-45 age group makes it nearly impossible to interpret model coefficients reliably. Unlike the immigrant population and urbanity level, there is no assumed baseline for validity by postal code. Notably, age bins over 15 years old did not show high collinearity with any single variable, indicating that effects for all ages over 15, and thus age-specific effects, are spread out and do not reflect local variation when compared to other urban morphology variables. However, they exhibited moderate levels of collinearity with several different variables. For these reasons,

all age-bin variables were removed to preserve coefficient stability. This approach is supported by the work of Kikkawa (2006), which not only justifies the removal of variables like age based on high VIF, but also emphasizes the importance of doing so to better stabilize results and enhance interpretability without sacrificing explanatory power.

Even though the variables relating to the population density and gross floor area of residential units generated VIF scores above the threshold, they were included given the minimal amount they exceeded the cutoff, their assumed importance to urban morphology, and anticipated importance in driving logistics consumption behavior.

The final list of predictors is presented on the right side of Table 8. The list is the product of an assessment of each variable's interpretability, theoretical foundation, and statistical relevance. The variables serve as independent inputs for the spatial regression and random forest models in the following sections, enabling the modeling of the relationship between urban morphology and logistics spatial-temporal claims with the intent of supporting future policy recommendations.

The correlation matrix of Spearman's rho was prepared for the final list of independent variables (see Table 9). All the independent variables were tested against the dependent variables for the predicted logistics traffic count. The correlation table highlights both the strength and significance (p-value) of each relationship. When it shows 'TRUE' under significant correlation, it indicates which variables are statistically significant in relation to the dependent variable, while 'FALSE' suggests no relationship or a weak one. The threshold for statistically significant correlations is $p < 0.05$. Among the dependent variables and their significant independent variables, parcel type of delivery has the highest variable count within each day segment, indicating that parcel logistics are influenced by a broader range of urban factors compared to truck or service logistic trips. This also reflects the greater complexity of parcel logistics. The remaining categories of dependent and independent variables are more stable.

Furthermore, Table 10 shows the positive and negative correlations indicate that variables counteract each other's effects on logistics traffic results. The correlation matrices inform variable selection for modeling. Note that variables such as tram stops, number of inhabitants, street width, certain gross floor area categories, and building age show consistent significance across all dependent variables (different logistic vehicle traffic counts in morning and evening peak as well as off-peak). In contrast, other variables, including density measures and urban infrastructure, exhibit more variation.

Table 8: Variance Inflation Factor Analysis for Independent Variables

Variable	VIF Round 1	VIF Round 2	VIF Round 3
Public Transit Stops	1.00	1.00	1.00
Building Height	1.02	1.02	1.01
Open Space Ratio	1.03	1.03	1.03
Urbanity, Moderately Urban	8064723417.30	1.09	1.03
Urbanity, Non-Urban	82891133640.16	1.89	1.11
Gross Floor Area; Retail Function	1.13	1.13	1.13
Standard deviation of Footprint Area within Buffer (50m)	1.14	1.14	1.13
Street Width Spread	1.18	1.18	1.16
Party Wall Area	1.19	1.19	1.19
Urbanity, Highly Urban	9409630324.46	1.36	1.26
Socio-Cultural, Non-European Dutch	1.49	3224482778.46	1.30
Socio-Cultural, Non-European Abroad	1.48	849299030.73	1.32
Property Value	1.85	1.85	1.55
Street Width	1.99	1.99	1.57
Simpson Diversity Index	1.60	1.60	1.58
Building Volume	1.66	1.66	1.66
Ratio of Neighbor Footprint Sum to Buffer Area (50m)	2.04	2.04	2.02
Year Built	2.14	2.14	2.14
Mixed Use Index	2.34	2.34	2.32
Gross Floor Area; Office Function	2.40	2.40	2.40
Household Size	11.63	11.63	2.43
Address Density	4.71	4.71	2.88
Minimum Bounding Rectangle	3.47	3.47	3.44
Complexity	4.33	4.33	4.29
Gross Floor Area; Residential Function	4.52	4.52	4.49
Gross Floor Area; Industrial Function	4.72	4.72	4.61
Population Density	5.00	5.00	5.00
Gross Floor Area; Meeting Function	5.12	5.12	5.00
Age, 45 to 65 Year Old	16.14	16.14	*eliminated*
Age, 15 to 25 Year Old	18.43	30.42	*eliminated*
Age, 65+ Year Old	23.45	23.45	*eliminated*
Age, 0 to 15 Year Old	30.42	18.43	*eliminated*
Age, 25 to 45 Year Old	69.63	70.20	*eliminated*
Socio-Cultural, Dutch	34991.45	*eliminated*	*eliminated*
Urbanity, Very Highly Urban	124023.48	*eliminated*	*eliminated*

Table 9: Spearman's Rho Correlation Significance (p < 0.05) Between Independent Variables and Dependent Variables

Dependent Variable	AM Truck	AM Service	AM Parcel	AM Agg.	PM Truck	PM Service	PM Parcel	PM Agg.	Other Truck	Other Service	Other Parcel	Other Agg.	All Agg
Building Volume	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Building Height	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
MBR	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Complexity	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Party Wall Area	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
Office GFA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Retail GFA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Industrial GFA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Residential GFA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Meeting GFA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
OSR	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE
MXI	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SDI	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Ratio to Buffer Area	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE
Standard deviation within Buffer	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Street Width	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE
Street Width Spread	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Year Built	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Population Density	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Household Size	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Property Value	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Address Density	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE
Public Transit Stops	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Urbanity, Highly Urban	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE
Urbanity, Moderately Urban	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Urbanity, Non-Urban	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Socio-Cultural, Non-European Dutch	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE
Socio-Cultural, Non-European Abroad	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

Table 10: Spearman's Rho Correlation Coefficients Between Independent Variables and Dependent Variables

Dependent Variable	AM Truck (ρ)	AM Service (ρ)	AM Parcel (ρ)	AM Agg (ρ)	PM Truck (ρ)	PM Service (ρ)	PM Parcel (ρ)	PM Agg (ρ)	Other Truck (ρ)	Other Service (ρ)	Other Parcel (ρ)	Other Agg (ρ)	All Agg (ρ)
Building Volume	-0.010	-0.037	-0.146	-0.041	-0.042	-0.037	-0.240	-0.060	-0.043	-0.039	-0.229	-0.074	-0.067
Building Height	0.161	0.155	0.034	0.155	0.150	0.155	-0.010	0.145	0.147	0.146	-0.020	0.126	0.135
MBR	-0.014	-0.013	0.020	-0.013	-0.002	-0.013	0.021	-0.013	-0.013	0.002	0.013	-0.009	-0.012
Complexity	-0.001	-0.002	0.009	-0.002	0.006	-0.002	0.021	-0.003	-0.003	0.010	0.013	-0.001	-0.003
Party Wall Area	0.020	-0.005	-0.121	0.000	-0.009	-0.005	-0.203	-0.019	-0.013	-0.015	-0.201	-0.040	-0.029
Office GFA	0.195	0.181	0.022	0.188	0.190	0.181	0.023	0.182	0.192	0.154	0.021	0.169	0.178
Retail GFA	0.135	0.100	-0.041	0.114	0.108	0.100	-0.090	0.097	0.103	0.089	-0.090	0.077	0.090
Industrial GFA	0.124	0.105	-0.036	0.111	0.110	0.105	-0.035	0.105	0.119	0.096	-0.028	0.100	0.105
Residential GFA	-0.216	-0.219	-0.255	-0.239	-0.247	-0.219	-0.385	-0.259	-0.246	-0.218	-0.368	-0.271	-0.267
Meeting GFA	0.140	0.112	-0.034	0.122	0.120	0.112	-0.031	0.110	0.121	0.109	-0.029	0.100	0.108
OSR	-0.062	-0.019	0.074	-0.026	-0.026	-0.019	0.101	-0.009	-0.037	-0.024	0.093	-0.013	-0.014
MXI	-0.027	-0.021	0.016	-0.021	-0.020	-0.021	0.009	-0.016	-0.017	-0.014	0.003	-0.012	-0.015
SDI	0.062	0.034	-0.026	0.040	0.043	0.034	-0.044	0.030	0.045	0.031	-0.039	0.029	0.031
Ratio to Buffer Area	0.060	0.028	-0.075	0.033	0.023	0.028	-0.107	0.017	0.041	0.017	-0.102	0.017	0.021
Standard deviation within Buffer	0.066	0.031	-0.028	0.040	0.028	0.031	-0.068	0.020	0.045	0.031	-0.067	0.025	0.026
Street Width	0.068	0.037	-0.023	0.045	0.040	0.037	-0.143	0.027	0.042	0.034	-0.153	0.011	0.021
Street Width Spread	0.139	0.120	0.095	0.128	0.121	0.120	0.093	0.122	0.138	0.122	0.085	0.130	0.129
Year Built	-0.062	-0.042	0.043	-0.045	-0.036	-0.042	0.061	-0.033	-0.043	-0.031	0.060	-0.025	-0.031
Population Density	-0.307	-0.320	-0.285	-0.341	-0.339	-0.320	-0.475	-0.360	-0.338	-0.308	-0.454	-0.366	-0.365
Household Size	-0.156	-0.097	0.035	-0.116	-0.112	-0.097	0.096	-0.095	-0.118	-0.091	0.079	-0.087	-0.094
Property Value	0.080	0.075	-0.083	0.070	0.050	0.075	-0.135	0.049	0.058	0.037	-0.130	0.027	0.041
Address Density	0.054	0.008	-0.128	0.016	-0.001	0.008	-0.230	-0.015	0.009	0.005	-0.229	-0.031	-0.019
Public Transit Stops	0.148	0.132	0.101	0.143	0.143	0.132	0.122	0.140	0.146	0.136	0.123	0.145	0.144
Urbanity, Highly Urban	0.037	0.044	0.081	0.051	0.038	0.044	0.099	0.052	0.035	0.013	0.110	0.046	0.050
Urbanity, Moderately Urban	-0.013	0.000	0.043	-0.001	-0.006	0.000	0.016	-0.001	-0.006	0.003	0.010	-0.001	-0.001
Urbanity, Non-Urban	0.116	0.066	0.065	0.108	0.120	0.066	0.090	0.113	0.119	0.071	0.085	0.120	0.117
Socio-Cultural, Non-European Dutch	-0.043	-0.030	-0.034	-0.038	-0.044	-0.030	0.032	-0.033	-0.033	-0.028	0.010	-0.026	-0.030
Socio-Cultural, Non-European Abroad	0.018	0.029	0.086	0.028	0.042	0.029	0.143	0.041	0.027	0.043	0.143	0.047	0.042

5.2 Results of Regression Analysis

This section uses a stepwise regression analysis approach, building upon the extension of a baseline linear Ordinary Least Squares (OLS) framework by exploring the modeling of spatial spillover effects across Amsterdam's postal codes. This is done to apply various statistical tests to explore possible correlations between the dependent variable of traffic counts and urban morphology. Within each test, the null hypothesis was assessed against the alternative hypothesis of whether the independent variable was statistically significant on the dependent variable [the null hypothesis represents no significant correlation between variables, whereas the alternative is that there is a significant correlation between variables]. Both the full set and significant-only specifications of independent variables are tested to identify the regression model that best fits the data statistically.

5.2.1 Baseline Linear Modeling

Ordinary Least Squares (OLS) is a type of linear regression model initially used to estimate the outcome of logistics traffic counts for the dependent variable, using a set of independent variables identified through Spearman correlation analysis. The models utilized 10,055 observations, or N as shown in Table 11, and the number of predictor variables, labeled as IV Count in Table 11, ranged from 16 to 21 depending on the dependent variable specification. These variables include street attributes, built form indices, demographic variables, and land use explanatory variables to explain variation in logistic traffic counts, aggregated by postal code 6.

Table 11: Ordinary Least Squares Model Results for Amsterdam

Dependent Variable	N	IV Count	Adj R2	AIC	BIC	CV RMSE	MAE Over Mean	Moran's I	Moran's p
AM Truck	10055	20	0.0636	145267.284	145418.817	331.162	1.417	0.4951	0.001
AM Service	10055	18	0.0483	139462.836	139599.937	248.184	1.282	0.3708	0.001
AM Parcel	10055	21	0.0539	66789.645	66948.393	6.686	1.280	0.3788	0.001
AM Aggregated	10055	19	0.0592	154591.104	154735.421	526.551	1.305	0.4180	0.001
PM Truck	10055	19	0.0538	145517.775	145662.091	335.346	1.389	0.4811	0.001
PM Service	10055	18	0.0483	139462.837	139599.937	248.184	1.282	0.3708	0.001
PM Parcel	10055	21	0.0803	68091.372	68250.120	7.134	0.841	0.3472	0.001
PM Aggregated	10055	16	0.0598	155047.401	155170.070	538.795	1.293	0.4093	0.001
Other Truck	10055	18	0.0531	183830.827	183967.928	2253.943	1.408	0.4840	0.001
Other Service	10055	17	0.0401	146782.344	146912.229	357.182	1.358	0.3567	0.001
Other Parcel	10055	20	0.0960	97448.537	97600.069	30.715	0.848	0.2913	0.001
Other Aggregated	10055	17	0.0656	185976.751	186106.636	2508.010	1.367	0.4529	0.001
All Aggregated	10055	18	0.0604	192810.907	192948.008	3522.704	1.344	0.4486	0.001

The OLS models show a relatively low explanatory power across all dependent variables. Low OLS results indicate that, across all postal codes, less than 10% of traffic variation is explained solely by morphology in a non-spatial framework (see Table 11). Therefore, without accounting for spatial factors, a linear model captures only a small fraction of the observed traffic flow variation which is informed by adjusted R². Adjusted R² is a statistical metric used to evaluate how well the model explains the dependent variables (Hyndman, 2017). Calculated from Equation 11 for R-squared and Equation 12 for adjusted R², these two metrics evaluate the fit of the models. In Equation 11, SS_{res} is the sum of squared residuals and SS_{tot} is the sum of squares

(Hyndman, 2017). In Equation 12, n is the total number of observations, and k is the number of independent variables (Hyndman, 2017). Using adjusted R² instead of R² in this study is important because the models include different numbers of predictor variables while aiming to prevent overfitting.

Equation 11: R Squared Formula

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Equation 12: Adjusted R Squared Formula

$$Adjusted\ R^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1}$$

Furthermore, AIC estimates the quality of statistical models and aims to explain the data best while considering model complexity and overfitting (Hyndman, 2017). AIC, as shown in Equation 13, is calculated using k, the number of model parameters, and L the maximum likelihood of the model (Hyndman, 2017). Similarly, BIC is based on Bayesian probability and is designed to balance model fit with complexity, much like AIC. BIC is calculated using Equation 14, where k is the number of parameters, L is the maximum likelihood, and n is the number of data points (Hyndman, 2017). Together, these two equations provide insight into how well a model fits the data while penalizing any extra parameters that could lead to overfitting. The relatively high values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) indicate a weak fit within each model (a lower AIC or BIC would suggest a better fit).

Equation 13: Akaike Information Criterion Formula

$$AIC = 2k - 2\ ln\ ln\ (L)$$

Equation 14: Bayesian Information Criterion Formula

$$BIC = k * ln(n) - 2\ ln\ ln\ (L)$$

Additionally, the root mean squared error (RMSE) and the coefficient of variation of the root mean square error (CV RMSE), a tool used in normalizing RMSE, highlight the model's absolute prediction error. Equation 15 presents the RMSE equation, where n is the number of observations, y_i is the observed value, and $\hat{y}_i$ are the predicted values (Hyndman, 2017). For the normalized version of RMSE, CV RMSE, the formula is shown in Equation 16. In it, $\bar{y}$ is the mean of the observed values (Hyndman, 2017). The lower the RMSE and CV RMSE, the better the performance of a regression model. The wide range of CV RMSE, from 6 to 3,000, highlights that the model behaves very differently across dependent variables.

Equation 15: Root Mean Squared Error Formula

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Equation 16: Coefficient of Variation of the Root Mean Square Error Formula

$$CV\ RMSE = \frac{RMSE}{\bar{y}} * 100\%$$

Moreover, Mean Absolute Error (MAE) and Mean Absolute Error Over Mean (MAE Over Mean) are both metrics that quantify prediction deviations compared to actual observations in regression modeling (Hyndman, 2017). MAE is the average of the absolute differences between predicted values and observed values and is calculated using equation 17. In the equation, like RMSE, n is the number of observations, y_i is the observed value, and $\hat{y}_i$ are the predicted values. In comparison, for MAE Over Mean, a metric used to normalize MAE as it is a proportion of the mean of the actual values, the equation used in calculation is seen in equation 18, where, $\bar{y}$ is the mean of the observed values (Hyndman, 2017). Looking at Table 11, with all the MAE Over Mean ratios being above 0.84 and most above 1, it indicates that the model error is close to or larger than the typical value being predicted, which suggests that the model's predictions are as large as or larger than the observed value, thus reflecting low predictive accuracy.

Equation 17: Mean Absolute Error Formula

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Equation 18: Mean Absolute Error Over Mean Formula

$$MAE\ Over\ Mean = \frac{MAE}{\bar{y}}$$

When outliers are accounted for and removed, the number of observations drops to 8,150, and the adjusted R² increases from 0.7 to 0.15, though it remains quite low. For the remainder of the analysis, outliers will be kept in the dataset since they account for 20% of the dataset and removing them has little to no effect on the statistical results. Preserving the outliers is justified because the data is heavily skewed, and the outliers offer valuable information while preventing overfitting of the model. When examining predictor significance, the F-tests consistently reject the null hypothesis of no explanatory power at $p < 0.001$. However, a key finding across all diagnostic checks is the strong spatial clustering, as indicated by Moran's I. In all models, the residuals range from 0.30 to 0.50, with all p-values less than 0.001. This level of spatial autocorrelation thus violates the OLS assumption of no spatial autocorrelation. See the Method section for a breakdown of Moran's I. (See Table 11 for reference).

5.2.2 Spatial Dependence

As the OSL baseline model highlights, ignoring spatial autocorrelation can lead to drastically underestimated model fits and an overstatement of the level of uncertainty. To correct for this error, tests for each spatial autocorrelation outcome were done using the LM, or Lagrange Multiplier, tool. The appropriate spatial regression models to use in this stepwise approach were inferred from these diagnostic tests. Informed by Rüttenauer's outline of spatial regression modeling, the statistical methods chosen to explore were LM error spatial regression and LM lag

spatial regression spatial regression (Rüttenauer, 2019). Within the diagnostics, tests were performed for each dependent variable to understand the spatial effect.

All of the diagnostic tests reject the OLS- required assumption of no spatial autocorrelation as inferred by all LM error and LM lag having 'p' less than 0.001 (see Table 12). Both the normal and robust versions of the LM tests were performed, with the robust version testing for different types of spatial dependence, such as whether it is robust LM lag testing for error dependence and vice versa, while in the standard version, the tests are conducted separately. The robust LM tests provide insight on the appropriate test for the data. As seen with the robust LM lag p, for all outcomes, there is high significance, p less than 0.05, even after considering possible error. In contrast, for robust LM error, this is only the case for three of the models. This informs us that once lag dependence is accounted for, there is a lack of spatial autocorrelation in the errors alone.

Table 12: Lagrange Multiplier Test Results for Spatial Dependence in Amsterdam Logistics Traffic Model

Dependent Variable	N	Robust LM Lag p	Robust LM Error p	Robust LM Lag Stat	Robust LM Error Stat	Preferred Model
AM Truck	10055	5.614E-07	1.110E-06	25.041	23.728	Both significant; choose Lag
AM Service	10055	1.205E-03	1.916E-05	10.483	18.272	Both significant; choose Error
AM Parcel	10055	1.403E-04	3.541E-05	14.498	8.505	Both significant; choose Lag
AM Aggregated	10055	3.123E-06	9.067E-06	21.739	19.699	Both significant; choose Lag
PM Truck	10055	5.563E-07	3.467E-06	25.058	21.539	Both significant; choose Lag
PM Service	10055	1.205E-03	1.915E-05	10.483	18.272	Both significant; choose Error
PM Parcel	10055	8.819E-03	5.052E-08	6.859	29.697	Both significant; choose Error
PM Aggregated	10055	5.956E-06	1.257E-05	20.502	19.075	Both significant; choose Lag
Other Truck	10055	1.964E-06	7.322E-07	22.629	24.528	Both significant; choose Error
Other Service	10055	2.009E-02	2.188E-05	5.404	18.019	Both significant; choose Error
Other Parcel	10055	3.976E-01	1.547E-11	0.716	45.474	Both significant; choose Error
Other Aggregated	10055	7.776E-06	5.917E-07	24.992	24.939	Both significant; choose Lag
All Aggregated	10055	4.834E-06	5.443E-07	25.202	25.100	Both significant; choose Lag

Based on the diagnostic tests, the spatial lag regression model and the error lag regression are almost evenly split, indicating that they are both significant. For the decision rule, the preferred model is chosen based on the Robust LM Lag and Robust LM Error (Rüttenauer, 2019). The logical conditions for the rule are presented below. The selection of the appropriate model was guided by the workflow of Anselin & Rey (2014). See Appendix D.

- *Preferred Model Spatial Lag:* When Robust LM Lag p-value is below 0.05 and Robust LM Error p-value is equal to or above 0.05.

- *Preferred Model Spatial Error:* When Robust LM Error p-value is below 0.05 and Robust LM Lag p-value is equal to or above 0.05.

- *Both Significant; Choose Lag:* When both Robust LM Lag and Robust LM Error p-value is below 0.05 and the Robust LM Lag statistic is larger than the Robust LM Error statistic.

- *Both Significant; Choose Error:* When both Robust LM Lag and Robust LM Error p-value is below 0.05 and the Robust LM Error statistic is larger than the Robust LM Lag statistic.

For context, Robust LM Lag p, Robust LM Error p, Robust LM Lag Stat, and Robust LM Error Stat are statistical tests used to determine spatial lag or spatial error dependence within the data. They also account for overall spatial effects (Rüttenauer, 2019). The term 'robust' is used to adjust for the possible presence of other spatial correlations, such as spatial error in the spatial lag test and vice versa, thus enabling the isolation of the lag or error effect. As seen in Equations 19 and 20, the robust LM tests consider the other form of spatial dependence, seen through values LM_{lag} and LM_{error} (Anselin, Bera, Florax, & Yoon, 1996). These equations both use LM_{lag} and LM_{error} formulas as shown in Equations 21 and 22 (Anselin, Bera, Florax, & Yoon, 1996). In these, e is the OSL residual, W is the critical spatial weights matrix, y is the dependent variable, and $\hat{\sigma}^2$ is the OLS error variance, S and T are different scaling factors providing spatial structure as they fit the test (Anselin, Bera, Florax, & Yoon, 1996). Note that the LM_{lag} equation differs from the spatial lag equation as it is a test equation rather than a model. The Robust LM Lag p and Robust LM Lag Stat are tests used to detect spatial lag dependence, which indicates if the spatial lag of the dependent variables, specifically, whether a spatial location influences a neighboring value. The Robust LM Error p and Robust LM Error Stat tests for spatial error dependence in the model residuals. For both models, the p value and statistic are tests and measures that quantify the strength of the spatial effect, either lag or error.

Equation 19: Robust LM for Lag Formula

$$RLM_{lag} = LM_{lag} - \frac{Cov(LM_{lag}, LM_{error})}{Var(LM_{error})} * LM_{error}$$

Equation 20: Robust LM for Error Formula

$$RLM_{error} = LM_{error} - \frac{Cov(LM_{lag}, LM_{error})}{Var(LM_{lag})} * LM_{lag}$$

Equation 21: LM Lag Formula

$$LM_{lag} = \frac{[(e'Wy)/\hat{\sigma}^2]^2}{S}$$

Equation 22: LM Error Formula

$$LM_{error} = \frac{[(e'We)/\hat{\sigma}^2]^2}{T}$$

When the outliers were removed (see Table 13), however, the LM spatial lag regression model is clearly the preferred model for 12 of the dependent variables, with three indicating that both are significant. Based on this, the LM spatial lag regression model was selected as the spatial regression model.

Table 13: Lagrange Multiplier Test Results for Spatial Dependence in Amsterdam Logistics Traffic Models with Outlier Removal

Dependent Variable	N	Robust LM Lag p	Robust LM Error p	Robust LM Lag Stat	Robust LM Error Stat	Preferred Model
AM Truck	8150	1.650E-25	0.573	108.967	0.318	Spatial-Lag
AM Service	8150	4.220E-15	0.243	61.594	1.364	Spatial-Lag
AM Parcel	8150	7.905E-08	0.000	28.829	20.700	Both significant; choose Lag
AM Aggregated	8150	2.672E-20	0.856	85.218	0.033	Spatial-Lag
PM Truck	8150	1.042E-28	0.129	123.578	2.310	Spatial-Lag
PM Service	8150	4.220E-15	0.243	61.594	1.364	Spatial-Lag
PM Parcel	8150	2.380E-05	0.000	17.858	14.165	Both significant; choose Lag
PM Aggregated	8150	7.779E-23	0.653	96.772	0.202	Spatial-Lag
Other Truck	8150	6.003E-29	0.471	124.672	0.521	Spatial-Lag
Other Service	8150	9.213E-19	0.521	78.221	0.413	Spatial-Lag
Other Parcel	8150	4.866E-05	0.000	16.500	19.350	Both significant; choose Error
Other Aggregated	8150	1.280E-29	0.451	127.739	0.568	Spatial-Lag
All Aggregated	8150	1.836E-26	0.578	113.321	0.309	Spatial-Lag

5.2.3 Spatial Lag Regression

To account for the spatial spillover effect among the observations, a spatial lag regression model was developed for each dependent variable using the statistically significant predictors identified through previous correlations. The model, when applied to the data, resulted in an adjusted R² range between 0.20 and 0.40 (see Table 14). Furthermore, the range of the spatial parameter ρ is between 0.37 and 0.55, with all variables being highly significant as indicated by p being less than 0.001. This confirms the spatial clustering in the data. Spatial parameter ρ, calculated within the framework of the spatial lag model, measures the spatial spillover effects that the built social environment characteristics in one unit influence adjacent units. Furthermore, across AIC and BIC, all models see a decrease in error, averaging 2,500 when compared to the aspatial OSL linear regression model.

Table 14: Spatial Lag Regression Model Results for Amsterdam

Dependent Variable	N	IV Count	Adj R2	Spatial Rho	Spatial Rho p-value	AIC	BIC	CV RMSE	MAE Over Mean
AM Truck	10055	20	0.382	0.566	<0.001	141846.387	142005.136	3.067	1.018
AM Service	10055	18	0.217	0.394	<0.001	137839.860	137984.177	2.970	1.054
AM Parcel	10055	21	0.280	0.500	<0.001	64613.563	64779.527	2.729	0.996
AM Aggregated	10055	19	0.287	0.472	<0.001	152309.866	152461.398	2.768	1.014
PM Truck	10055	19	0.361	0.552	<0.001	142286.834	142438.367	2.974	1.012
PM Service	10055	18	0.217	0.394	<0.001	137839.861	137984.178	2.970	1.054
PM Parcel	10055	21	0.266	0.461	<0.001	66307.023	66472.987	1.590	0.747
PM Aggregated	10055	16	0.279	0.462	<0.001	152867.850	152997.735	2.737	1.013
Other Truck	10055	18	0.368	0.561	<0.001	180512.889	180657.206	3.188	1.010
Other Service	10055	17	0.206	0.397	<0.001	145217.134	145354.235	3.534	1.113
Other Parcel	10055	20	0.218	0.369	<0.001	96288.018	96446.766	1.478	0.765
Other Aggregated	10055	17	0.341	0.531	<0.001	183122.858	183259.959	3.057	1.017
All Aggregated	10055	18	0.329	0.517	<0.001	190049.954	190194.271	2.899	1.007

Various models were tested with a variety of different numbers and combinations of independent variables. After the initial testing, only those variables that had a significant relationship with logistics traffic intensity based on Spearman correlations were used. Furthermore, the best model was selected based on the performance metrics of adjusted R² and AIC. The best model for each

dependent variable in terms of performance has been chosen for further reporting. The coefficients are reported in Table 15.

The built form predictors of street width, average building height, and building age, along with the accessibility measurements of tram stops and address density, tend, on average, to have a positive effect across different time periods and trip types. This contrasts with socio-economic variables, which generally display a negative effect. The large numerical range in coefficients highlights that each coefficient is measured in units of the dependent variable, which is the absolute vehicle count per one standard deviation change in the independent variable. This is because the independent variables were standardized using z-scores before model estimation. This approach aligns with recent research practices, which typically preserve the outcome in its original units, vehicle count, rather than applying a scaling effect (Gu et al., 2024). Nonetheless, the wide range of variables is influenced by the study's methodology and the type of normalization employed.

Standardizing the independent variables using z-scores as coefficients represents the expected change in the dependent variable, which is vehicle count, per standard deviation change in the independent variable. This was done for all the independent variable data used in the study. Furthermore, because the dependent variable's unit of vehicle count has not been normalized, the standard-deviation increase in a predictor causes the predictor coefficient to be directly linked to the variation in vehicle count outcomes (Goldstein-Greenwood, 2023). Due to the large variability of vehicle count among postcode 6s across the city and the skewness of the data, the absolute magnitudes of the coefficients are inherently scaled to reflect the dependent variable. Therefore, those with stronger relationships to traffic variability tend to have larger model coefficients (Goldstein-Greenwood, 2023). As a result, the range of coefficients mirrors the variability and units of the dependent variable which allows the dependent variable to be reported in real-world units, enhancing interpretability.

For example, street width spread, which captures variations in street widths, has a positive coefficient in every model, with values ranging from 0.5 to 341 trips per one standard deviation increase, as shown in Table 15. The average coefficient across all 12 models for street width spread is +78 (see the last row of Table 15). This strongly indicates that wider streets may have more space for vehicle movement but also tend to experience higher traffic volumes. Similarly, gross floor area combined with residential usage (a proxy for population density) consistently shows positive and often large coefficients. Building height, year of construction, and tram stops (proxies for accessibility) also display positive coefficients.

Numerous socio-economic factors negatively impact model performance. These include household size, resident density, land values, and certain built environment indicators related to office and industrial floor space. It is useful to remember that having more people per hectare, or higher population density per cell, does not directly indicate its importance. Instead, it functions as an indicator of the number of measured trips per cell. This is due to the larger full-load capacity of each truck and the fact that people usually live in residential areas rather than along major traffic routes. As a result, logistics traffic in these areas is limited to trips with a specific need to

enter highly populated residential zones. Thus, the physical form of the city has a generally positive pull-on logistics traffic, while socio-economic factors, despite their presumed importance, tend to negatively influence trip generation within each postcode.

All predictors are statistically significant in their relationship to urban logistics. However, they do not all carry the same weight when it comes to the variation that they explain. To paint a clearer picture of feature importance, scores were calculated based on the absolute magnitude of the maximum-likelihood spatial lag and then converted to percentages. Figure 4 shows these results, highlighting the top predictors for the spatial lag model. As seen, across all variables, population density is the most influential independent variable, contributing an average of 20 to 30% of the variation, making it the model's best explanatory variable and the strongest factor in logistics activity clustering. Furthermore, it aligns with the understanding that fewer logistic operation movements occur in densely populated residential areas. This demonstrates how street width (an indicator of available space for vehicles) and the number of residential properties influence demand. Moreover, regarding street width, there is also a demand-driven choice, as logistics drivers tend to prefer wider roads, which reinforces demand. Building height is another strong predictor, accounting for an average of 8% of the variability. Throughout the models for the dependent variable, the main predictors remained relatively stable.

Beyond these top four predictors, additional factors such as complexity, types of floor area, household size (which serves as a proxy for population density), tram stops, year of construction, and other built form predictors account for between 1% and 7% of the variability in logistics traffic. The remaining predictors (all accounting for less than 1%) are minor control variables such as land value, building footprint, and Simpson diversity index. While these are statistically significant, they have minimal impact on logistics vehicle activity. In short, the model indicates that population density influences logistics traffic as much as the built urban form (i.e., street geometry and house density). Together, these predictors explain nearly 100% of the variation in urban logistics activity, with an error term. See Figure 4 for a visualization of predictor impact percentages.

Table 15: Coefficients for Spatial Lag Models in Amsterdam

Dependent Variable	AM Truck	AM Service	AM Parcel	AM Agg.	PM Truck	PM Service	PM Parcel	PM Agg.	Other Truck	Other Service	Other Parcel	Other Agg.	All Agg	Mean Var. Coeff
Intercept	19.806	32.435	0.739	55.78	22.006	32.435	1.602	60.011	133.701	38.14	9.923	187.5	289.4	67.964
Building Volume	0	1.126	-0.066	-0.37	-2.471	1.126	-0.037	-0.453	-17.523	1.507	0.039	-21.28	-14.7	-4.084
Building Height	-1.85	14.747	0.011	15.48	3.541	14.747	0	20.677	4.601	19.284	1.153	31.95	65.2	14.580
MBR	0	0	-0.051	0	0	0	0.023	0	0	0	0	0	0	-0.002
Complexity	0	0	0	0	0	0	-0.121	0	0	0	0	0	0	-0.009
Party Wall Area	-6.196	0	-0.183	0	0	0	-0.246	0	0	0	-1.229	-50.8	-99	-12.127
Office GFA	-9.154	-7.184	-0.157	-15.67	-9.269	-7.184	-0.283	-16.66	-59.764	-9.444	-1.384	-74.95	-106.6	-24.435
Retail GFA	-2.098	-2.332	-0.037	-5.002	-2.498	-2.332	-0.057	-4.95	-19.699	-2.875	-0.256	-18.45	-25.42	-6.616
Industrial GFA	-4.32	-6.549	-0.243	-9.193	-5.981	-6.549	-0.406	-10.027	-31.6	-12.237	-1.819	-39.01	-53.27	-13.938
Residential GFA	24.344	27.419	0.588	56.26	28.707	27.419	1.099	59.402	177.838	33.811	5.538	202.2	328.8	74.876
Meeting GFA	9.006	9.462	0.255	17.32	9.895	9.462	0.459	18.739	62.141	14.673	2.238	78.07	115	26.673
OSR	-1.112	0	-0.026	-1.466	-1.232	0	-0.049	0	-6.405	-0.456	-0.177	0	0	-0.840
MXI	1.388	-0.351	0	1.181	1.955	-0.351	0	0	0	0	0	0	0	0.294
SDI	0.449	0.294	-0.045	-1.326	0.168	0.294	0.06	-1.183	-7.597	1.911	0.062	-3.91	-4.763	-1.199
Ratio to Buffer Area	1.547	-1.492	-0.035	-1.674	-0.701	-1.492	-0.009	0	-9.244	0	0.237	0	-12.71	-1.967
Std. Dev. within Buffer	1.083	1.992	0.058	1.775	0.207	1.992	0.071	1.239	-1.19	0.156	0.288	4.529	6.372	1.429
Street Width	6.762	8.769	0.13	12.47	2.777	8.769	0.102	11.82	27.678	11.891	0.347	0	74.83	12.796
Street Width Spread	25.046	26.72	0.537	56.6	29.581	26.72	0.834	59.363	194.599	34.572	4.289	217.6	341.9	78.331
Year Built	2.432	-0.254	0.057	3.11	2.309	-0.254	0.009	3.372	23.468	-2.324	0.023	23.68	26.48	6.315
Population Density	-42.686	-50.351	-0.987	-100.3	-48.954	-50.351	-1.939	-106.215	-299.81	-63.018	-9.998	-337.9	-575	-129.811
Household Size	-9.436	-0.655	-0.111	-4.891	-3.214	-0.655	-0.051	-4.67	-15.994	-0.551	-0.163	-101.7	-43.92	-14.311
Property Value	-2.127	-0.089	-0.091	-8.466	-4.956	-0.089	-0.132	-7.922	-38.224	-0.179	-0.736	10.21	-46.83	-7.664
Address Density	-11.76	0	-0.346	0	0	0	-0.399	0	0	0	-2.044	-102.1	0	-8.972
Public Transit Stops	7.101	6.038	0.152	13.07	6.912	6.038	0.22	13.191	40.396	8.094	1.255	53.49	76.99	17.919

Figure 4: Relative Variable Importance Across Logistics Operation Categories in Amsterdam

	AM Truck	AM Service	AM Parcel	AM Aggregated	PM Truck	PM Service	PM Parcel	PM Aggregated	Other Truck	Other Service	Other Parcel	Other Aggregated	All Aggregated
■ MBR	0.00000	0.00000	0.01091	0.00000	0.00000	0.00000	0.00325	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
■ Complexity	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.01714	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
■ MXI	0.00814	0.00211	0.00000	0.00362	0.01179	0.00211	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
■ OSR	0.00653	0.00000	0.00553	0.00450	0.00743	0.00000	0.00699	0.00000	0.00617	0.00210	0.00527	0.00000	0.00000
■ SDI	0.00263	0.00177	0.00958	0.00407	0.00101	0.00177	0.00848	0.00347	0.00732	0.00879	0.00183	0.00285	0.00236
■ Ratio to Buffer Area	0.00907	0.00897	0.00743	0.00513	0.00423	0.00897	0.00127	0.00000	0.00000	0.00000	0.00704	0.00000	0.00630
■ Standard deviation within Buffer	0.00635	0.01199	0.01245	0.00544	0.00125	0.01199	0.00999	0.00364	0.00115	0.00072	0.00857	0.00330	0.00316
■ Volume	0.00000	0.00678	0.01408	0.00114	0.01490	0.00678	0.00518	0.00133	0.01688	0.00693	0.00117	0.01550	0.00728
■ Year Built	0.01427	0.00153	0.01212	0.00954	0.01392	0.00153	0.00128	0.00991	0.02260	0.01069	0.00068	0.01725	0.01312
■ Retail GFA	0.01231	0.01403	0.00800	0.01534	0.01506	0.01403	0.00807	0.01455	0.01897	0.01323	0.00762	0.01345	0.01259
■ Property Value	0.01247	0.00054	0.01952	0.02596	0.02988	0.00054	0.01872	0.02328	0.03681	0.00082	0.02188	0.00744	0.02320
■ Party Wall Area	0.03635	0.00000	0.03928	0.04905	0.00000	0.00000	0.03483	0.00000	0.00000	0.00000	0.03652	0.03702	0.00000
■ Household Size	0.05536	0.00394	0.02383	0.01500	0.01938	0.00394	0.00715	0.01372	0.01540	0.00253	0.00485	0.07414	0.02176
■ Address Density	0.06899	0.00000	0.07412	0.00000	0.00000	0.00000	0.05646	0.00000	0.00000	0.00000	0.06074	0.07439	0.00000
■ Street Width	0.03967	0.05275	0.02782	0.03824	0.01674	0.05275	0.01443	0.03473	0.02666	0.05470	0.01031	0.00000	0.03708
■ Public Transit Stops	0.04165	0.03633	0.03257	0.04007	0.04167	0.03633	0.03115	0.03876	0.03891	0.03723	0.03729	0.03898	0.03815
■ Industrial GFA	0.02534	0.03940	0.05209	0.02819	0.03606	0.03940	0.05742	0.02946	0.03043	0.05629	0.05407	0.02842	0.02639
■ Height	0.01085	0.08872	0.00230	0.04746	0.02135	0.08872	0.00000	0.06075	0.00443	0.08871	0.03426	0.02328	0.03231
■ Office GFA	0.05370	0.04322	0.03361	0.04805	0.05588	0.04322	0.04011	0.04895	0.05756	0.04345	0.04114	0.05461	0.05280
■ Meeting GFA	0.05283	0.05692	0.05467	0.05310	0.05965	0.05692	0.06492	0.05506	0.05985	0.06750	0.06653	0.05689	0.05700
■ Street Width Spread	0.14693	0.16075	0.11514	0.17355	0.17833	0.16075	0.11807	0.17442	0.18741	0.15904	0.12748	0.15854	0.16939
■ Residential GFA	0.14281	0.16496	0.12607	0.17250	0.17306	0.16496	0.15552	0.17454	0.17127	0.15554	0.16460	0.14732	0.16291
■ Population Density	0.25041	0.30292	0.21172	0.30765	0.29511	0.30292	0.27435	0.31208	0.28874	0.28990	0.29718	0.24622	0.28490

The results demonstrate the effectiveness of spatial regression modeling in predicting urban logistic activity patterns in urban areas compared to a linear model. The coefficient of variation of the root mean square error (CV RMSE) highlights relatively low values for the spatial regression (between 1.5 and 3), in contrast to the OSL model, which produced values ranging from 6 to 3000. The lower coefficient values indicate a more accurate and reliable model. In terms of magnitude, this translates to a two- to three-level decrease in values, thereby increasing the reliability of the statistic. Likewise, when examining the mean absolute error relative to the mean, the spatial lag model yields values in the 0.7 to 1.00 range, whereas the OSL model has values in the 1.3 to 1.5 range. In other words, the spatial model reduces the mean absolute error by around 30%. Reference results in Table 11 for the OSL model and Table 14 for spatial lag model.

5.3 Results of the Random Forest Model

The assumptions that needed to be considered were collinearity and the understanding of potential bias in variable importance. The use of the random forest model and a 10-fold cross-validation yields performance metrics that are likely overly optimistic, as they probably overstate the model's true predictive accuracy for unseen cities. See the concept and method section for the rationale; therefore, the results should be viewed with this understanding in mind. This is because the folds are based on the underlying Amsterdam data set. In the absence of external data, the results for Utrecht or Rotterdam, explored in the scenario results section, are in-fold estimates and are likely to be the most optimistic upper bounds.

Building on the insights from the spatial lag regression model regarding the importance of the selected variables in explaining logistic traffic flows, the goal of the machine learning model is to apply it to different cities to see if logistics traffic patterns are similar (Hagenauer & Helbich, 2017). The random forest methodology is useful for its generalization and exploratory value in data-limited contexts (Chaurasia, 2025).

Trained on the Amsterdam observations, the random forest model seeks to predict the 13 logistics count targets based on subsets of the independent variables. The spatial statistics employed within the forest-based classification and regression model examine not only nonlinear relationships but also the order of variable importance for the morphological predictors. Given the model's operation, it is evident that it offers significant improvements and increased predictive accuracy compared to linear and spatial lag regression models.

Table 16 shows the results of the Amsterdam-calibrated random-forest model for the Amsterdam dataset. Across all 13 dependent variables, the random forest models explained between 87% and 90% of the variance, with R^2 values ranging from 0.87 to 0.90. Meanwhile, error rates remain low. Performance is measured by the mean absolute error divided by the mean, which ranges from 0.27 to 0.40. This is roughly a 60% reduction compared to the spatial lag regression model and an 80% reduction compared to the linear non-spatial regression model. Remember, the mean absolute error calculates the average of the absolute differences between predicted and actual values, with lower values indicating better performance.

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However, the random forest model still produces coefficients of variation of the root mean square error (CV RMSE) in the range of 6 to 3,000, comparable to the OSL model (CV RMSE scores were 100 units lower for the random forest model). The root mean square deviation (RMSE) of the random forest model was smaller than that for spatial lag regression, with lower RMSE values suggesting better model performance.

When examining Table 16 closely, one observes that dependent counts with higher independent variable counts have the lowest errors in terms of MAE and RMSE (see column IV Count). In other words, including more independent variables as informative predictors captures more variance and reduces prediction error, as seen when comparing models like AM Parcel with 21 predictors, which has an MAE of 0.897 and an RMSE of 2.318, to Other Truck with 18 predictors, which has an MAE of 236.092 and an RMSE of 728.580. Thus, adding more independent variables tends to lower error since each additional variable captures more variation. This pattern demonstrates that each extra informative predictor captures more variation in the dependent variable. However, when all possible independent variables are included, the overall metrics, i.e. R^2, MAE, and RMSE, for the entire model increase further. This suggests that the model is type-dependent, as only the aggregated parcel van traffic (i.e., only, the last mile to the household). This is already problematic because it measures only the last mile and not the full round trip.

Table 16: Random Forest Model Results for Amsterdam

Dependent Variable	N	IV Count	R2	MAE Over Mean	CV RMSE	MAE	RMSE	Moran's I	p-value
AM Truck	10055	20	0.901	0.413	293.149	36.457	108.791	0.201	1.233E-208
AM Service	10055	18	0.880	0.421	248.319	32.377	93.491	0.178	7.146E-164
AM Parcel	10055	21	0.887	0.418	6.312	0.897	2.318	0.182	1.406E-170
AM Aggregated	10055	19	0.892	0.401	497.157	67.112	184.132	0.182	1.404E-171
PM Truck	10055	19	0.899	0.411	297.000	38.263	110.898	0.211	4.119E-228
PM Service	10055	18	0.880	0.421	248.519	32.420	93.275	0.178	1.459E-163
PM Parcel	10055	21	0.895	0.272	6.629	1.095	2.430	0.174	1.527E-156
PM Aggregated	10055	16	0.893	0.396	506.739	68.869	187.725	0.179	1.467E-164
Other Truck	10055	18	0.902	0.407	1993.192	236.092	728.580	0.197	2.521E-200
Other Service	10055	17	0.877	0.446	360.087	41.628	133.918	0.155	1.025E-123
Other Parcel	10055	20	0.896	0.279	29.064	5.416	10.790	0.138	1.131E-98
Other Aggregated	10055	17	0.899	0.405	2264.807	280.305	835.944	0.198	2.007E-201
All Aggregated	10055	18	0.898	0.398	3204.905	411.845	1181.981	0.191	5.412E-188

The random forest model uses a concept noted as out-of-bag (OOB) error, which is a tool for measuring the model's prediction error. OOB is calculated by "bagging" samples not used in the given tree model because these samples were not used in training, "*their predictions serve as an unbiased estimate of the model's performance.*" This provides a robust means of validating the model (Jain, 2024). In doing so, OOB helps reduce the risk of overfitting and provides a measure of the model's performance on unseen data. OOB is built using mean squared error, mean absolute error, and root mean squared error.

The combination of explaining 90% of the variance and having an average error level of 40% is significant in describing urban morphology's impact on logistics vehicle traffic. Although the random forest model seems to outperform the spatial regression model, it is important to

remember that it is a standard model that does not consider spatial autocorrelation. Moran's I values between 0.13 and 0.21 indicate mild positive spatial autocorrelation in the residuals, with p-values confirming that this mild spatial clustering is highly statistically significant. This implies that the model is missing some key spatial information. However, its stability across different dependent variables shows that the model consistently performs well across different time periods and types of logistics activity.

5.4 Scenario Analysis

Building on these analyses, a simple non-linear, random forest model was used to evaluate its predictive capabilities for Rotterdam and Utrecht. This analysis provides a general sense of the robustness and transferability of urban morphological predictors in explaining urban logistics operations.

The scenario analysis uses a case study approach to assess how well the Amsterdam-trained random forest model performs when applied to different urban contexts. In this case, Rotterdam and Utrecht serve as out-of-sample performance tests (i.e., how well a model performs on data it has not been trained on). However, the main goal of applying such a model is to see if the predictions follow patterns similar to those observed in Amsterdam, focusing on a visual perspective rather than data metrics. This is important because detailed data for scenario cases are lacking, so the analysis concentrates on the mapped results.

Comparative metrics and residual diagnostics (e.g., the goodness of fit of a model) were used to assess the predictive accuracy and spatial capabilities of the random forest model. The prediction abilities of the random forest were then compared to the explanatory power of the regression model. These comparisons are further discussed in the Discussion section below to evaluate their relative strengths and weaknesses, as well as the usefulness of each for planners and policymakers when implementing new interventions in urban contexts.

5.4.1 Scenario Results

Rotterdam

Applying the Amsterdam-trained model to Rotterdam's 18,148 postcodes generates predicted spatial patterns using the random forest model.

The Getis-Ord Gi* statistic was used to identify statistically significant clusters of high or low values relative to each other at a 95% confidence level with respect to logistics traffic. From a statistical standpoint, the random forest regression model produces mean prediction ranges between 11 and 4,000, with median values ranging from 3 to 3,000 (see Table 17). The fact that the mean is above the median indicates positive skewness. The skewness values range from 1.6 to 3.4, indicating substantial non-normality of the data. In other words, a minority of postcodes are predicted to have large values, a pattern already observed in the Amsterdam-trained datasets. It suggests that a few of Rotterdam's postcodes dominate the model's high-value predictions. Not surprisingly, these postcodes encompass the city's main roads.

Table 17: Descriptive Statistics from Cluster Analysis of Postcode Logistics Vehicle Counts in Rotterdam

Dependent Variable	Mean	Median	Std. Dev.	Min	Max	Sum	Skewness	Kurtosis
AM Truck	556.852	341.022	738.964	6.358	3691.470	10105746.061	1.903	2.502
AM Service	300.471	154.054	372.602	5.851	2537.242	5452943.498	2.254	5.023
AM Parcel	11.616	3.310	20.744	0.090	141.860	210803.070	2.416	5.559
AM Aggregated	664.858	282.259	843.505	10.046	5361.771	12065848.667	1.816	2.362
PM Truck	497.257	236.336	653.429	5.232	3178.558	9024227.451	1.813	2.173
PM Service	316.571	168.991	391.601	5.690	2735.220	5745133.460	2.292	5.381
PM Parcel	13.032	3.695	21.381	0.747	109.892	236508.281	2.002	2.483
PM Aggregated	630.786	211.921	801.841	9.901	5084.388	11447498.089	1.604	1.492
Other Truck	2896.668	1307.114	4219.836	33.522	23883.378	52568728.381	2.089	3.429
Other Service	300.471	154.054	372.602	5.851	2537.242	5452943.498	2.254	5.023
Other Parcel	55.558	28.505	69.993	3.290	467.740	1008267.810	2.391	5.781
Other Aggregated	3378.784	1582.826	4780.724	52.648	23509.766	61318169.980	1.947	2.609
All Aggregated	4796.103	3099.881	5745.351	66.760	29688.255	87039678.906	1.812	2.463

See Appendix B, Figure 7 for the Rotterdam maps. The analysis shows clustering throughout the city across nearly every dependent variable, whether time-based or aggregate. Western and central Rotterdam consistently appear as hot spots, including the western port area (A), the western industrial zone such as the Hook of Holland (B), and the highways connecting western Rotterdam to the central city, such as the northern highway A20 and southern A15 (C and D). These areas appear to generate significant freight and logistics activity, with large, predicted volumes indicating strong hot spot clusters. The concentration of activity along west-to-east highways suggests shipping movements and inland transfers from industrial areas to the inner city. Even when isolating for time blocks, the port-related postcodes remain areas of high activity, indicating shift patterns and 24-hour operations. Furthermore, the AM logistic types reflect inbound flows, with the PM blocks, specifically PM Parcel and PM Aggregated, show increased activity spreading into residential and mixed-use areas. As in Amsterdam, the service logistics sector shows more fragmented clustering. Cold spots are concentrated in the southeast residential areas such as Feijenoord (E) and the central business district of Rotterdam (F). The dense urban center has low predicted logistics intensity, despite its high population density, which highlights the critical difference between through traffic and destination route traffic. Given that navigating the inner city is challenging and time-consuming, through traffic tends to be relatively low as operators avoid these routes for financial and scheduling reasons. These cold spot clusters persist even in the fully aggregated data, indicating that they experience lower levels of activity regardless of the time of day.

While the hot and cold spot patterns are generally similar across all temporal and aggregated indicators, there is a slight hot spot intensity shift around the in-city port region in the morning. This indicates higher levels of morning departures and arrivals. In contrast, in the afternoon, these patterns shift toward more exit paths from the city's hot spots. Notably, as expected for parcel delivery, the afternoon and other time periods show higher residential hot spot activity compared to the morning, indicating typical consumer preferences. Overall, the random forest model reflects the expected logistics flows in the adjacent hot spots and movement along Rotterdam's critical thoroughfares. Furthermore, the cold spots in the city center are a byproduct of the concentration of freight in certain postcodes, leading to congested zones.

To compare the logistic intensity data to Rotterdam's independent variable data, see Appendix C, Figure 10 for the indicators' spatial distribution, including socio-economic and built environment variables. The industrially built environment mostly aligns with the city's freight intensity hot spots. Likewise, the higher traffic volumes on wider streets exactly match what the logistics Gi* hot spots analysis would predict, since these streets can handle greater volumes and provide more space for vehicle maneuvering. In terms of the mixed-use index and address density, they show low traffic volumes while still contributing to Rotterdam's freight economy. This is mainly due to warehouse and land-use patterns, which display clear divisions at the postcode level 6. The reverse pattern also appears, with cold spots for logistics near high livability clusters, as high residential areas tend to have low freight activity, partly because of limited space for movement. This is supported by the separation between tram stops in freight hot spot areas, creating two transportation hierarchies—one for the public and another for logistics traffic.

The case study shows that a predictive picture of Rotterdam's logistics traffic can be developed using statistical skewness, qualitative spatial clustering, and hot spot analysis.

Utrecht

Applying the Amsterdam-trained model to Utrecht's 7,185 postcodes reveals important spatial patterns, much like the Rotterdam case study did.

The Utrecht case study shows the same overall patterns of behavior as Rotterdam, just on a smaller scale. As shown in Table 18, across the 13 prediction variables, the mean values range from 11 to 5,000, while the median values range from 2 to 1,000. As with Rotterdam, Utrecht's mean exceeds the median, indicating positive skewness. This is supported by the skewness scores, which are between 1 and 2.5, confirming moderate positive skew. Specifically, a small set of postcodes has the highest predicted freight intensities, while most are relatively low. This pattern matches those of Rotterdam and Amsterdam. These results align with expectations for urban logistics, where a few main thoroughfares handle most of the logistics flows.

Table 18: Descriptive Statistics from Cluster Analysis of Postcode Logistics Vehicle Counts in Utrecht

Dependent Variable	Mean	Median	Std. Dev.	Min	Max	Sum	Skewness	Kurtosis
AM Truck	603.362	85.544	1007.702	3.178	3768.530	4335156.669	1.546	0.552
AM Service	261.230	91.510	368.283	5.946	2291.035	1876939.258	2.051	3.557
AM Parcel	11.804	2.530	20.915	0.050	138.170	84809.49	2.413	6.103
AM Aggregated	740.774	190.893	1095.894	17.588	4564.910	5322462.048	1.525	0.619
PM Truck	535.428	95.049	875.472	8.758	3124.304	3847048.355	1.558	0.588
PM Service	259.450	91.652	368.554	5.407	2447.804	1864145.702	2.089	3.814
PM Parcel	14.935	4.438	22.168	0.885	109.020	107306.1953	1.757	1.763
PM Aggregated	720.870	222.641	987.394	13.452	3956.437	5179449.63	1.475	0.582
Other Truck	3518.108	632.844	5870.560	30.382	22809.385	25277607.95	1.601	0.782
Other Service	465.051	114.047	943.746	10.754	5068.692	3341391.278	3.159	9.318
Other Parcel	61.057	20.410	85.275	3.240	477.370	438695.97	1.909	2.784
Other Aggregated	3953.539	608.006	6497.268	60.089	23850.221	28406175	1.546	0.584
All Aggregated	5112.749	1011.200	8001.013	96.832	27502.193	36735099.24	1.511	0.458

The Getis-Ord Gi* hot spot analysis creates a visual representation of predicted logistics activity (see Appendix B, Figure 8). Compared to Rotterdam and Amsterdam, Utrecht is a smaller city

with significantly less industrial activity. For Utrecht, the hotspot maps display more intertwined patterns, with large areas of neutral zones mixed with continuous hot and cold spots, reflecting Utrecht's smaller size and mixed land use. Utrecht's logistics hot spots are clustered around the northwestern industrial zone, such as Lage Weide (A) and near the ring road, like Papendorp in the southwest of the city (B), eastern areas like Oost (C), and the north-central area of Overvecht-Noord (D). Overvecht-Noord is also known for its warehouses and logistics hubs, making it another node with higher logistics traffic.

The differences in the dependent variable model at AM hotspots are mainly along inbound road corridors, while PM hotspots are more spread into residential areas. As with Rotterdam, service vehicle traffic is more dispersed. The historic city center (E), characterized by the canals, shows a cold spot cluster. These cold spots are mainly in residential neighborhoods and mixed-use areas, where logistics activity is predictably lower. Reflecting the high level of foot traffic, tight street layout, and delivery restrictions, these areas are characterized by the absence of heavy logistics intensity. While some service logistics generate movement in residential neighborhoods and the city center, these zones are small and relatively few in number. Across different times and aggregate patterns, the distribution of hot spots and cold spots remains consistent, with only minor differences. In the morning, hot spots are more common along inbound roads and near distribution and operation hubs. Conversely, in the afternoon, logistics activity tends to shift toward residential areas, reflecting consumers' preferred delivery windows.

Cross-comparing logistics intensity to the model's independent variables for Utrecht illustrates the relationship with the built environment and socio-economic variables. See Appendix C, Figure 11 for the spatial distribution of the indicators. Again, hot spots are associated with street widths that correspond to the main roads within the road network hierarchy in terms of freight flows. As with Rotterdam, the hot spots for logistic intensity cluster near signal-use zones and low address density areas, indicating single-use industrial districts. Cold spots appear in high-density residential zones with higher home values and access to public transport. The predictions for Utrecht align with those of Amsterdam, possibly because it shares, on a smaller scale, similar structural patterns.

5.4.2 City Comparison

Taken together, the results for Amsterdam, Rotterdam, and Utrecht suggest that the Amsterdam-trained random forest model provides a coherent picture of logistics patterns across these three cities despite their structural differences. Although these cities differed meaningfully in terms of their industrial development, population size, and physical dimensions, the model produced logically consistent patterns. First, a few major thoroughfares and industrial zones, which account for a limited number of PC6 postcodes, produce most of the predicted freight intensity. This is true even when freeway volume is removed, revealing that all three cities display the same positive skewness. This contrasts with the dense, mixed-use areas and city centers, which consistently appear as cold spots. This is true even though these areas are highly populated, illustrating the crucial difference between through- and destination-logistics traffic. In Rotterdam, the location of hot spots is overwhelmingly driven by the port terminal, the largest in Europe, with ports in Utrecht and Amsterdam showing similar patterns despite being smaller

(Port of Rotterdam, 2021). In contrast, the constrained dimensions of the historical centers of Utrecht and Amsterdam produce logistics cold spots, with hot spots concentrated instead on the ring roads. Temporally, the three cities show similar patterns, with the overall findings highlighting the importance of urban form and infrastructure in shaping logistics traffic patterns. As such, these findings underscore the importance of considering urban form in approaching and prioritizing urban logistics interventions.

Chapter 6

Discussion and Conclusions

As planners and policymakers work to develop urban areas that support the UN's 17 Sustainable Development Goals (SDGs), the critical role of urban morphology will become increasingly significant. This research demonstrates, through empirical analysis, urban morphology's statistically significant influence and potential predictive power regarding the spatial-temporal distribution of logistics vehicle intensity within Dutch urban environments. The research findings emphasize the importance for urban planners and policymakers to carefully consider urban morphology and its influence on logistics operations. Moreover, specific morphological features that influence logistics hot spots are highlighted, distinguishing between logistics flows and spatial-temporal variations. Additionally, the study examines the effectiveness of spatial-econometric and machine-learning methods in developing targeted intervention strategies.

6.1 Critical Analysis

The empirical analysis of logistics vehicle activity across three Dutch cities shows non-uniform clusters across the spatial-temporal distribution of logistics activity. Using both statistical tools and visual insights, a dual analysis was conducted to understand how urban morphology relates to the spatial and temporal patterns of logistics vehicle traffic.

The visual analysis enabled the identification of spatial patterns of logistics vehicle traffic throughout the city. The hot spot analysis utilized the Getis-Ord Gi* statistic to generate results and reveal underlying patterns. Analysis of the Amsterdam baseline data showed distinct clustering patterns of logistics traffic counts across different times of day and for various delivery types. During the morning peak, hotspots were concentrated around multimodal nodes and high-density corridors linking the industrial zone to the city. At the same time, residential and historic zones appeared as cold spots, however, it should be noted that while the zones appear as cold spots in the current dataset, other empirical studies and observational data from municipal surveys and curb monitoring, among other sources, indicate that such areas may actually experience significant logistics activity, especially in the morning and within retail and mixed-use areas (ITF, 2024; Behrends, 2016). The discrepancy likely reflects the inherently complex nature of the data and the differences in data coverage at both macro and micro spatial and temporal resolutions.

Consequently, the emphasis lies on the valuable potential of integrating multiple data sources into future research to identify a variety of urban logistic patterns in a field characterized by

limited and disaggregated data on a spatial-temporal scale. In part, these patterns reflect regulatory limits on delivery operations as well as the physical differences of these dense and often pedestrian-oriented environments. As the analysis shifted to focus on afternoon and off-peak periods, activity shifted slightly to areas near industrial zones, busy streets, and mixed-use residential neighborhoods. This suggests that logistics operations adapt based on commuter traffic patterns, resulting in a reallocation of road space, a pattern which remain consistent across various load types (Gui, Bhardwaj, & Sam, 2024).

These findings support Dalla Chiara and Goodchild's (2020) argument that logistics operations are highly dynamic, with vehicle movements resulting in different spatial claims throughout the day. To a significant degree, these patterns reflect the fact that vehicle operators themselves are adjusting their activities in pursuit of the most efficient means of navigating within large urban networks. This process of adapting logistics operations shifts from industrial to mixed-use zones during off-peak hours while adjusting to meet consumer demands. This finding is supported by the work of Jaller, Holguín-Veras, and Hodge (2013) and Dablanc and Beziat (2015), who demonstrate how freight activity concentrates in curb space during off-peak hours because it is often underutilized during peak times. They also show how logistics operations adapt to different street segments based on varying time periods and regulation regimes, thereby optimizing efficiency. These patterns highlight the complex dynamics of developing management policies to ensure logistics operations run efficiently throughout the day.

To compare observations from Amsterdam with those of Rotterdam and Utrecht, an optimistic 10x in-fold analysis was performed to account for geographic spatial autocorrelation. A simple random forest regression model was used solely for prediction comparison. In a simple machine learning model like random forest, limitations include capturing complex realities. However, in this study, the model's purpose was only to generate visual prediction cues from morphology data to serve as a baseline. A more complex and developed model would be necessary to create a more robust predictive system.

Random forest regression produces a non-linear model used for its predictive ability. It was applied to analyze how urban morphological indicators can predict logistics activity across different urban settings. Recognizing that it is an optimistic model, the performance of the random forest model exceeds that of linear and spatial regression models. The main goal of the model was to assess whether the supported functions align with the theoretical foundation. These results are consistent with the findings reported by the Massachusetts Institute of Technology's Transportation and Logistics Department (2020), with the model showing predictive accuracy and strong spatial autocorrelation and showing similar morphological patterns in out-of-sample cities. However, key aspects of spatial structure are underrepresented, suggesting that a hybrid machine learning approach incorporating spatial weights or spatial lag in a tree ensemble model might be the best modeling choice.

Applying the random forest model to Rotterdam and Utrecht reveals many of the same patterns in logistics activity related to morphology seen in Amsterdam. This is despite the cities differing significantly in physical size, population, and structure. Thus, they serve as valuable case studies

for assessing whether the patterns observed in Amsterdam can occur in different types of cities across the Netherlands. The model trained on Amsterdam data accurately predicted hotspot patterns in Rotterdam and Utrecht, demonstrating its transferability across diverse urban contexts. As expected, based on the work of Sadeghi and Li (2019) and Biljecki and Chow (2022), variable importance is weighted toward land use, street width, building height, and population density, which also align with the findings from the regression model. Land use, such as industrial zones and postcodes with major thoroughfares, is shown to drive most of the predicted logistic intensity, even when freeway volume is removed, a finding that is supported by the work of Dalla Chiara & Goodchild (2020) and Barendregt (2023). They found that industrial zones and logistic hubs generate significantly higher trip rates compared to other land-use types. Likewise, major arterial roads with their large street geometry serve as the backbone of urban logistics networks. This contrasts with cold spots in residential and historic city areas where limited street networks and strict delivery schedules restrict logistics flows (Quak et al., 2021; Allen et al., 2018; Rodrigue, Dablanc, & Giuliano, 2017). Similar patterns seen across all three cities confirm the findings of the research literature.

Based on Spearman's rank correlations of the 16 to 21 independent variables, the built form indicators of street width, building height, and building complexity, along with socioeconomic variables like population density and household size, and the accessibility measure of transit stop density, were chosen for modeling. The results support the idea that the built environment influences traffic flow, as found by Sadeghi and Li (2019). This demonstrates that density and space significantly affect logistic vehicle behavior. Both the ordinary least squares and random forest models indicated the presence of spatial correlation in the data, a finding also supported by Dablanc and Beziat (2015).

The spatial regression model employed, known as a spatial autoregression model, accounts for spatial spillover effects and identifies which variables have positive and negative impacts. It also critically highlights which indicators are of relatively greater importance within the equation; see the results section for more detailed information. The results demonstrate that population density accounts for 20-30% of the variance in logistic traffic, a finding consistent with previous research by Biljecki and Chow (2022). This supports the baseline assumption that higher concentrations of people lead to greater demand for logistics activities, as does address density which explains a significant portion (15%), of the variation in the model's results (Dablanc and Beziat, 2015). Furthermore, street geometry (i.e., street width and building height) accounts for another 15% and 7% of the model's variance, respectively. This aligns with the research of Sadeghi and Li (2019) and Butrina et al. (2017). Taken together, the remaining variables related to accessibility, socioeconomic factors, and built form indicators account for approximately 9% of the variance. Despite this, Spearman's rank correlations demonstrated that all are statistically significant in relation to logistics intensity. The results are visualized in Figure 5, which shows the relative variable importance values derived from the spatial autoregression model based on logistic data for Amsterdam.
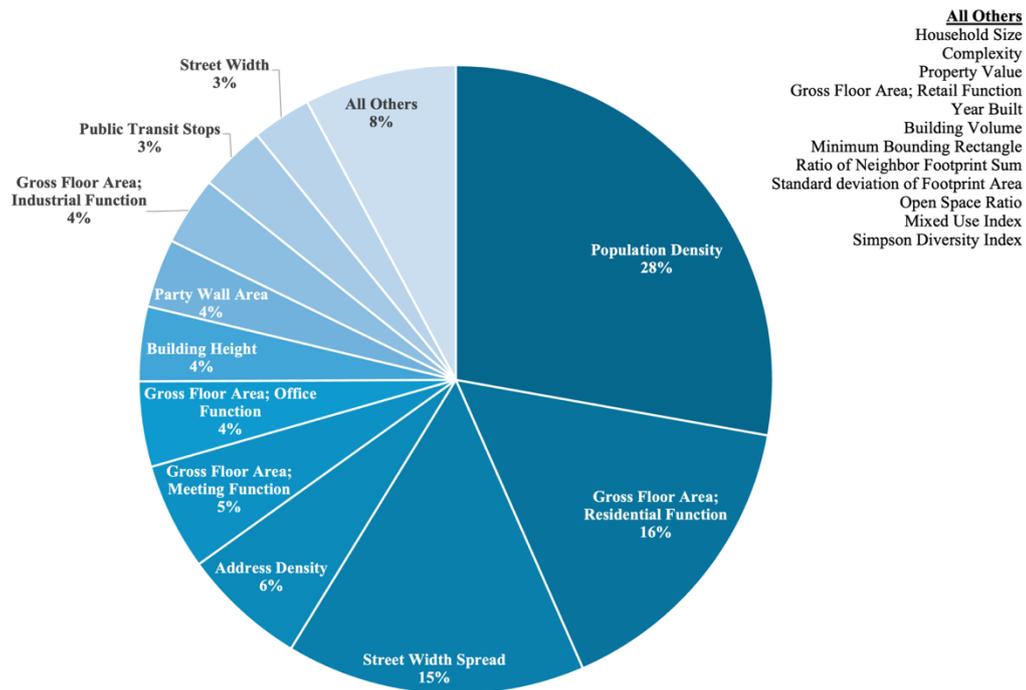
Figure 5: Variable Importance from the Spatial Autoregression Model Explaining Logistics Intensity in Amsterdam

The findings align with previous academic research and reinforce the theory that urban morphology can, at least in part, explain patterns in urban logistics operations. The results enhance the academic understanding of how urban morphology influences the spatial-temporal aspects of logistics and address a gap in current literature by measuring the explanatory power of morphological indicators. Additionally, the results were spatially and visually validated across multiple Dutch cities to establish a foundation for future research into a potential predictive model. Finally, it supports the advancement of geographic information sciences and spatial and random forest modeling as tools to emphasize the significance of the spatial and non-linear relationships evident in urban logistics operations.

6.2 Hypotheses, to Confirm or Reject

Before starting the research, the main question was, 'How does urban morphology, through its physical and socio-spatial indicators, explain the spatial-temporal claims of urban logistics vehicles?' Supporting questions included, 'How do logistics activities' spatial and temporal hotspots vary across different time frames?' and 'Which urban morphological indicators (e.g., road width, land use, building density) correlate most significantly with logistics vehicles' spatial-temporal claims?' These research questions translated into the following initial hypothesis:

- MORPHOLOGICAL: URBAN MORPHOLOGY SIGNIFICANTLY EXPLAINS THE SPATIAL-TEMPORAL CLAIMS OF LOGISTICS VEHICLES.

- MORPHOLOGICAL: THE SPATIAL AND TEMPORAL CLUSTERS OF LOGISTICS ACTIVITY ARE DRIVEN BY URBAN MORPHOLOGY INDICATORS.

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- CONTEXTUAL: URBAN MORPHOLOGICAL INDICATORS HAVE VARYING LEVELS OF INFLUENCE ON LOGISTICS INTENSITY ACROSS AND WITHIN URBAN CONTEXTS, WITH THEIR EFFECTS EXTENDING ACROSS ZONES AND INTO PERIPHERAL AREAS.

- PREDICTIVE: URBAN MORPHOLOGY INDICATORS ARE SIGNIFICANT PREDICTORS OF SPATIAL-TEMPORAL VARIATION IN URBAN LOGISTICS ACTIVITY.

Addressing the first hypothesis, the Spearman correlation indicates that urban morphology is statistically significant in explaining the spatial-temporal claims of logistics vehicles, thus confirming the initial hypothesis. The spatial regression analysis demonstrates that urban morphology accounts for, on average, 30% of the observed variation in urban logistics operations, and, therefore, the indicators are statistically significant and explain a meaningful portion of the variance in logistics activity when analyzed with spatial regression and random forest models.

The second hypothesis is supported by the empirical research, as hot spot analysis using a predictive model, along with an assessment of variable importance based on the regression model, indicates that logistics operations are concentrated in specific postcodes rather than being evenly distributed throughout the city. Therefore, as the findings suggest, features of the built environment primarily drive logistics hot spots, while socio-economic variables have a much smaller impact.

The third hypothesis is supported because the spatial regression model shows, using Moran's I index, that models addressing spatial autocorrelation are significantly better than non-spatial ordinary least squares models at explaining logistic operations. This highlights the spatial dependence in logistics intensity data. Additionally, the spatial regression model also reduces errors compared to the OLS model.

Finally, the fourth hypothesis is partially confirmed using a machine learning model. The simple random forest model achieved an average of 89% in predictive accuracy for logistics activity and was then applied to the cities of Rotterdam and Utrecht for case study pattern comparison. However, although the random forest model attains high predictive accuracy, it exhibits unexplained spatial structure.

Using spatial-econometric, machine learning, and spatial analytics, the research confirmed the initial hypothesis, laying a foundation for further research as the spatial and non-linear methods provide baseline tools for researchers, planners, and policymakers in urban logistics. Importantly, urban morphology is a statistically significant factor influencing the spatial-temporal claims of logistics vehicles.

6.3 Interpretation and Implications

From a practical perspective, the study provides a framework for understanding the connection between urban morphology and logistics operations. While complex, the evidence demonstrates the relationship between urban morphology and logistics vehicle activities. Additionally, specific

features of the built environment notably influence logistics behavior, especially regarding population density, street width, and address density. Furthermore, the spatial dependence of logistics is shown by the presence of spatial spillovers, indicating that the built environment in one postcode affects logistics intensity in nearby areas. This confirms the importance of understanding spatial interactions as part of urban logistics research (Gui, Bhardwaj, & Sam, 2024). The varying levels of morphological importance support this, with built-form variables being among the dominant drivers. In other words, the physical characteristics of cities significantly influence logistics networks on both spatial and temporal scales. Moreover, the findings emphasize the importance of considering temporal patterns that impact logistics, whether it involves commuter traffic, city regulations, or delivery preferences as multiple factors contribute to the formation of logistics hot spot clusters, with the presence of industrial zones and arterial roads being especially important.

The findings provide a dynamic understanding of logistics activity and emphasize the significance of spatial structure in modeling urban logistics operations. It demonstrates that trade-offs pose significant challenges within the study; therefore, it does not offer a definitive answer to the questions but instead provides a theoretical baseline for future research. The study underscores the value of a hybrid modeling framework that combines the strengths of random forest models with the inclusion of spatial autocorrelation.

6.3.1 Policy Actions

Turning to the practical implications, a data-driven foundation can be established to reduce the negative externalities of urban logistics while improving their efficiency. The following section explains the implications of the research.

First, in terms of urban planning and policy, understanding how urban morphology on both access to high-intensity logistics areas, or hot spots, and stopping behaviors within those areas (such as dynamic curbside management and unloading zones) provides an indicator for prioritizing regulations and design interventions. This can point to the need for targeted initiatives. Planners can use morphological indicators to identify logistic intensity hot spots and intervention zones, thus helping them better rethink the built environment and regulatory actions to take to reduce the negative externalities of logistics activities. Additionally, because of the spatial interdependence of urban areas, any changes and interventions in one postcode are likely to cause spillover effects that impact neighboring areas. This is important as when approaching redesign efforts as it is essential to consider both micro and macro perspectives.

Analysis showed that population density, street width, address density, building height, and land use type are the most influential predictors of logistics intensity, which relates to various activity types such as truck traffic, parcel distribution, and service and construction operations. While each category exhibits distinct spatial patterns (see Figure 4, for example), truck activities are more influenced by household size and address density, while parcel distribution is related to retail and residential gross floor area and service construction activities by residential, industrial, and office gross floor area. The distinct patterns show how various logistics sectors respond to spatial factors and how policy strategies should be tailored by area, vehicle type, and sector. The

visual analysis of maps from Amsterdam, Rotterdam, and Utrecht revealed where high-intensity logistics activity clusters.

Using this insight can directly inform targeted interventions. These interventions could include strategically locating dynamic curb management for loading and unloading zones. The allocation of space for dynamic curb management leverages data and design to adapt curb usage, thus optimizing the allocation of curb space throughout the day. Dedicated loading and unloading zones, which often have temporal restrictions, can further mitigate conflicts with other urban actors by reducing double and unauthorized parking (NCHRP, n.d.; ITF, 2024).

As shown in Amsterdam and Rotterdam, it is clear that postcodes with higher traffic are situated along main arterial roads. Establishing dynamic loading and unloading zones at the edges of these arterial roads and extending into residential and mixed-use areas can handle peak logistical demand without increasing activity in the limited neighborhood streets. This method helps reduce congestion and avoids conflicts with other urban actors. Setting up micro-hubs at key junctions of identified hot and cold spots, as shown by the model, can further improve last-mile delivery and lower vehicle traffic into congested areas. Micro-hubs, small-scale distribution points in urban areas, can coordinate with consolidation centers on the outskirts of the city (Wu, Shao, & Ng, 2015). Additionally, in supporting the dynamic aspect—as the three temporal analyses show—curb management can adapt to peak logistics times and their changing patterns, such as the shift toward residential areas in the afternoon. Therefore, space allocation should be adjusted throughout the day based on temporal intensity patterns.

The digitalization of the curb and street network offers opportunities to continuously adjust interventions in design and policy to meet current needs. This technology includes geofencing and curb digitalization, which further improve curb management systems by using geographic information to establish virtual boundaries that restrict access by vehicle, service, or time of day (Velcro, 2023). Analysis of low logistic intensity areas revealed patterns in higher residential, mixed-use zones, and historic centers. Implementing geofencing and curb digitalization can enforce access windows during specific times, helping to optimize space during off-peak demand periods, which can relieve pressure on main corridors and encourage shifting activities to off-peak hours.

Considering these interventions within the context of spatial patterns underscores the importance of context-specific solutions informed by urban morphology. As such, use of morphology for its predictive power supports developing scenario analysis for targeted spatial interventions, allowing cities to forecast the impact of future changes in design, land use, or regulatory policies and their potential effects on logistics. The analysis of the relationship between urban morphology and logistics has been used by planners in the development of the new port of Barcelona, a bus rapid transit system in Bogotá, and a regulatory framework in Lisbon (PierNext, 2022; Bocarejo & Tafur, 2013; UPPER, 2016). Thus, such a balance between livability, accessibility, and efficiency has already been supported by a data-driven approach that considers urban morphology. However, the urban morphology framework itself is much more versatile, and its predictive capabilities should be explored further.

The implications of policy from a spatial level approach are inherently interconnected. From a spatial perspective, the findings and insights from the study can be broken down into three distinct levels: macro urban, neighborhood, and street block postcode 6 scale.

First, at a macro urban level, the analysis highlights how land use and morphological indicators, such as industrial zones and arterial corridors, align with logistics hotspots. At the neighborhood level, the spatial-temporal cluster patterns inform where to target interventions, including but not limited to logistics facilities, spatial allocation, and regulation policies. These initiatives can reduce the negative externalities associated with logistic activity. Lastly, from the micro block level, or postcode 6 in the case of the Netherlands, the built form characteristics from street width to building complexity and building frontage drives how curb and street space is allocated. The block itself influences stopping behavior and dwell times. Future research can examine how urban morphology features can better inform the design of curb and the streetscape. By understanding how these different spatial levers interact and applying insights from the study to guide future targeted interventions, a comprehensive view of logistics operations' patterns is achieved, aiming to reduce externalities and enhance operational efficiency.

Planners often neglect the logistical needs of their cities. However, as tools for understanding the impact of urban morphology become more important, they will offer planners new ways to model different urban environments. This directly supports their practical application in urban logistics planning. Therefore, a key part of integrating these tools into urban planning involves using urban morphology, digitalization, and data-driven modeling to gain a comprehensive understanding of the built environment, which in turn helps develop plans to resolve urban conflicts. It emphasizes that a one-size-fits-all approach in urban planning and policy development must be adapted to ensure that context-specific solutions are guided by analytical models that can quickly serve as reference points for implementing measures. Therefore, integrating urban morphology into spatial planning promotes the development of sustainable and livable cities, while also considering logistics and helping to reduce conflicts and inefficiencies in urban logistics as cities grow.

Linking the baseline empirical results to both theoretical and practical strategies highlights the significance of urban morphology as an analytical tool and a design parameter in planning for efficient urban logistics.

6.4 Limitations

At the same time, the study does have and did encounter many limitations that need to be acknowledged. These limitations relate to data scope and availability, study design, and analytical techniques, which constrained the scope and findings of the study. Therefore, it is important to consider these limitations when reading the baseline research as a starting point for future studies.

Data Scope

Critically, the study relied on readily available datasets for the cities of Amsterdam, Rotterdam, and Utrecht. As a result, there were data constraints that are common in the field of logistics. The study, like many others, was limited by the availability and level of detail of datasets related to

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logistic operational variables and urban morphology. Logistics vehicle activity data is inherently highly disaggregated, often available on a company-by-company basis. Additionally, when the number of observations is limited, it can be challenging to make broad generalizations. This, in turn, leads to a sporadic view of data clusters when presented. Therefore, instead of relying on a single limited company vehicle data set, this study chose to use a multi-agent simulation system MASS-GT, which provided the most comprehensive baseline data on logistics flows and aggregated the most current data.

Regarding urban morphology, the data required for the study needed to be consistent across all cities in terms of coverage for each postcode. The absence of data on crosswalks, traffic light points, and detailed curbside attributes in some areas meant that these morphological indicators had to be excluded from the study. If it had been possible, including these indicators might have changed the study's results. The limitation arises from reliance on available data, even after preparation and enrichment. Additionally, multicollinearity diagnostics may have excluded indicators that could have added value to the analysis. Therefore, future studies might identify a more complex and comprehensive set of variables that could improve the results and deepen understanding of how urban morphology influences logistic operations.

Study Design

The geographic choices further limit the generalizability of the findings to other cities with different urban environments or regulations. As the study focused on three Dutch cities and analyzed data at the postcode 6 level, which is a highly granular and uniquely Dutch system. While this permitted a detailed analysis, it likely makes it more difficult to apply the findings to other urban areas. Unique morphology, logistical relationships, and regulatory policies may also influence the results. Additionally, the selected peak time frames (e.g., 7:00-9:00, 16:00-18:00), and the aggregation of other times, further limit the generalizability of the findings. The selection of these time windows was based on data availability. This may overlook other temporal details, such as early morning activity (before 7:00), afternoon (14:00 to 16:00), evening (18:00 to 20:00), and overnight hours (midnight to 4:00). Having only three bins causes smoothing of the temporal details. Similarly, the study did not consider seasonal variations or the day of the week, thus leading to simplification and limitations on the transferability of the findings.

Analytical Techniques

Examining analytical tools and their limitations raises awareness of model choices and their constraints, especially regarding validation bias within the models. While the random forest model is highly accurate, it does not account for spatial autocorrelation as indicated by residual clustering and its significant Moran's I. Although its optimistic performance was only selected as a baseline prediction for Rotterdam and Utrecht, there are inherent limitations in the non-linear modeling approach. Overall, it indicates that future research should explore a hybrid modeling method that incorporates spatial autocorrelation within a tree ensemble framework.

Nevertheless, the study provides valuable insights into how data-driven integration of urban morphology factors can explain logistics operations and supports future academic and societal applications. However, the limitations outlined above offer critical insights into the findings that

should be considered in the research analysis. Therefore, future research should identify the gaps to address to improve the use of urban morphology as a determinant of logistics vehicle spatial-temporal patterns and thus provide more robust evidence.

6.5 Recommendations and Future Directions

Future studies can develop more effective modeling solutions for addressing urban logistics challenges within the built environment. Integrating urban morphology into planning and policy is essential, but it should be done systematically. Urban morphological indicators have proven to provide explanatory power when it comes to logistic operations. Using these morphological features in planning and design can quickly provide a clear understanding of the potential demand requirements for urban spaces and allows for appropriate actions that will have the most significant impact on society's needs. Furthermore, beyond adopting a hybrid modeling approach and expanding the geographic and temporal scope, increasing data sharing between private and public organizations would enable a more comprehensive understanding of logistic operations across cities and support the development of a more robust and transferable model.

Critically, future studies should validate the modeling framework across a wider range of urban environments. It is essential to test the out-of-bag predictions of the models against observational logistics data in various urban settings, not just in the Dutch city of Amsterdam. This will help to evaluate the model's effectiveness in predicting the accuracy of logistics hot spots. Furthermore, it can inform future models and strategies for understanding and explaining the relationship between urban morphology and urban logistics, and refine which urban morphological indicators possess the most explanatory power for logistic operations.

A future research direction is to use spatial scenario modeling to understand how urban morphology guides targeted spatial interventions to reduce their impact and behavior in cities. To pursue this, two related questions could be explored:

- WHICH SPATIAL INTERVENTIONS MOST EFFECTIVELY REDUCE THE DISRUPTIVE IMPACT OF LOGISTICS VEHICLES' SPATIAL CLAIMS ACROSS DIFFERENT URBAN MORPHOLOGIES, THEREBY IMPROVING CURBSIDE RESOURCE MANAGEMENT AND STREET DESIGN?

- HOW DO SPECIFIC URBAN MORPHOLOGY TYPES RELATE TO HIGH-CONFLICT ZONES WHERE LOGISTICS VEHICLE OPERATIONS INTERSECT WITH COMPETING SPATIAL DEMANDS (E.G., BIKE LANES, TERRACES, PEDESTRIAN SPACE)?

Through the development of scenario-based modeling, design and policy impacts can be evaluated, such as new loading zones or on-street micro-hubs, and their potential effects on logistics flows can be analyzed. These specific spatial intervention sites can be examined using evidence-based urban morphology hot spots mapping, leading to the creation of context-sensitive planning. This approach would enable detailed curb analysis, field testing, surveying, and more dynamic solutions to reduce impacts on logistics' spatial and temporal demands.

A Spatial-Temporal Analysis of Logistics Vehicles

Creating compelling visualizations can help policymakers and urban planners better understand the complex relationship between urban morphology and logistics vehicle operations. Up-to-date dashboards and spatial support tools provide the latest data forecasts and offer easy-to-use features to highlight concepts and areas most in need of change. This approach ensures equitable responses and aims to address the needs of marginalized communities. Urban morphology is a powerful tool that reveals the reality of the built environment and offers an unfiltered view of its current state and needs.

By presenting this for future research, this study aims to promote theoretical and practical advancements for using urban morphology to explain the spatial impacts of urban logistics.

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Appendix A

Standardization of Independent Variables

Below are reported the standardized z-score transformations for all independent variables used in the analysis and the corresponding descriptive geographic postcode aggregation method. Shown are the mean and standard deviation of the raw data and z-score statistics of mean, standard deviation, minimum, maximum, and median, enabling the creation and use of standardized values in order to compare independent variables with different scales and units.

Table 19: Z-Score Standardization of Independent Variables

Indicator	Postcode Aggregation	Mean of Raw Data	Std. Dev. of Raw Data	Mean of Z	Std. Dev. of Z	Min of Z	Max of Z	Median of Z
Building Volume	Sum	48025.85	138165.344	0	1	-0.3476	21.73	-0.23
Building Height	Sum	0.01	1.0375	0	1	-0.1236	70.31	-0.03
MBR	Median	-0.02	0.9354	0	1	-0.2777	13.29	-0.23
Complexity	Median	-0.02	0.9441	0	1	-0.9561	8.81	-0.30
Party Wall Area	Median	0.02	1.0187	0	1	-0.9568	18.65	0.02
Office GFA	Sum	3469.33	14016.398	0	1	-0.2475	21.34	-0.24
Retail GFA	Sum	1239.83	4947.9081	0	1	-0.2506	29.53	-0.22
Industrial GFA	Sum	1928.39	13691.1298	0	1	-0.1409	41.61	-0.13
Residential GFA	Sum	23963.77	25702.6001	0	1	-0.9324	10.71	-0.24
Meeting GFA	Sum	1344.05	4874.2891	0	1	-0.2758	25.70	-0.23
OSR	Median	0.01	1.0315	0	1	-0.1038	47.06	-0.08
MXI	Median	0.01	0.9852	0	1	-2.6306	0.79	0.44
SDI	Median	0.01	0.9979	0	1	-0.9761	3.03	-0.31
Ratio of Neighbor Footprint Sum to Buffer Area	Median	0.04	1.0005	0	1	-1.6465	3.11	0.06
Std. Dev. of Footprint Area within Buffer	Median	0.02	0.99	0	1	-0.87	13.02	-0.27
Street Width	Median	0.06	0.99	0	1	-2.40	2.91	-0.02
Street Width Spread	Spread	0.03	1.03	0	1	-1.45	8.36	-0.24
Year Built	Median	0.01	0.98	0	1	-4.38	0.51	0.29
Population Density	Sum	14168.83	4969.89	0	1	-2.85	2.43	0.02
Household Size	Mean	-0.05	0.99	0	1	-2.73	4.56	-0.30
Property Value	Mean	0.05	1.03	0	1	-2.65	3.79	-0.11
Address Density	Sum	0.06	1.01	0	1	-1.97	1.77	-0.15
Public Transit Stops	Sum	0.02	0.13	0	1	-0.12	15.28	-0.12
Age, 0 to 15 Year Old	Sum	1833.99	928.94	0	1	-1.97	3.28	-0.07
Age, 15 to 25 Year Old	Sum	1831.06	782.54	0	1	-2.34	3.86	-0.15
Age, 25 to 45 Year Old	Sum	5242.76	2018.86	0	1	-2.59	2.19	0.01
Age, 45 to 65 Year Old	Sum	3320.34	1258.46	0	1	-2.63	2.54	-0.12
Age, 65+ Year Old	Sum	1940.67	778.15	0	1	-2.49	2.38	-0.01
Socio-Cultural, Dutch	Ordinal Category	42.29	12.05	0	1	-2.67	3.12	-0.18
Socio-Cultural, Non-EU European	Ordinal Category	16.86	8.31	0	1	-2.02	2.78	-0.82

Indicator	Postcode Aggregation	Mean of Raw Data	Std. Dev. of Raw Data	Mean of Z	Std. Dev. of Z	Min of Z	Max of Z	Median of Z
Socio-Cultural, Non-EU abroad	Ordinal Category	23.86	7.54	0	1	-3.16	3.46	-0.51
Urbanity, Very Highly Urban	Ordinal Category	0.92	0.28	0	1	-3.45	0.28	0.28
Urbanity, Highly Urban	Ordinal Category	0.07	0.25	0	1	-0.26	3.73	-0.26
Urbanity, Moderately Urban	Ordinal Category	0.01	0.05	0	1	-0.05	18.28	-0.05
Urbanity, Non-Urban	Ordinal Category	0.01	0.09	0	1	-0.08	11.45	-0.08

A Spatial-Temporal Analysis of Logistics Vehicles

Appendix B

Getis–Ord Gi* Hot-Spot Maps
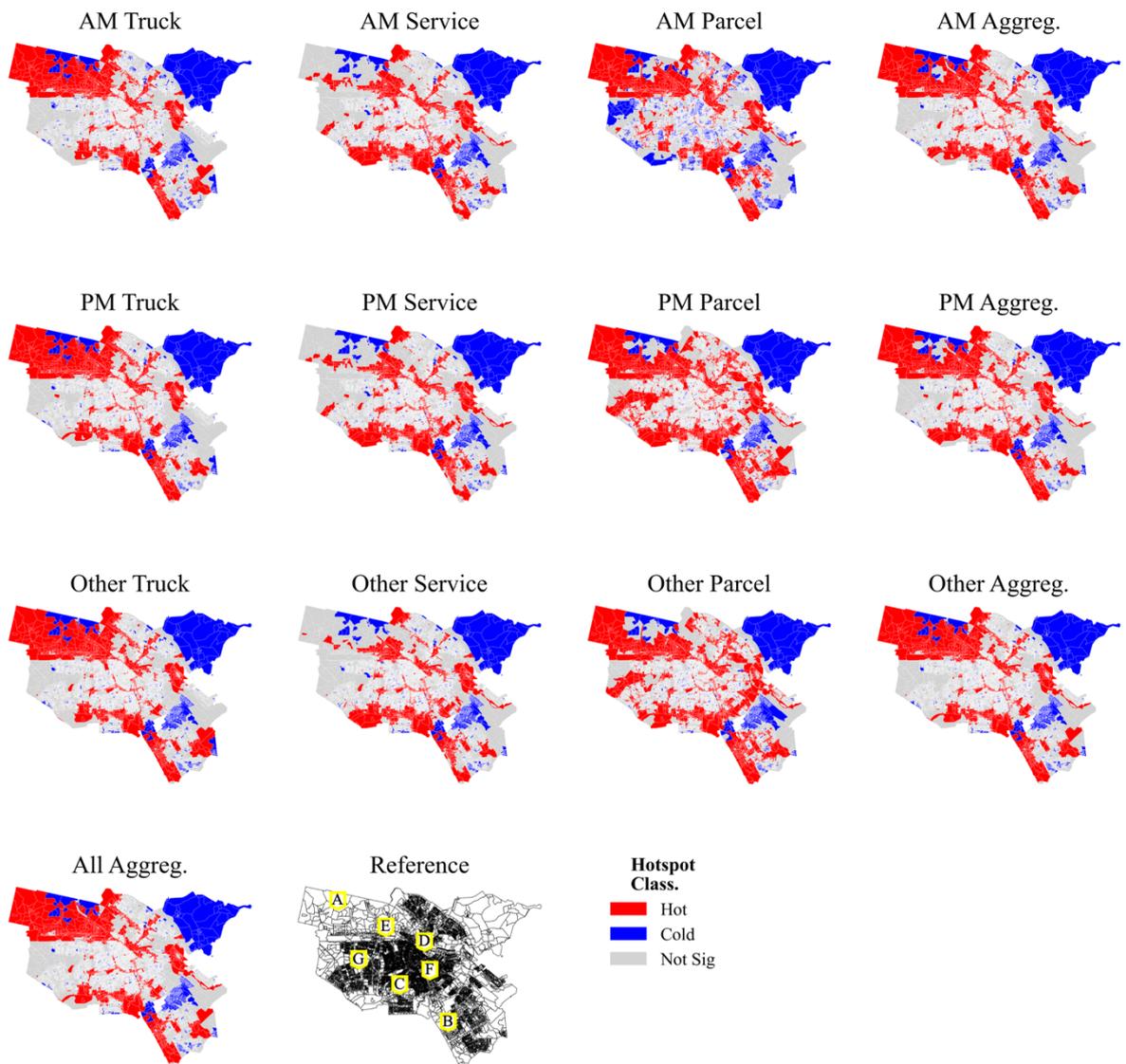
Figure 6: Getis–Ord Gi* Hot-Spot Classification of Observed Logistics Vehicle Counts in Amsterdam

A: Western Industrial Zone (Westpoort)   *E: Central City (Sloterdijk)*
B: South-Eastern City Entry (A2/S111)   *F: South-Central (Amstel)*
C: Southern Ring (Zuid)   *G: West (Oud-West)*
D: Central Station
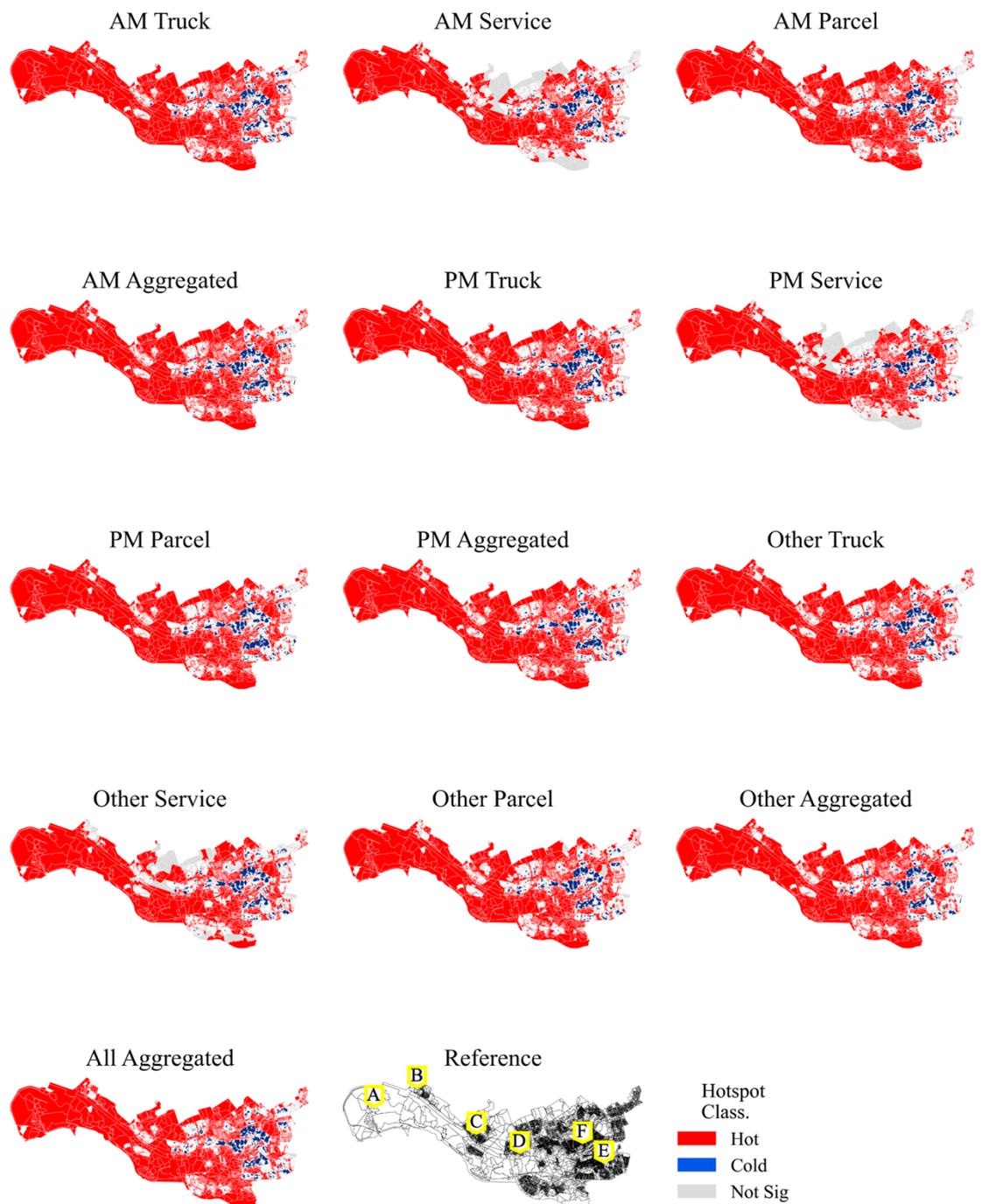
Figure 7: Getis–Ord Gi* Hot-Spot Classification of Predicted Logistics Vehicle Counts in Rotterdam

A: Western Port Zone

B: Western Industrial Zone (Hook of Holland)

C: Northern West to East Path (A20)

D: Northern West to East Path (A15)

E: South East Residential Area (Feijenoord)

F: Central Business District of Rotterdam

A Spatial-Temporal Analysis of Logistics Vehicles
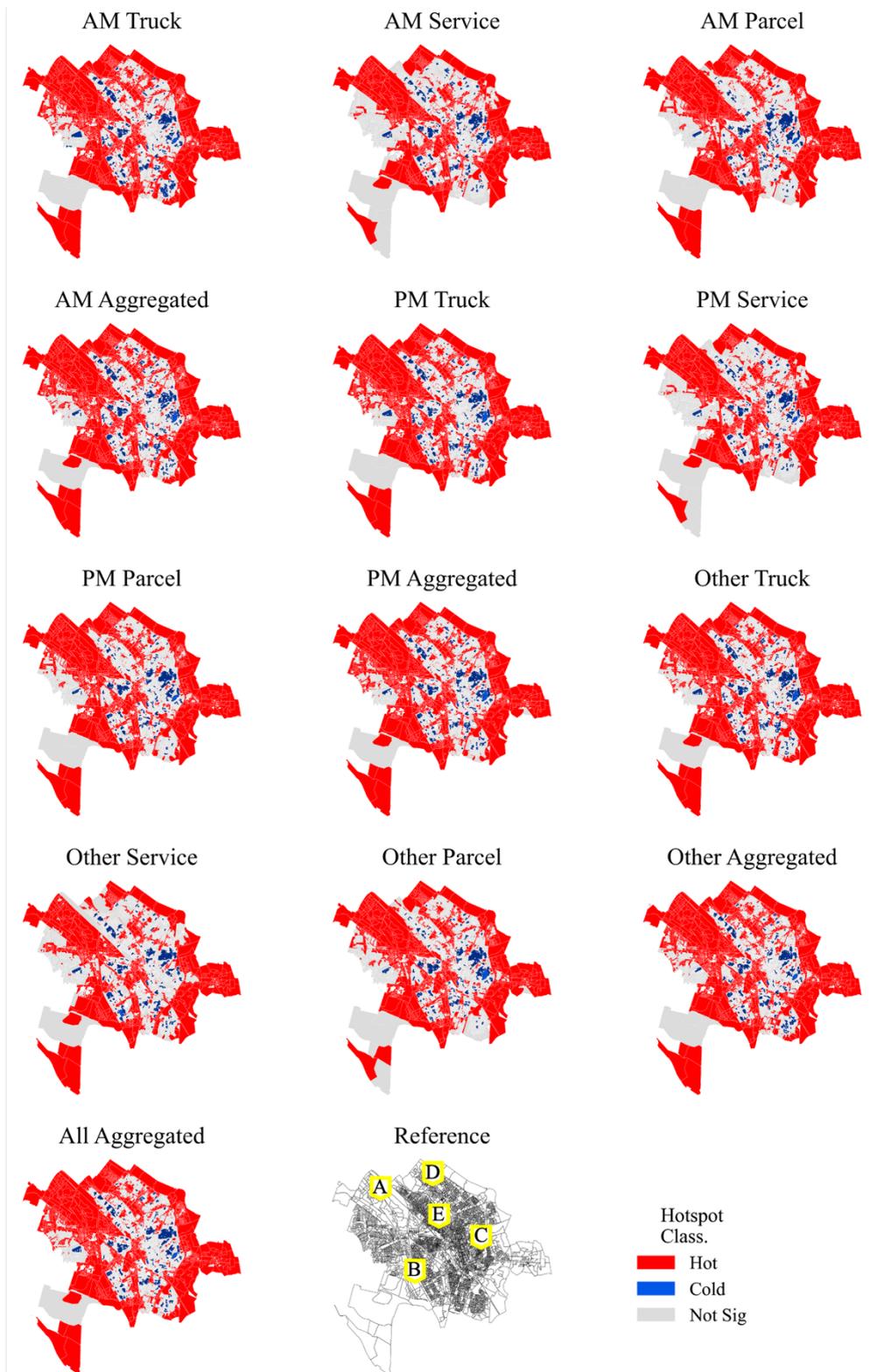
Figure 8: Getis–Ord Gi* Hot-Spot Classification of Predicted Logistics Vehicle Counts in Utrecht

A: Northwest Industrial Zone (Lage Weide)
B: Southwest Area (Papendorp)
C: Eastern Area (Oost)

D: North Central Area (Overvecht-Noord)
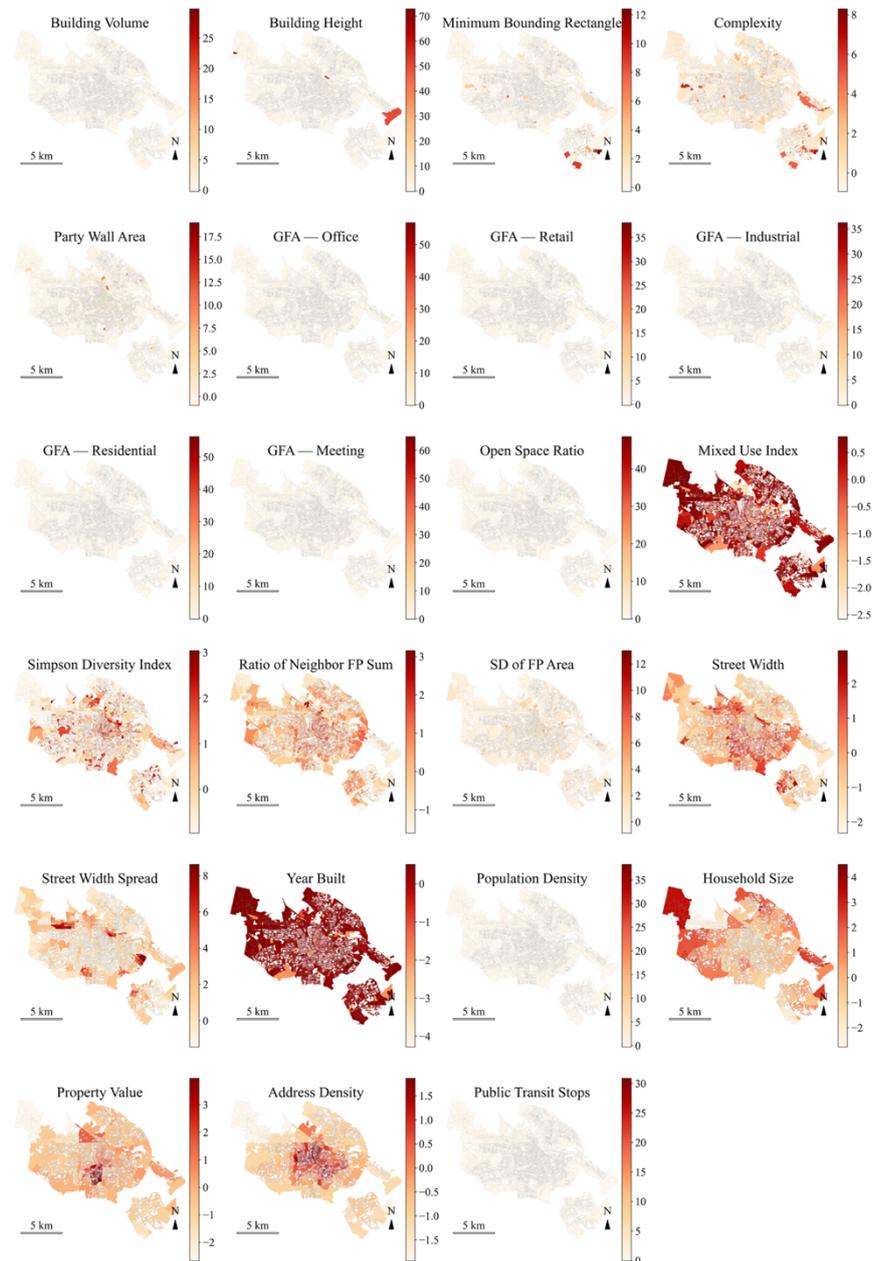*E: City Center*

A Spatial-Temporal Analysis of Logistics Vehicles

Appendix C

Spatial Distribution of Urban Morphology Indicators

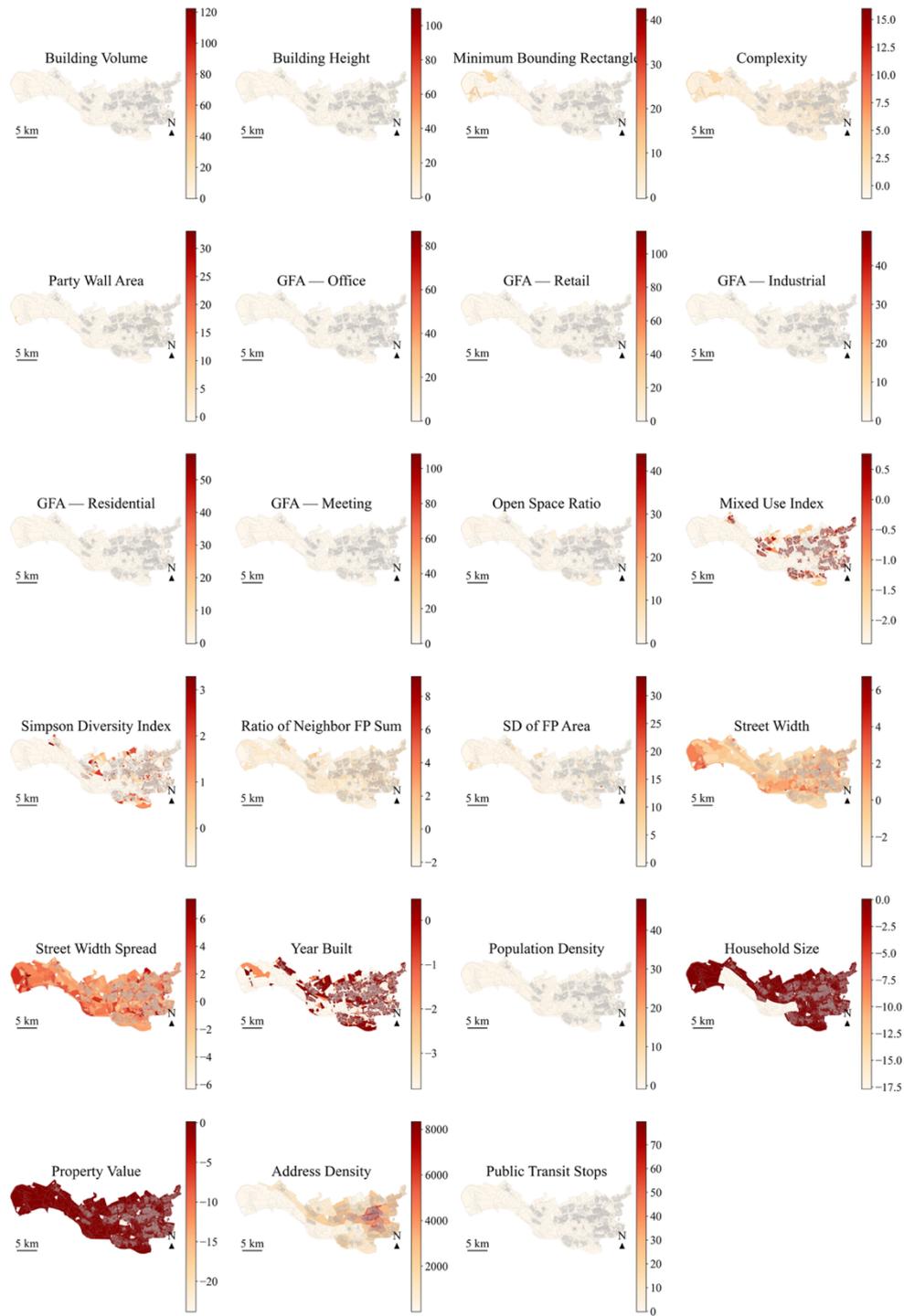*Figure 9: Spatial Distribution of Urban Morphology Indicators in Amsterdam*

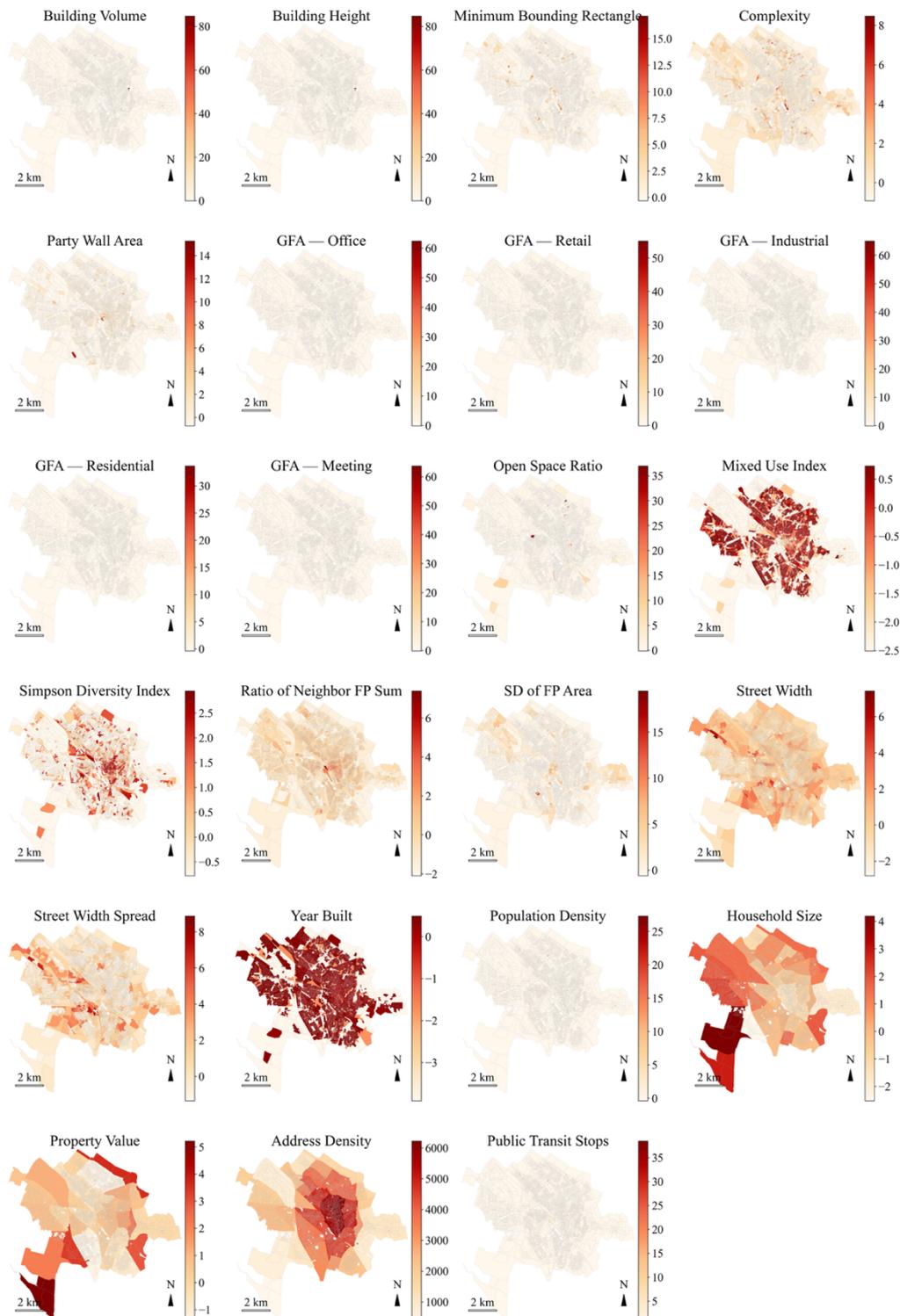*Figure 10: Spatial Distribution of Urban Morphology Indicators in Rotterdam*

A Spatial-Temporal Analysis of Logistics Vehicles

Figure 11: Spatial Distribution of Urban Morphology Indicators in Utrecht

Appendix D

Lagrange Multiplier Test

Anselin and Rey (2014)'s lagrange multiplier (LM) test workflow, shows how to choose the appropriate LM model based on the statistically significant p-value, testing, and statistics.
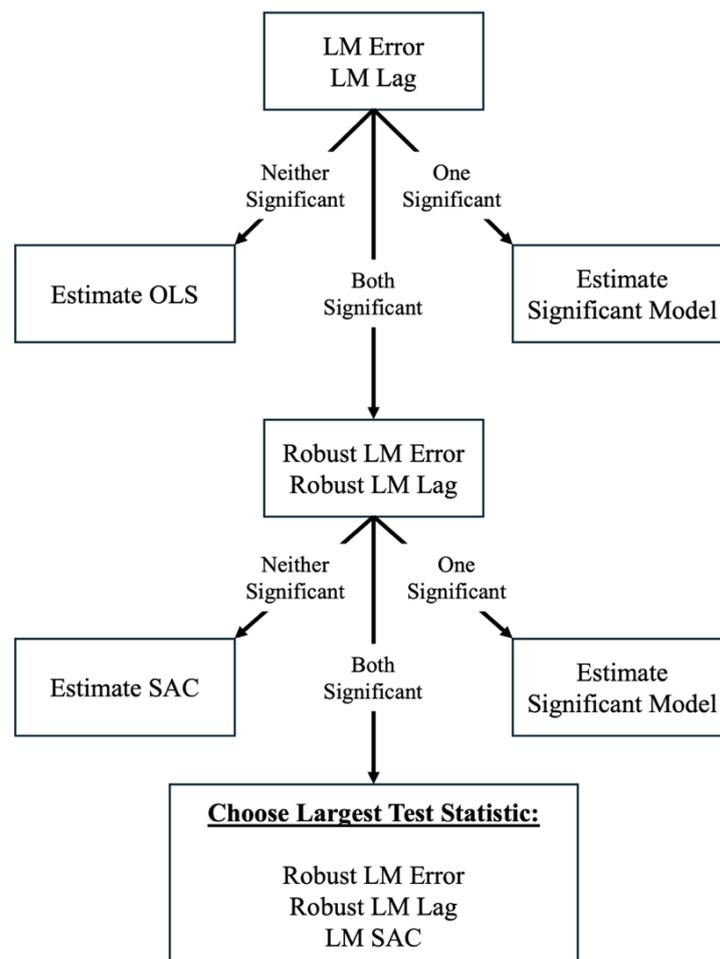

Figure 12: Lagrange Multiplier Test