Spatial and Modal Patterns of Traffic Law Enforcement in Barcelona: Insights from Open Government Data

Master Thesis

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Summary

Road traffic injuries remain as a major public health challenge for cities worldwide, with traffic violations and unsafe driving behaviors significantly contributing to crash hazards. Although traffic law enforcement is an important instrument for improving road safety, limited empirical evidence available on how enforcements activities are distributed across space, time and transport modes in cities. Addressing this gap, this thesis investigates the spatial, temporal, and modal patterns of traffic law enforcement in Barcelona.

The study applies a geospatial analytical framework to observe whether enforcement activities concentrate in specific locations, differ across different time intervals or vary by vehicle types and violation categories. The analysis uses traffic infringement records from the Barcelona Open Government data portal, containing more than 260,000 geocoded traffic violations recorded during first quarter of 2024.

Methodologically, the research integrates Geographic Information System (GIS) techniques and statistical analysis. Network Kernel Density Estimation (NKDE) is used to model infringement intensity along the street networks, while Getis-Ord Gi* statistics identifies statistically significant spatial hotspots across the city. A Monte Carlo randomization approach is applied to test whether observed clustering varies from a random spatial distribution.

The analysis emphases on urban street networks of Barcelona and investigate spatial clustering patterns as well as temporal variations during peak hours, weekdays, and weekends. The results revealed a distinct spatial clustering of enforcement activity within central districts and along major corridors. Temporal analysis display clear peaks during weekday traveling hours, while subgroup analyses indicate differences in enforcement intensity across vehicle types and violation severity.

Overall, the findings demonstrate that traffic law enforcement in Barcelona follows a strong spatial and temporal structure rather than random distribution. The study also highlights the value of geospatial analytical approaches for evaluating enforcement strategies and their implementation.

Preface

Road safety and urban mobility are not only technical or policy issues, but also part of everyday life in cities across the globe. Through my studies in geoinformatics and my observations of cities, I became interested in how traffic behavior, infrastructure design and enforcement practices affect urban safety and accessibility.

In densely populated cities such as Barcelona the high traffic demand and interactions between different transports modes make effective traffic enforcement important for road safety. This interest motivated me to explore traffic law enforcement from spatial and analytical perspectives. Although more studies focus on traffic crashes or mobility networks, less attention has been given to the spatial patterns and distribution of traffic enforcement.

In addition, the availability of detailed open government data enabled the investigation of where, when, and on whom traffic laws enforced. Geospatial and statistical analysis were used to examine enforcement patterns in a structured and data-driven way to produce the results presented in this thesis.

I would like to express my sincere gratitude to my supervisor, Dr. Martin Loidl, for his guidance and valuable feedback throughout this work. I would also like thank my colleagues, friends and fellow students for their support and insightful discussions during this research. Finally, I would like to thank my family for their encouragement and continuous support throughout my studies and the completion of this thesis.

1. Introduction

The scientific motivation underlying this research is explained in this chapter. Following the formulation of the problem statement and description of proposed approaches, the main research objectives and their corresponding hypotheses are presented. Finally, the chapter introduces a roadmap presented in this Thesis.

1.1 Motivation

Road traffic crashes being considered as a major public health challenge across urban areas worldwide, which cause significant human and economic losses each year. Traffic related injuries and fatalities leads to extensive burdens on healthcare systems, communities and national economies. In addition to the loss of life and long term disabilities, traffic crashes resulted considerable economic costs to the community, which are estimated to count for about 3% of a country's gross domestic product (GDP) (Abdulhafedh, 2017; Elfahim et al., 2023; Pérez et al., 2025).

According to the World Health Organization (2023) report, road traffic crashes result in approximately 1.19 million deaths and between 20 and 50 million nonfatal injuries annually. The report stated that road traffic injuries are considered one of the leading causes of death for children and young adults aged 5 to 29 years, while nearly two thirds of traffic fatalities occur among the working individual aged between 18 and 59 years. These figures highlight significance of this issue and urgent need for effective strategies to improve road safety and reduce traffic related risks in our society.

At the same time, traffic violations are a primary contributor to road traffic crashes which cause risks in our daily life. Therefore, the unsafe driving behaviors such as speeding, red light running, and illegal parking not only increase the probability of crashes, but also intensify the severity of traffic crashes (Wang & Liang, 2025).

Large-scale analyses of traffic violation data show that such behaviors reveal distinct spatial and temporal patterns but not occurred randomly which reflect underlying traffic conditions and driver behavior dynamics (Srikanth et al., 2019).

To address these issues, governments and international organizations have introduced policies to improve driver behavior and strengthen traffic law enforcement. However, many of these policies emphasize on human error which is widely known as one of the key causes of road crashes resulting from noncompliance with traffic regulations (Castillo-Manzano et al., 2019).

In Spain, several legislative reforms including the implementation of a points based driver's license system and amendments to Penal Code have been introduced to strengthen traffic safety across the country (Castillo-Manzano et al., 2019). At the local level, the City Council of Barcelona has implemented multiple initiatives to enhance road safety and sustainable urban mobility. For instance, one of the most important initiatives was the 2013–2018 Local Road Safety Plan (LRSP), which introduced 24 strategic measures and 80 specific actions that reduced fatalities and serious injuries by 20% compared with 2012 levels (Bermúdez & Morillo, 2023).

Understanding where and when traffic violations occur is essential for designing and implementing effective enforcement strategies. Hence, identifying locations with high violation frequencies enables authorities to allocate enforcement resources more efficiently and develop evidence based policy measures. Li et al. (2020) emphasize the importance of considering both spatial and temporal dimensions when analyzing traffic violations to support effective and evidence-based policies. They also note that incidents occurring in different locations at the same time may influence by similar traffic or environmental conditions.

Previous research has demonstrated that traffic violations and crashes often display significant spatio-temporal clustering rather than occurring randomly across urban environments. For example, Li et al. (2020) stated that violations frequently concentrate at particular intersections and time periods which reflect underlying traffic dynamics and infrastructure conditions. Similarly, Iamtrakul and Chayphong (2025) highlight that traffic accidents display systematic spatial and temporal variations which reinforcing the significance of geospatial methodologies to identify high risk locations.

Geographic Information Systems (GIS) have become essential tools to analyze such patterns and support relevant decision-making processes. Recent studies show that geospatial techniques are useful for mapping accidents and identifying significant hotspots using traffic and spatial data.

Kazmi et al. (2022) demonstrate how GIS and kernel density estimation can be used to detect spatial concentrations of traffic accidents and analyze associated environmental risk factors. Likewise, Gilardi et al. (2022) underline the importance of spatial analytical approaches to identify clusters of traffic incidents and support data driven road safety interventions.

Meanwhile, several of spatial statistical methods have been developed to analyze traffic safety patterns. The kernel density estimation (KDE), Moran's I, and Getis-Ord Gi* statistics are widely used to identify clusters of traffic accidents and violations (Bermúdez & Morillo, 2023). KDE, for instance, transforms crash location points into continuous density surfaces which help researchers to visualize spatial concentrations of incidents. In addition, advanced approaches integrate density estimation with spatial autocorrelation statistics to assess the statistical significance of observed clusters (Ge et al., 2022; Le et al., 2022).

A recent study focuses primarily on developing predictive models for accident occurrence using machine learning and large urban datasets (Hébert et al., 2019). These approaches are effective for prediction, but they focus less on the spatial patterns of violations and enforcement in urban road networks (Behboudi et al., 2024). Despite these methodological advancements, several gaps remain in the literature regarding the spatial dynamics of traffic violations and enforcement within urban areas. To address this gap, this research uses geospatial analysis to study traffic violation clusters across space and time and their relationship with enforcement practices in urban mobility systems.

1.2 Problem Statement

Traffic law enforcement is a key part of urban road safety strategies, but there is still a disconnect between policy implementation and the systematic analysis of enforcement deployment. Although Barcelona uses traffic enforcement widely for road safety, there is little evidence on whether enforcement matches safety priorities over space and time or is fairly distributed across transport modes.

Despite the availability of detailed open data on traffic infringements and relevant policies that focus to improve road safety, a data-driven understanding of enforcement patterns remains limited. In particular it remain unclear to determine whether traffic enforcement in Barcelona is spatially and temporally aligned with identifiable high-risk locations and periods. It also remains uncertain whether enforcement intensity varies systematically across vehicle types, which could produce inequitable enforcement outcomes (e.g., Abdulhafedh, 2017; (Bermúdez & Morillo, 2023).

Therefore, this research is going to address below fundamental questions:

a) How traffic law enforcement efforts are spatially and temporally distributed?
b) What do spatial, temporal and modal enforcement patterns reveal about the distribution and characteristics of traffic enforcement activities in the city?
c) How can spatial analysis techniques improve the understanding and evaluation of traffic law enforcement patterns in Barcelona?

1.3 Objectives and Hypotheses

Research Objectives:

1. Identify and map statistically significant spatial hotspots of traffic violation across Barcelona using network-constrained NKDE, and Getis-Ord Gi* statistics, validated through Monte Carlo random-point simulations.
2. Investigate enforcement dynamics over different time intervals and identify significant temporal shifts in hotspot intensity.
3. Compare enforcement patterns across violation types and vehicle categories by producing subgroup-specific hotspot surfaces.

The outcomes will be synthesized into a suite of spatial and spatio-temporal maps that visualize enforcement concentration and provide evidence based insights to guide data-driven traffic safety decisions.

Hypotheses:

H1 (Spatial Clustering): Traffic fines in Barcelona are not randomly distributed but form statistically significant spatial clusters (hotspots and cold spots).

H2 (Temporal Patterning): The intensity of enforcement follows distinct temporal patterns, with significant peaks during weekdays, weekends and rush hours.

H3 (Modal and Violation-Type Disparity): Traffic infringement hotspot patterns differ significantly across vehicle types and violation severity classes.

1.4 Structure of the Thesis

- **Chapter 2:** Theoretical and contextual foundation reviews along with relevant literature on traffic safety as a public health issue, Barcelona's urban mobility context and spatial traffic violation analysis.
- **Chapter 3:** Research design and methodology including the research framework and methodological approach, outlining the analytical workflow, relevant datasets, and geospatial tools used to address the assigned objectives.
- **Chapter 4:** Data curation and geospatial processing describes the procedures for data cleaning, attributes preparation, and pre-processing undertaken to transform raw datasets into an analysis ready geospatial database.
- **Chapter 5:** Analytical results that show empirical findings of the stud including spatial clustering patterns, variations across temporal periods, vehicle categories, and violation types.
- **Chapter 6:** Synthesis and discussions that interpret the analytical results in relation to the research questions and existing literature, underlining implications for urban mobility policy and traffic enforcement strategies.
- **Chapter 7:** Conclusions and future research possibility, key findings and study contributions

2. Theoretical Framework and Literature Review

This chapter covers the theoretical and empirical literature relevant to traffic law enforcement and urban mobility. It begins by framing traffic safety as a public health and equity issue, followed by discussion on enforcement policies and their impact on road safety. The chapter then inspects the urban mobility context of Barcelona and explores spatial perspectives on enforcement and inequality. Finally, it identifies key research gaps and positions the contribution of this study within the existing body of knowledge.

2.1 Traffic Safety as a Public Health and Equity Issue

Road traffic injuries are known as a major public health challenge which requires preventive strategies. Research shows that monitoring and evaluating road safety measures helps reduce injuries (Pérez et al., 2025). This suggests that the causes of traffic injuries come from original system level factors

Road safety outcomes are unevenly distributed across populations and modes of transport. Vulnerable road users such as pedestrians, cyclists, and motorcyclists display distinct injury patterns (Pérez et al., 2025). This inequitable distribution positions traffic injuries not only as a public health concern but also as a matter of social justice between different population groups.

Spatial and statistical analyses further illustrate the structural and geographic dimensions of traffic risks. Research conducted by Elfahim et al. (2023) demonstrates that traffic violations and associated risks are neither random nor evenly distributed but clustered in specific urban locations. This analysis underscore the necessity of data driven-enforcement strategies to target high risk areas.

The framing of road safety as both a public health and health equity issue is increasingly recognized by McCullogh et al. (2023). Road traffic injury risks are influenced by characteristics of the built environment, including urban design, traffic speed and infrastructure plan. Evidence indicates that vulnerable road users such as children, older adults, persons with disabilities are disproportionately in higher exposure to traffic related risks. Therefore, these groups receive fewer benefits from safety measures like traffic calming and pedestrian infrastructure, reflecting inequalities in road safety resources (McCullogh et al., 2023).

Additionally, governance and planning processes can impair inequitable safety outcomes. When the decision-making mechanisms are based on community complaints or participation, it may favor certain political group or wealthier population (McCullogh et al., 2023). Consequently, areas with the highest injury burden may remain less protected because of traffic safety.

Thus, framing traffic safety within public health and equity considerations provides a critical foundation for investigating enforcement practices. The literature highlights that traffic risks and violations are spatially uneven and tend to cluster in specific areas which supports the first hypothesis of this research to spatial clustering patterns of infringements.

2.2 Traffic Infringements, Enforcement Policies, and Road Safety Outcomes

A narrative review by Yasanthi et al. (2024) summarizes prior research and identifies four categories of factors. These factors are individual, situational, organizational, and community-level which influence the willingness of professionals to engage in traffic safety enforcement.

In addition, the relationship between traffic infringements, enforcement intensity and safety outcomes has been also examined in the literature. Castillo-Manzano et al. (2019) studied the effect of traffic enforcement on road fatalities and found that speeding and alcohol-related offences are linked to fatal crashes. Importantly, their findings underscore that enforcement presence measured through police visibility and control activities can help to reduce fatalities even with low detection rates. This suggests that the effectiveness of enforcement lies not only in traffic violations offenders but also in determining perceived risk because drivers will try to avoid punishments. Also, the study shows that different types of infringements results unequal effects on safety outcomes which emphasize to examine their spatial relationship to enforcement practices.

Advancements in spatial analysis have improved the use of infringement data in road safety research through enabling the examination of enforcement sensitive patterns across space and time (Li et al., 2020). This investigation revealed that traffic violations captured through automated enforcement systems show spatio-temporal variability at urban intersections. The study conceptualizes infringements as observable expressions of risky driving behavior influenced by enforcement technologies.

This contribution highlights the importance of spatio-temporal approaches for understanding how enforcement practices shape the observed geography of traffic risks. Within this framework, traffic infringement data serve as a valuable foundation for examining the interaction between enforcement policies and road safety outcomes. Hence, by incorporating the spatio-temporal analytical methods, this analysis builds on existing literature to investigate how enforcement patterns relate to observed infringement distributions across urban space.

2.3 Urban Mobility and Enforcement Context in Barcelona

Barcelona is known an example of a city that integrates public health principles into urban mobility governance and traffic enforcement. This combination is formed through an inter sectoral model that links transport planning, law enforcement, and public health institutions which allowed a continuous monitoring of road safety outcomes (Borrell et al., 2025); (Pérez et al., 2025).

The study confirmed a high-density urban environment with approximately 1.6 million residents and more than 6.1 million daily trips. It indicated that three quarters of these trips are undertaken using sustainable modes. The study also revealed that, traffic enforcement measures such as speed regulation, usage of automated enforcement technologies, and helmet legislation are embedded to reduce injuries (Pérez et al., 2025).

Recent research has further explained the complex relationship between urban form, mobility intensity and traffic safety in Barcelona. Galaktionova et al. (2026) used spatial regression and computer vision methods to study street activity based on functional density. The derived results show a positive association with both perceived safety and crash frequency at citywide scale. This finding also indicates that inherent tension within dense and mixed use environments, where increased pedestrian activity along with urban livability may simultaneously elevate exposure to traffic conflicts. These results underscore the need for context specific enforcement and design interventions, especially within dense urban morphologies such as Barcelona's Example district, where crash concentrations display clear spatial cluster.

Complementing these findings, Graells-Garrido et al. (2021) reveal that Barcelona's polycentric urban structure shapes mobility flows in highly localized ways. Using mobile phone data and geographically weighted regression, the authors reveal that access to neighborhood level services significantly influences travel behavior. This results support the argument that mobility management and enforcement strategies must be spatially differentiated rather than uniformly applied.

Evaluations of Barcelona's Road Safety Plan further indicate mixed effectiveness across intervention types. Preventive measures such as traffic calming, improved crossings, cycling infrastructure and road safety education show clear benefits, whereas enforcement measures such as speed control and alcohol and drug testing show less consistent effects on injury severity (Bermúdez & Morillo, 2023).

2.4 Spatial Perspectives on Traffic Enforcement and Inequality

The existing research demonstrates that traffic enforcement is not spatially neutral and can generate unequal safety and legal outcomes across urban populations. The spatial analyses further show that these differences are often not because of driving behavior but resulted by distribution of surveillance technologies, policing strategies and urban structures Cai et al. (2022); (Hu et al., 2018).

Cai et al. (2022) provide evidence of enforcement driven inequality by integrating large scale telematics data with geocoded speeding citation records across Ten U.S. Cities. Their findings reveal that actual speeding behavior varies minimally across neighborhoods but enforcement intensity is disproportionately concentrated in demographically non-representative areas. This spatial mismatch and targeted policing lead to unequal enforcement outcomes across cultural and ethnic groups, not explained by behavior.

At the citywide scale, broader spatial conditions such as traffic congestion further redistribute crash risk and enforcement relevance across urban networks. Through analyzing the panel data from 129 European cities, Albalate and Fageda (2021) identify a nonlinear relationship between congestion and road fatalities. It stated that moderate congestion can improve safety by reducing speeds, while severe congestion increases fatalities due to higher exposure and effects across the wider road network.

These findings indicate that how spatial externalities shift risk beyond individual corridors which underlining need for spatially informed enforcement strategies. Micro-scale analyses show strong spatial and temporal clustering of traffic violations. Li et al., (2020) found that violations are concentrated at specific locations and tend to occur during non-peak hours. Similarly, Hu et al. (2018) reveal that pedestrian and cyclist involved crashes are disproportionately concentrated at particular intersections which are associated with traffic control infrastructure and intersection design. These studies show that enforcement infrastructure and urban form are linked and can lead to unequal safety outcomes. Thus, they highlight the need for spatial analyses of traffic enforcement that explicitly consider equity.

2.5 Literature Gaps and Contribution of This Study

Recent scholarship in urban mobility and transport governance underlines the importance of spatially informed, data driven approaches for improving road safety and regulatory effectiveness (Magkafas et al., 2025). However, despite considerable advances in traffic crash analysis and infrastructure based safety assessment, spatial and modal distribution of traffic law enforcement itself remains relatively under examined. Many studies focus on crash frequency and injury severity, and treat enforcement as a background factor instead of something that can be analyzed as a spatial practice.

Methodologically, GIS based road safety studies rely on Kernel Density Estimation (KDE) to identify hotspots, often without complementary statistical validation or cross method comparison (Magkafas et al., 2025). The limited use of local spatial statistics such as Getis-Ord Gi* and Monte Carlo randomization restricts the ability to distinguish meaningful clustering from random spatial variation. Furthermore, enforcement data are rarely analyzed across multiple dimensions simultaneously like spatial, temporal and modal patterns. As a result, it remain unclear whether enforcement patterns follow a clear strategy or are simply reactive and scattered practices.

Another critical gap concerns data sources. Although open government data initiatives have greatly expanded access to detailed enforcement records, their analytical potential remains underutilized in urban traffic research.

Addressing these gaps, this work contributes an integrated spatial analytical framework for examining traffic law enforcement in Barcelona. By combining NKDE for exploratory visualization, Getis–Ord Gi* statistics along with Monte Carlo significance testing for robust hotspot detection.

Moreover, it provides new evidence on how traffic law enforcement is distributed across space, time and transport modes. In doing so, the study directly responds to calls for equity oriented and spatially explicit analyses of traffic management.

3. Study Design and Methodology

This chapter covers the general research design and methodological framework of this research. It introduces the study area and describes data sources used for the analysis. The chapter then presents the analytical workflow and explains methods applied to investigate spatial, temporal, and modal patterns of enforcement. Finally, the software tools and implementation environment used in the study are described.

3.1 Research Design and Workflow Overview

This analysis adopt a multi stage analytical framework that integrates spatial data processing, network-based spatial analysis, statistical modeling, and cartographic visualization. The research design is organized to systematically transform raw geospatial datasets into analytically meaningful representations which lead to identify of spatial clusters, temporal variation and violation types disparities.

This work uses geocoded traffic infringement data from the first quarter of 2024. This three month observation period allows for the investigation of short term spatio-temporal dynamics including daily, weekly, weekends, and variations in enforcement intensity across different times of the day. The temporal scope of the study is intentionally limited to facilitate detailed high resolution analysis of intra period variability rather than long term trends. Consequently, the research does not seek to evaluate seasonal effects, infrastructure changes, or shifts in enforcement policy, which would require longitudinal datasets spanning multiple years.

3.2 Study Area: Barcelona City

Barcelona is a high density Mediterranean city (approximately 1.6 million inhabitants and 16,000 inhabitants per km²) characterized by intense daily mobility flows with significant modal diversity (Pérez et al., 2025). These characteristics make the city a suitable representative case for urban traffic safety research.

In this context, motorcyclists account for nearly half of all traffic-related injuries in the city. This mirrors Barcelona's high reliance on two-wheeled motor vehicles compared to other European cities. Cars, pedestrians, and emerging micro-mobility users show different patterns of exposure and injury risk (Pérez et al., 2025).

Since the early 1990s, Barcelona has maintained a comprehensive, geocoded road traffic surveillance system integrating police, health, and mobility data. So, it allowed a detailed spatial analyses of crashes, injuries and enforcement outcomes (Pérez et al., 2025).

In addition, this data system has shaped road safety and mobility plans that view traffic enforcement as a public health measure. These plans include speed cameras, 30 km/h zones, and targeted enforcement on major roads and ring highways(Bermúdez & Morillo, 2023); (Borrell et al., 2025). Hence, these characteristics make Barcelona a particularly suitable case for examining network based spatial analysis of infringement data considering different time and vehicle type categories.

3.3 Data Sources and Preparation

To support the network constrained kernel density estimation (NKDE), multiple spatial datasets were integrated to construct a comprehensive analysis framework for Barcelona. The primary datasets include a detailed geocoded traffic infringement database covering the first quarter of 2024 and street network derived from OpenStreetMap (OSM). Traffic infringement data consist of 260,486 recorded events distributed across all ten administrative districts of Barcelona, with the highest concentration observed in the Eixample district. The street network comprises 16,474 segments representing highways, arterial roads, and local streets, with a fine spatial resolution that enables network-based density estimation. In addition, a crash dataset covering the same temporal period (Q1 2024) was incorporated into the analysis. This dataset includes 1,831 individually geocoded crash incidents, each associated with a precise location along the urban road network.

Moreover, an administrative boundary layer delineating Barcelona's districts was used to support spatial aggregation and contextual interpretation, while a national level Spain boundary layer was included for reference mapping purposes. The combination of mentioned datasets form a spatially and temporally rich foundation for analyzing enforcement patterns, hotspot formation, and modal disparities along Barcelona's urban street network.

All datasets used in for analysis are publicly available through open data portal and contain no personal or individually identifiable information; therefore, ethical approval was not required for the use, analysis, or publication of this data.

3.4 Data Cleaning, Preprocessing, and Integration

Data cleaning and preprocessing was performed primarily in Python to ensure data consistency and spatial accuracy. To prepare the dataset for subsequent analysis, a series of preprocessing steps were applied.

- **Data integrity checks:** Remove duplicate infringement records and missing coordinates. Outlier was excluded through filtration and coordinates values beyond the city boundary were excluded.
- **Temporal normalization:** The temporal normalization was converted to infraction date and time fields into continuous date time formats, enabling hour, day, week and weekend level aggregation.
- **Coordinate consistency:** A consistent coordinate reference systems was used for all datasets to ensure accurate spatial joins and overlap.
- **Attribute filtering:** keep only relevant or required columns
- **Spatial joining:** This join snapped each infringement point to the nearest street segment (using osmnx or geopandas.sjoin_nearest) to prepare dataset for further analysis.

3.5 Methodological Framework

This research follows a multi-phase methodological framework designed to transform raw traffic infringement point data along with contextual GIS layers into meaningful spatial insights for enforcement equity and urban policy. The framework integrates geospatial, statistical and computational approaches to identify and validate spatio-temporal hotspots of traffic violations in study area. As illustrated in Figure 3.1, the methodology comprises four interrelated phases: (1) data acquisition and cleaning, (2) spatial and temporal hotspot detection, (3) traffic violation and vehicle type comparison and (4) synthesis and policy interpretation.

- **Phase 1:** Data acquisition and cleaning focuses on collecting and harmonizing datasets.
- **Phase 2:** NKDE and spatial autocorrelation indices (Moran's I, Getis-Ord Gi*) are used to locate spatial hotspots, while temporal analysis applied to detect peak violation periods by hour, day, and week. A Monte Carlo null model simulation is used to validate spatial clustering.
- **Phase 3:** Traffic violation and vehicle type comparison were explored through relevant subsets.
- **Phase 4:** Synthesis and policy integrates analytical outputs into spatial dashboards and indices which support policy oriented recommendations.

3.5.1 Overview of Analytical Approach

The overall analytical process is visually summarized in Figure 3.1, which illustrates the sequential and iterative logic connecting data collection, preprocessing, spatial analysis and policy synthesis. In Phase 1, diverse datasets including infringement records and contextual GIS layers are standardized and spatially integrated to build a clean analytical foundation. Phase 2 applies spatial clustering and temporal analysis techniques, supported by Monte Carlo null model. Phase 3 extends this framework by disaggregating results by vehicle type and violation category, allowing for targeted interpretation of enforcement.

Finally, Phase 4 synthesizes results into interpretable outputs maps and graphs that translate analytical findings into actionable insights for decision makers.

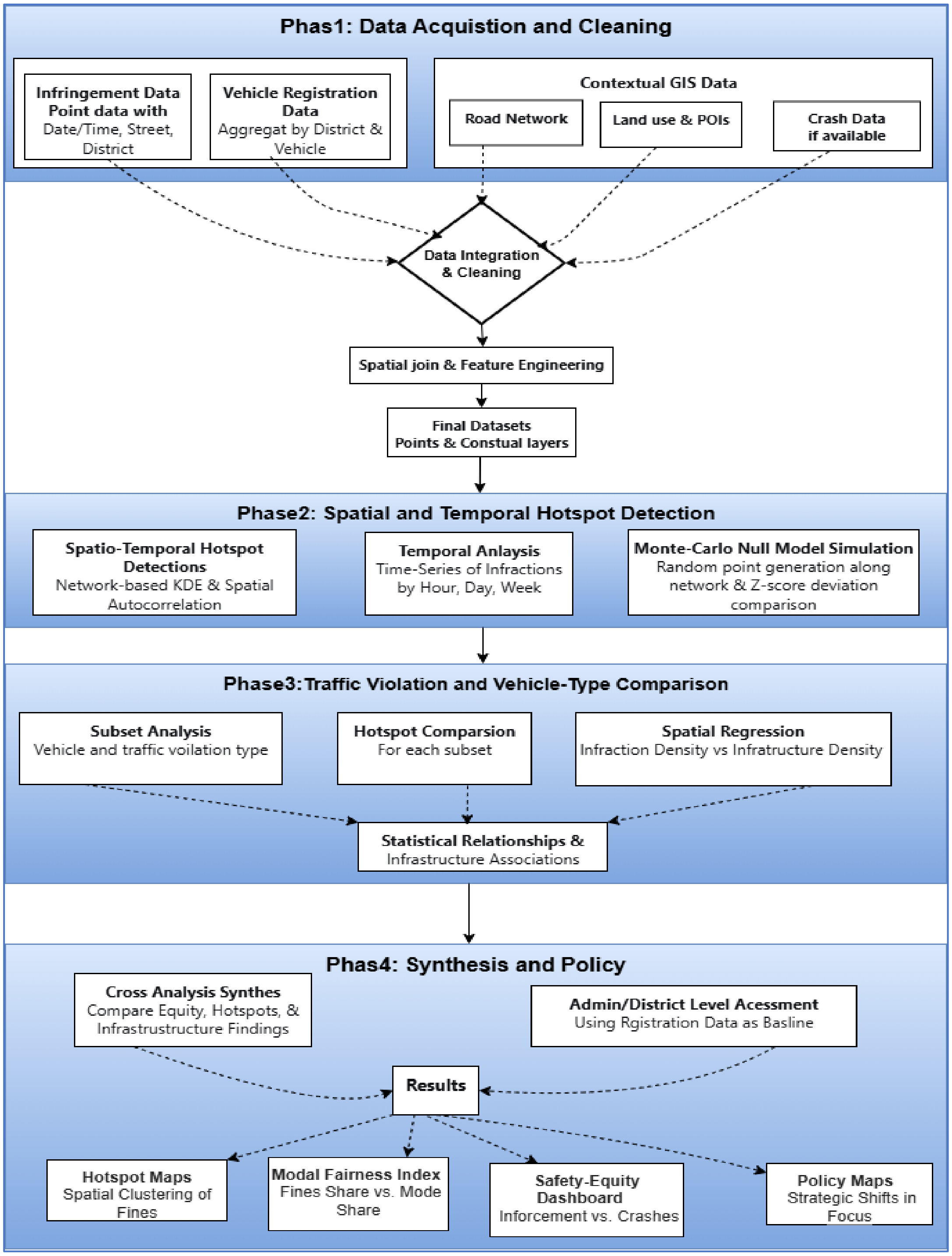

Figure 3.1: Methodological workflow for spatial–temporal analysis

3.5.2 Objective 1: Spatial Hotspot Detection

- Getis-Ord Gi* Statistic for Hot/Cold Spot Analysis

Spatial enforcement hotspots are identified through network constrained NKDE that characterized density patterns street network. In parallel, the Getis-Ord Gi* statistic is applied to identify local hotspots. A Monte Carlo-based null model is used as a reference to test the overall significance of clustering and assess whether the observed patterns differ from random distribution

3.5.3 Objective 2: Temporal Variation Analysis

- Temporal Aggregation and Heat mapping

Temporal variation is examined by binning enforcement events by hour, day and week to enable identification of recurrent time series variations in enforcement activities.

3.5.4 Objective 3: Subgroup Comparison by Violation and Vehicle Type

- Data Sub setting and Comparative Hotspot Analysis
- Spatial Similarity and Overlap Indices

To examine heterogeneity across modes and infraction types, enforcement events are disaggregated by Violation_Code and Vehicle_Type_Code prior to analysis. Spatial hotspot results are generated separately for each subgroup to make comparison of modal clustering patterns.

3.5.5 Monte Carlo Null-Model Validation

A Monte Carlo simulation is used to test if the clusters are meaningful. It generates random enforcement patterns along the street network and compares them with the observed hotspots. This shows whether the clustering is different from random. Subsequently, subgroup analyses in R explored differences across violation types and vehicle categories through spatial overlap and similarity metrics. These results are synthesized into maps, graphs using ArcGIS Pro and QGIS, which provide actionable insights for traffic management decision.

3.6 Software and Tools

This research employed an integrated set of GIS software and open source statistical programming environments to support spatial data preparation, analysis, and visualization. ArcGIS Pro was used to prepare, explore and map spatial data. This included harmonizing coordinate systems, classifying traffic infringement records, applying the Getis-Ord Gi* statistic, performing spatial overlays and creating maps.

Advanced network based spatial analysis was conducted in R, which served as the main platform for data analysis and inferences. Python complemented these workflows by facilitating dataset manipulation and integration tasks, such as attribute table management using open source libraries including GeoPandas and Pandas. Together, the combined use of ArcGIS Pro, QGIS, R, and Python provided a fit and complementary analytical framework that enabled efficient processing and spatial temporal analysis.

4. Data Preparation and Analytical Methodology

This chapter describes the data preparation procedures and analytical methods applied in the study. It begins with a description of data sources and preprocessing steps. The chapter then explains the construction of the street network and spatial units used for analysis. Subsequently, it introduces the key analytical techniques, including network kernel density estimation, spatial statistical testing, and temporal aggregation. Finally, the chapter outlines the procedures used for subgroup analysis and cartographic representation.

To provide an overview of the analytical framework employed for this analysis, Figure 4.1 presents a conceptual workflow of the research design. The figure clarifies the logical progression of the analytical steps described in this chapter and distinguishes methodological procedures.

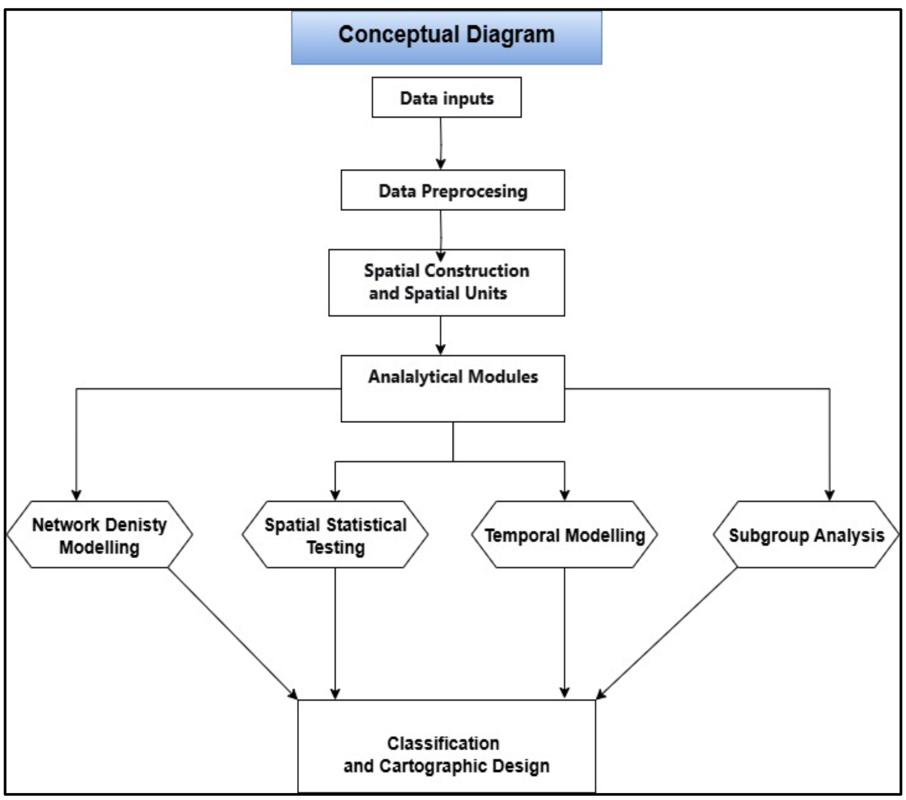

Figure 4.1: Conceptual Workflow of the Study

4.1 Data Preprocessing

Prior to analysis, both the traffic infringement dataset and street network layer were prepared to ensure spatial consistency and compatibility with subsequent network-based analysis.

All spatial datasets were harmonized to a common projected coordinate reference system (ETRS89 / UTM Zone 31N; EPSG: 25831) to maintain metric consistency across layers. Following projection, geocoded infringement records were spatially aligned with the Barcelona street network. To enable accurate network-based modelling, each infringement event was then snapped to its nearest street segment to ensure point based observations were properly integrated within the network structure.

This integrated dataset provided the foundation for subsequent network construction, density modelling, and spatial statistical analysis.

4.2 Network Construction and Spatial Units

The street network used in current study derived from OpenStreetMap and was initially stored in a geographic coordinate reference system (WGS 84; EPSG: 4326), in which spatial coordinates are expressed in angular units (degrees). Since this representation is appropriate for data storage and visualization but it is unsuitable for network based spatial analysis as linear distances cannot be interpreted directly in metric units. As well as, the topological operations such as intersection detection, node snapping, and distance based calculations may not give reliable results. As a result, shortest path distances and kernel bandwidths required for (NKDE) would lack physical meaning if applied directly to the geographic coordinate network.

To address these limitations, the street network was re-projected to a metric coordinate reference system prior to analysis. This transformation converted all spatial measurements from angular units to meters which enabled the accurate computation of segment lengths, shortest path distances and kernel bandwidths consistent.

Following re-projection, the street network was processed in Python using GeoPandas and Shapely to construct a topologically consistent network representation suitable for graph-based spatial analysis. The workflow included geometry validation, line segmentation and topological cleaning to ensure that street segments were explicitly connected at intersections. During this process, implicit geometric crossings present in the original dataset were converted into explicit shared vertices using topological Nodes.

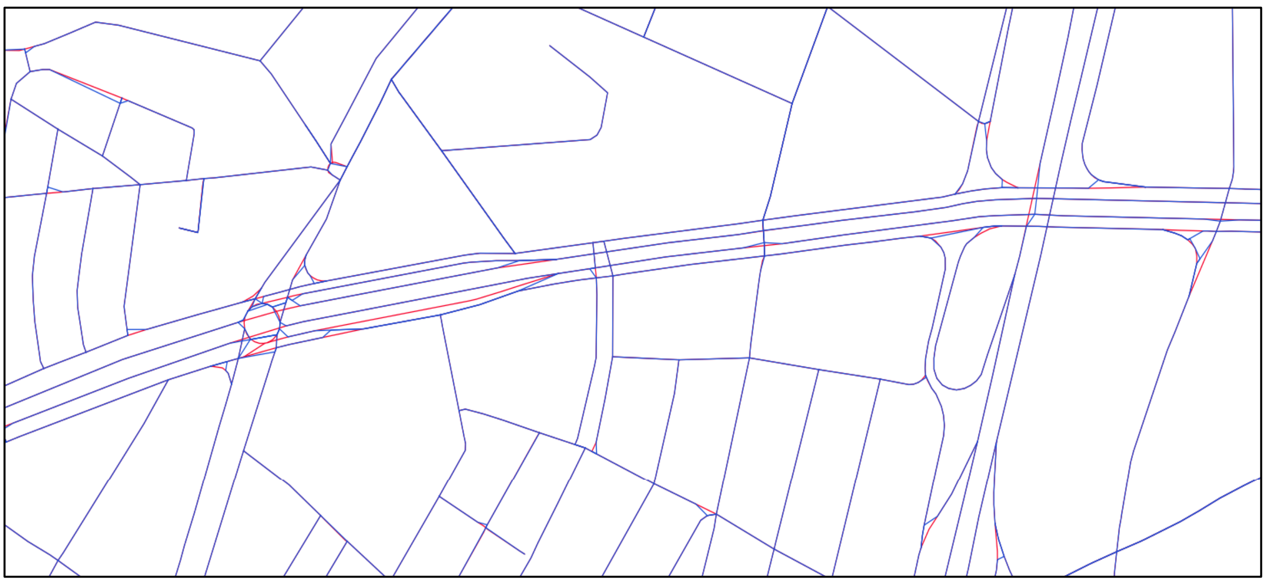

Figure 4.2: Topological corrected street lines

As displayed in figure 4.2, the blue color street line are split and has more segmented which is topologically corrected. As a result, street geometries were subdivided into smaller edge segments bounded by adjacent nodes representing intersections or dead ends.

Comparison between the original and processed networks demonstrated improved endpoint connectivity, increased node sharing at intersections. The resulting network therefore represents a topologically correct graph in which street connectivity and distance relationships are accurately defined.

4.3 Exploratory District Level Density Assessment

The network based spatial analysis draws on a comprehensive dataset of georeferenced traffic infringement events recorded explained in Section 3.3 within the municipality of Barcelona. Each observation is represented as a point geometry referenced in the ETRS89 / UTM Zone 31N coordinate system. The dataset contains 25 attribute fields describing temporal, spatial and contextual characteristics.

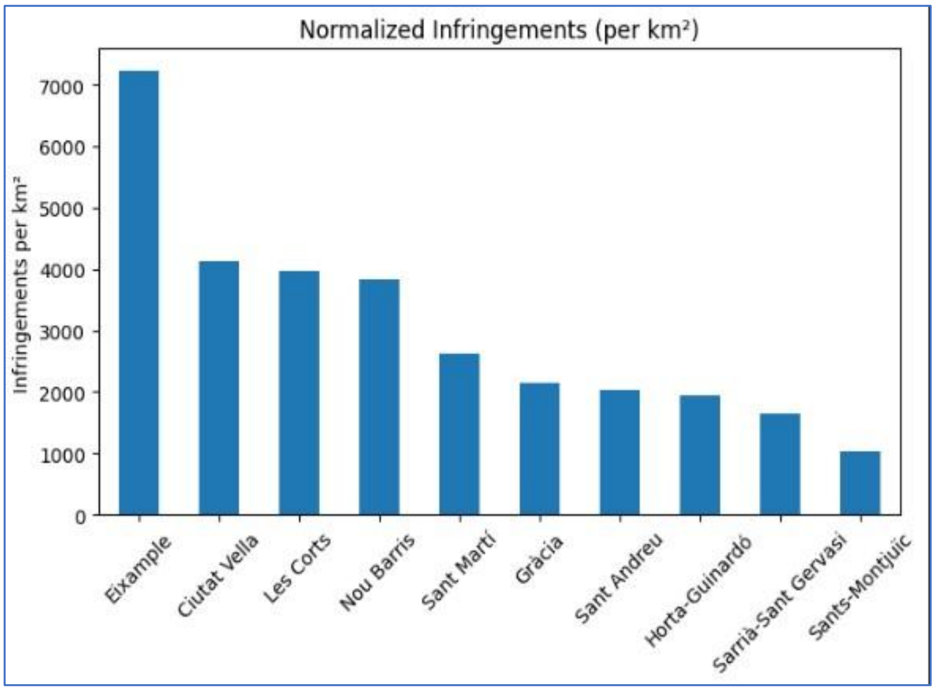

Figure 4.3: Bar chart of normalized infringement densities per km²

As an initial exploratory step, infringement events were aggregated at the administrative district level to examine broad spatial patterns prior to finer scale network analysis. Figure 4.3 presents infringement density (events per km²) across districts which make it easier to compare districts across the city. The results reveal a noticeable spatial imbalance in the city. As showed, the Eixample district records the highest infringement density or above 7,000 events per km². As well as the Ciutat Vella, Les Corts, and Nou Barris also have substantially higher densities compared to the citywide average. In contrast, outer and lower density districts such as Sarrià–Sant Gervasi, Horta-Guinardó, and Sants-Montjuïc recorded considerably lower normalized infringement events.

4.4 Network Kernel Density Estimation (NKDE)

Network Kernel Density Estimation (NKDE) was applied following the theoretical framework proposed by Okabe et al. (2009). The method estimates the intensity of events occurring along a network by summing kernel contributions from all observed events, where distances are measured as shortest path distances along the network rather than Euclidean distances.

Formally, the estimator is defined as:

$$f(s) = \frac{1}{h} + \sum_{n=1}^{n} w_i \ . K \ \left(\frac{d_N(s, x_i)}{h}\right)$$

Where xi denotes event locations, dN (s,xi) is the shortest path distance between location s and event xi, h is the kernel bandwidth, K is a kernel function, and wi represents event weights.

NKDE was implemented using the nkde() function from the spNetwork R package, which operationalizes the equal split network kernel framework originally proposed by Okabe et al. (2009) and subsequently applied to traffic safety analysis by (Abdulhafedh, 2017) .

Unlike planar kernel density estimation, NKDE computes event intensity along linear networks by measuring shortest path distances constrained to the network topology rather than Euclidean distances. As a result, the estimated density values represent event intensity per unit length of roadway, providing a spatial representation that is consistent with the network constrained nature of traffic violations. Gaussian kernel functions were applied with bandwidths of 200 m and 300 m in order to capture spatial patterns at multiple scales.

The smaller bandwidth emphasizes localized concentrations of events along individual street corridors, while the larger bandwidth highlights broader or wider neighborhood level trends.

Exploratory testing showed that a bandwidth of 200 m was the most suitable parameter. It preserved local spatial patterns while reducing excessive scattering between road segments. This methodology empowers the identification of continuous density patterns along the street network while minimizing over segmentation.

4.5 Spatial Statistical Testing

To move beyond exploratory density estimation and formally assess the presence of spatial clustering, two complementary statistical procedures were employed. The Getis–Ord Gi* statistic was applied to identify localized clusters of high infringement intensity along the street network. This method detect statistically significant hotspots at the segment level. Although Gi* evaluates local spatial association among adjacent segments, it does not directly test whether the overall spatial formation deviates from a random network constrained process.

To address this limitation, a Monte Carlo randomization procedure was implemented to generate a null distribution under length weighted random allocation of events across the network. This simulation based framework provides a global assessment of whether observed density patterns differ significantly from spatial randomness. Together, these methods enable both localized hotspot detection and overall validation of clustering against a theoretically grounded null model. Hence, the spatial analysis becomes more robust.

4.5.1 Getis–Ord Gi Local Hotspot Analysis

To assess the statistical significance of spatial clustering observed in the network kernel density patterns, a local Getis–Ord Gi* hotspot analysis was applied to traffic infringement data using a street network based spatial representation. Whereas the NKDE analysis provides a continuous, exploratory depiction of infringement intensity along the network. The Gi* statistic enables the identification of statistically significant clusters of high values that deviate from spatial randomness.

Rather than operating at the point event level, traffic infringement records were aggregated to street network segments to reflect the linear and network constrained nature of traffic law enforcement outcomes. The Barcelona Street network was preprocessed to ensure geometric consistency and subdivided into approximately 100 m segments i to standardize spatial units and reduce bias associated with variable street lengths.

Infringement points were snapped to the nearest street segment within a 10 m tolerance and duplicated locations were removed to prevent overrepresentation of stacked observations. For each segment, infringement counts were normalized by segment length, yielding a standardized measure of infringements per 100 m.

Local Getis–Ord Gi* statistics were computed using a Queen contiguity based spatial weights matrix, with row standardized weights to ensure comparability across segments. This contiguity based approach captures spatial dependence among adjacent street segments and is appropriate for detecting localized clustering within a dense urban road network. Street segments were classified as statistically significant hotspots or not significant based on Gi* z-scores and associated p-values, using confidence thresholds of 90%, 95%, and 99%.

4.5.2 Monte Carlo Randomization for Statistical Significance Assessment

The Monte Carlo null model simulation was used to test whether the observed network-based infringement intensity differs from a random spatial pattern. The method follows established applications of network-constrained kernel density estimation in transport safety research (Loidl et al., 2016).

Under null hypothesis that traffic infringements are randomly allocated along the street network, the total number of observed events was repeatedly redistributed across network segments using a length weighted allocation scheme. This approach preserves both the geometry and topology of the network while accounting for unequal exposure associated with varying segment lengths. The simulation was repeated 999 times, generating an expected distribution of NKDE intensity values for each segment under random network constrained allocation.

This spatial configuration closely mirrors patterns reported in prior Monte Carlo NKDE applications, where statistically significant hotspots emerge along specific corridors rather than uniformly across the network (Loidl et al., 2016).

4.6 Temporal Aggregation and Spatio-Temporal Hotspot Analysis

Prior to conducting the temporal analysis, the time variable required standardization to ensure consistent aggregation across the dataset. In the original infringement records, time values were stored in mixed numeric formats (HMMSS and HHMMSS). To ensure consistency, the hour component was extracted using an integer based procedure. The method allowed all observations to be converted into a standardized hourly format suitable for temporal aggregation and subsequent spatio-temporal hotspot analysis.

During this preprocessing step, a small proportion of records contained invalid or non-standard time encodings were therefore excluded from the analysis. Specifically, 0.6% of records in the minor violations dataset and 2.7% of records in the serious violations dataset were removed. The exclusion of these records ensured the reliability of hourly aggregation while having only a negligible effect on the overall distribution of violation events.

Following this standardization process, the dataset was temporally distributed to examine how enforcement activity varies across different temporal periods. This temporal segmentation provides the basis for subsequent spatio-temporal hotspot analysis and enabled comparisons between periods characterized by different levels of traffic demand and mobility intensity.

4.6.1 Morning and Evening peak hours

To inspect the temporal dynamics of traffic law enforcement, the main infringement dataset was stratified into distinct time periods, including morning peak hours and evening peak hours. The morning peak sub-dataset cover the time from (07:00 -10:00) comprises 42,484 records, while the evening peak sub-dataset (17:00-20:00) time contains 55,554 records. This temporal disaggregation enables the assessment of how enforcement intensity and spatial concentration vary across different daily activity phases.

4.6.2 Weekday-Weekend Temporal Patterns

To observe variations in traffic law enforcement activity across different temporal regimes, the full infringement dataset was classified into weekday and weekend subsets. This classification allows a comparative assessment of enforcement intensity during official working days (Monday to Friday) and non-working days (Saturday and Sunday). This allowed to capture a potential shifts in enforcement dynamics associated with changes in travel behavior and mobility intensity.

The weekend subset comprises 45,982 traffic infringement records that represent events occurring on Saturdays and Sundays for the study period. The weekday subset contains 214,322 records that cover Monday to Friday period. The size of both subsets provides a sufficiently strong empirical basis for subsequent density estimation and spatial analysis.

This temporal segmentation facilitates the evaluation of whether enforcement intensity and spatial concentration patterns differ between routine weekday traffic conditions and weekend mobility contexts.

4.7 Subgroup Analysis by Violation Severity and Vehicle Type

To investigate potential heterogeneity in spatial enforcement patterns, the infringement dataset was stratified according to violation severity and vehicle type. This subgroup analysis enables the assessment of whether different categories of traffic offences and vehicle classes exhibit distinct spatial intensity clusters.

Based on the legal classification provided in the dataset, infringements were subdivided into two severity levels which include minor and serious violations. These categories reflect differences in regulatory gravity and penalty structure rather than inherent spatial characteristics. Stratifying the dataset by severity allows for a comparative evaluation of whether higher intensity network density patterns are associated disproportionately with specific violation categories.

In addition, the dataset was classified by vehicle type. Three vehicle classes such as Cars, Motorcycles, and trucks were selected for analysis, as they collectively account for more than 95% of all recorded infringement events. Focusing on these three dominant categories ensures statistical strength while maintaining analytical clarity. This vehicle based stratification enables the examination of whether enforcement intensity varies systematically across different vehicle types.

4.7.1 Violation type

To enable a differentiated analysis of traffic violation severity, the original dataset of traffic infringement records was subdivided into two analytically meaningful sub datasets representing minor and serious violations. This classification is based on the official administrative coding scheme provided by the Barcelona City Council and used by the Institut Municipal d'Hisenda in the processing of traffic violations.

The subdivision relies on the variable SUBTYPE_FI, which encodes the legal and administrative severity of each infringement. According to the official metadata, this field distinguishes violations by their legal gravity and associated consequences. In particular, records classified as CR correspond to minor violations, while records classified as CH represent serious or very serious violations. These categories reflect differences in legal severity rather than spatial or behavioral characteristics.

Two sub-datasets were therefore created:

- Minor Violations Dataset (CR) include 135,569 records that contains all infringement records classified as minor violations which are associated with lower penalties and reduced legal consequences.
- Serious Violations Dataset (CH) Contains 103,922 records that covers all infringement records classified as serious or very serious violations.

The separation of violations based on severity allows a more detailed analysis of enforcement patterns. It also helps identify differences between minor and serious violations more clearly.

4.7.2 Vehicle Types

To facilitate the analysis of vehicle specific of traffic violations, the dataset was classified according to vehicle categories derived from the official administrative coding scheme provided by the Barcelona City Council. Each infringement record includes a vehicle type code, which was used as the basis for classification. Following standard practice in transport and spatial analysis, detailed administrative labels were aggregated into broader functional categories to improve analytical clarity and comparability.

The hotspot and density analyses focused on the three dominant vehicle categories Cars (n = 178,134), trucks (n = 42,447), and motorcycles (n = 27,390). These all three categories account for over 95% of all recorded traffic violations and provide sufficient spatial density for robust NKDE analysis.

4.8 Classification and Cartographic Design

To ensure methodological transparency and consistency in the visualization of analytical results, a standardized classification and cartographic design framework was applied to all maps produced in this work. The objective was to facilitate clear interpretation and enable a meaningful comparison across multiple spatial representations.

For the thematic maps of analytical outputs, an equal interval classification scheme was primarily adopted. This method divides the range of values between the minimum and maximum into classes of identical size. Equal interval classification was selected because it provides a straightforward representation and supports comparability across maps.

In some cases, the mapped variables were classified into four classes, which provided an appropriate balance between visual simplicity and the ability to represent spatial variation. A limited number of classes reduces visual clutter and improves interpretability, particularly when maps are intended to support comparative analysis across different datasets or categories.

This approach uses the same value ranges and color intensities across all maps. As a result, the maps can be compared more easily and consistently. In case of highly skewed distributions, especially kernel density surfaces, a logarithmic transformation was applied before classification. The log transformation compresses extreme high values while expanding lower value ranges and this leads to more balanced class intervals and improved visual differentiation between density levels. Hence, the transformation enhances the interpretability of spatial patterns without altering the underlying spatial relationships.

Furthermore, a consistent sequential color scheme was applied throughout the thematic maps, where lighter shades represent lower values and progressively darker shades represent higher values.

Overall, the selected classification and mapping approach makes the thematic maps easier to interpret and compare. This improves the scientific reliability of the spatial analysis presented in this work.

5. Analysis Results

This chapter presents the empirical results of the spatial, temporal, and modal analyses of traffic law enforcement and traffic crashes in Barcelona. Building on the methodological framework and data preparation procedures described in Chapters 3 and 4, the focus here is exclusively on the presentation of analytical outcomes, without interpretive or normative assessment. The results are derived from network based spatial analysis, spatial statistical testing, and spatio-temporal modelling applied to traffic infringement and crash datasets.

5.1 Results

The results are organized around three primary analytical dimensions. First, spatial patterns of traffic enforcement and traffic crashes are examined using network-constrained kernel density estimation and local spatial statistics to identify concentrations and clustering along the urban road network. Second, the statistical significance of observed spatial patterns is assessed through Getis–Ord Gi* hotspot analysis and Monte Carlo network based simulations. This provide an inferential evidence regarding the presence or absence of nonrandom clustering. Third, temporal dynamics are explored by analyzing variations in enforcement intensity across hours of the day, weekdays and weekends to capture changes in spatial patterns over time.

In addition, the results are further disaggregated by violation severity and vehicle category to examine heterogeneity in enforcement patterns across different types of traffic infringements and modes. Subgroup specific hotspot maps and quantitative spatial comparison metrics are presented to support systematic comparison between categories.

Interpretation of these findings, their implications for traffic enforcement strategiesand their relevance to urban road safety and equity considerations are addressed in Chapter 6.

5.2 Exploratory District Level Patterns

The spatial distribution of traffic infringements across the administrative districts of Barcelona is illustrated in Figure 5.1. This choropleth map displaying traffic violations density per square kilometer. The normalization of traffic violations counts by district area to allows meaningful comparison and highlights variations in the relative intensity of rather than absolute totals. A sequential color scheme is used, where darker shades represent higher densities of traffic violations.

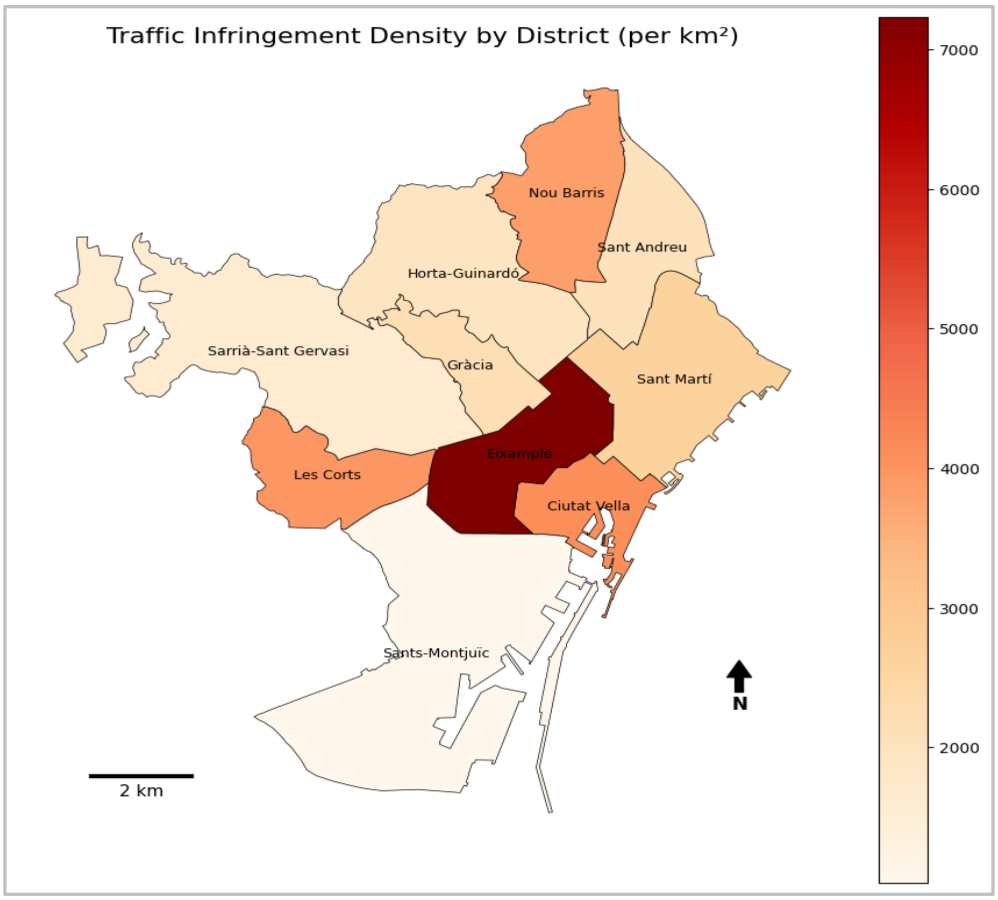

Figure 5.1: Choropleth map of Infringements events

The map reveals a clear spatial concentration within the central urban districts. In particular, Eixample emerges as the dominant hotspot at the city scale which shows the highest infringement density among all districts.

This results are consistent with the district's dense street grid, high traffic volumes and central location within the metropolitan road networks. Likewise, the adjacent central districts such as Ciutat Vella and Les Corts, also display comparatively elevated densities which form an attached cluster of higher intensity across the central portion of the city. This spatial pattern suggests that areas characterized by high levels of mobility activity and dense street networks tend to experience greater concentrations of traffic violations.

In contrast, several outer districts exhibit lighter shades on the map that indicate a lower infringement densities relative to their land area. This pattern suggests a center periphery slope, where violation intensity gradually decreases from the highly high-traffic central districts toward the outer districts. Such spatial difference likely reflects differences in road network density, traffic demand and land use patterns and enforcement activity across the urban area.

The underlying dataset of geocoded traffic infringement events, cover all ten administrative districts of Barcelona. In terms of absolute counts, the largest share of violations occurs in Eixample (approximately 21% of all recorded events), followed by Sarrià–Sant Gervasi and Nou Barris. The comprehensive spatial coverage and high temporal resolution of the dataset provide a strong basis to identify spatial concentrations of traffic violations and explore their distribution across urban road network.

Overall, this district level exploratory analysis provides an initial overview of the spatial structure of traffic violations at the city scale. These findings motivate the more detailed spatial analyses presented in the subsequent sections, which examine street network hotspots and temporal patterns of traffic violations in greater detail.

5.3 Network Kernel Density Patterns

The NKDE surface derived from main dataset described in Section 3.3 that provides a network constrained representation of infringement intensity across the Barcelona road system. Figure 5.1 illustrates the spatial distribution of infringement density along transportation routes. As shown in the map, warmer color indicate higher levels of infringement concentration, while yellow and gray tones represent lower traffic violation intensity.

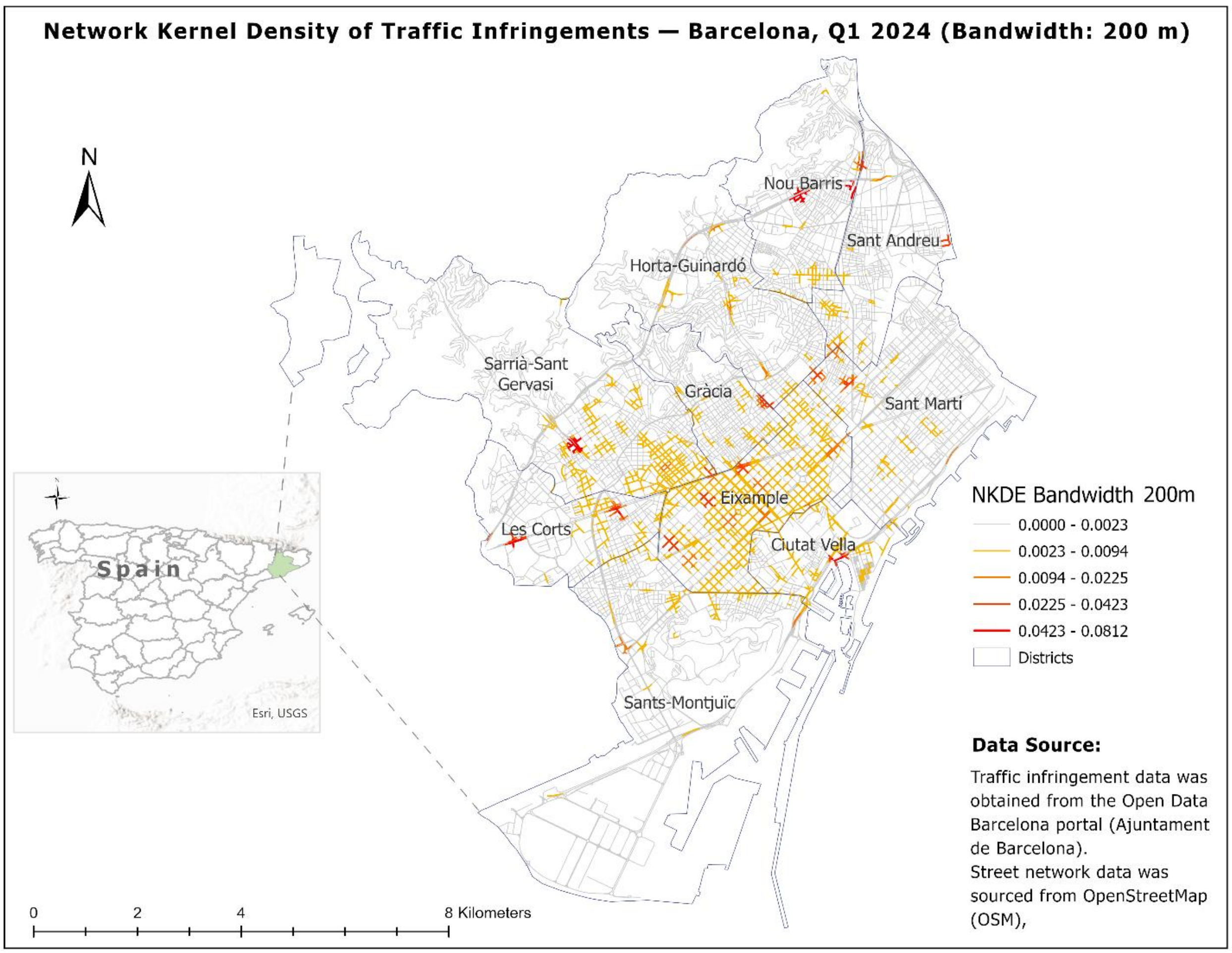

Figure 5.2: NKDE map of infringements in Barcelona

The resulting density surface shows clear spatial differences across the urban network. High infringement intensities are mainly concentrated in central districts and along major roads. These areas form connected linear clusters which follow the main road network.

These high intensity corridors are characterized by spatial continuity across multiple connected segments that create structurally coherent hotspot zones rather than isolated point concentrations.

Around these central areas, moderate-density segments extend along secondary roads and connected routes. These areas create gradual transitions between high density in center and lower density outer districts. This intermediate zone also contains concentrated spots at major intersections and junctions. This pattern reflects the influence of road network connectivity on infringement density.

The gradient structure of the NKDE surface therefore demonstrates a clear spatial transition from concentrated and central clusters to increasingly diffuse and discontinuous patterns toward the outer urban boundary. Importantly, the network-based kernel density method preserves the linear shape of the road network.

Thus, the NKDE surface establishes the foundational geography of infringement intensity during the study period. It provides a descriptive benchmark against which subsequent analyses including bandwidth sensitivity test, subgroup comparisons and spatial statistical validation are conducted in the subsequent sections.

5.3.1 Spatial Pattern Variation Across NKDE Bandwidths

The NKDE surface produced with a 200m bandwidth reveals localized concentrations of traffic violations along specific street segments. As illustrated in Figure 5.3, this fine scale representation emphasizes sharp density peaks along major corridors and complex intersections within central districts, including Eixample and Ciutat Vella. The limited smoothing preserves micro spatial variability, allowing discrete hotspot segments to emerge as clearly delineated clusters.

In contrast, the NKDE surface generated using a 300m bandwidth exhibits a smoother and more spatially continuous pattern. While high density zones remain concentrated within central Barcelona and along principal corridors. The intensity gradients appear more gradual and cohesive across connected network segments. The broader bandwidth reduces short range fluctuations and highlights corridor level clustering structures that extend across multiple adjoining street segments.

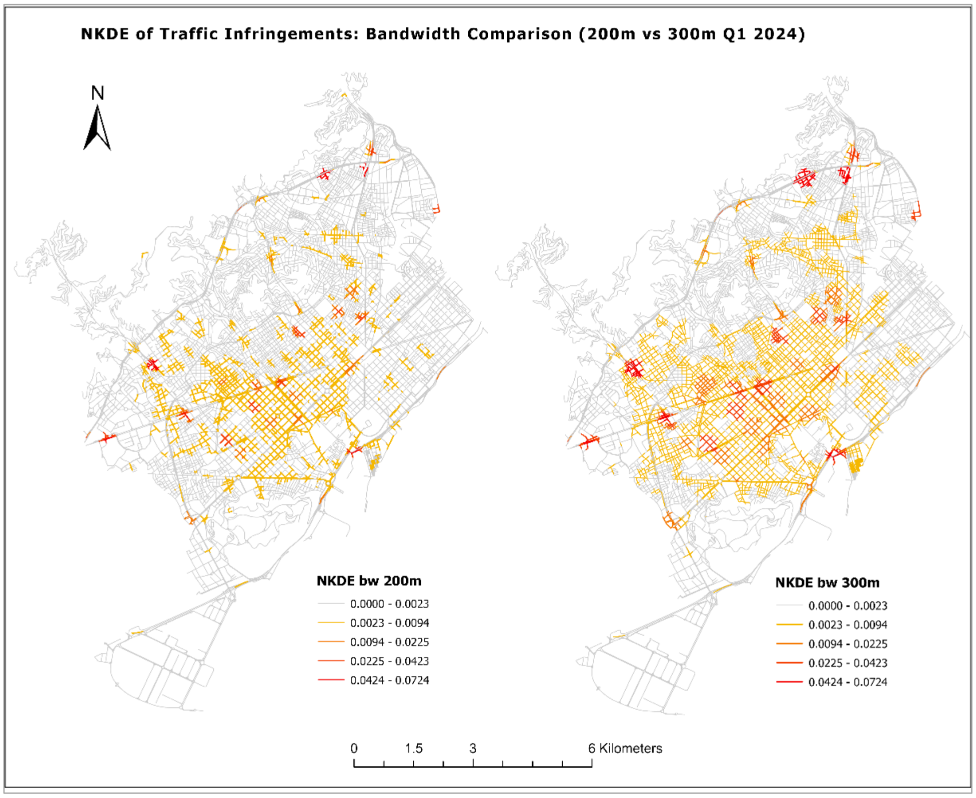

Figure 5.3: NKDE based on different bandwidth

A direct comparison of the two bandwidths indicates that major high density corridors remain spatially consistent across both scales, particularly within central Barcelona. This consistency across scales suggests that these areas are real concentrations of infringement intensity rather than patterns caused by bandwidth selection. At the same time, the 200 m surface reveals additional localized peaks that are not retained in the 300 m representation. This shows a short range spatial variability that is smoothed at broader scales. Thus, these results demonstrate that while localized clustering is sensitive to bandwidth choice, the broader corridor level hotspot structure remains robust across scales.

5.3.2 NKDE of Traffic Crashes

Given that traffic crashes are inherently constrained to road networks, the NKDE was employed to estimate crash intensity. The conventional planar kernel density estimation treats space as a continuous two-dimensional surface. This can produce inaccurate hotspot results for network-constrained events such as traffic accidents (Abdulhafedh, 2017). NKDE addresses this limitation by calculating density along network distances and expressing intensity per unit of road length rather than per unit area. This approach provides a more accurate representation of crash concentration within urban transport systems and allows intensity to be interpreted relative to the underlying road hierarchy.

The NKDE results reveal an obvious spatial concentration of crash intensity within Barcelona's central urban built-up area. High intensity segments form a connected corridor across the Eixample district and extend into adjacent inner city areas. As shown in Figure 5.4, the spatial shape reflects the structural characteristics of Barcelona's grid road network, which concentrates traffic flows, intersection density, and multimodal interactions within a compact urban core.

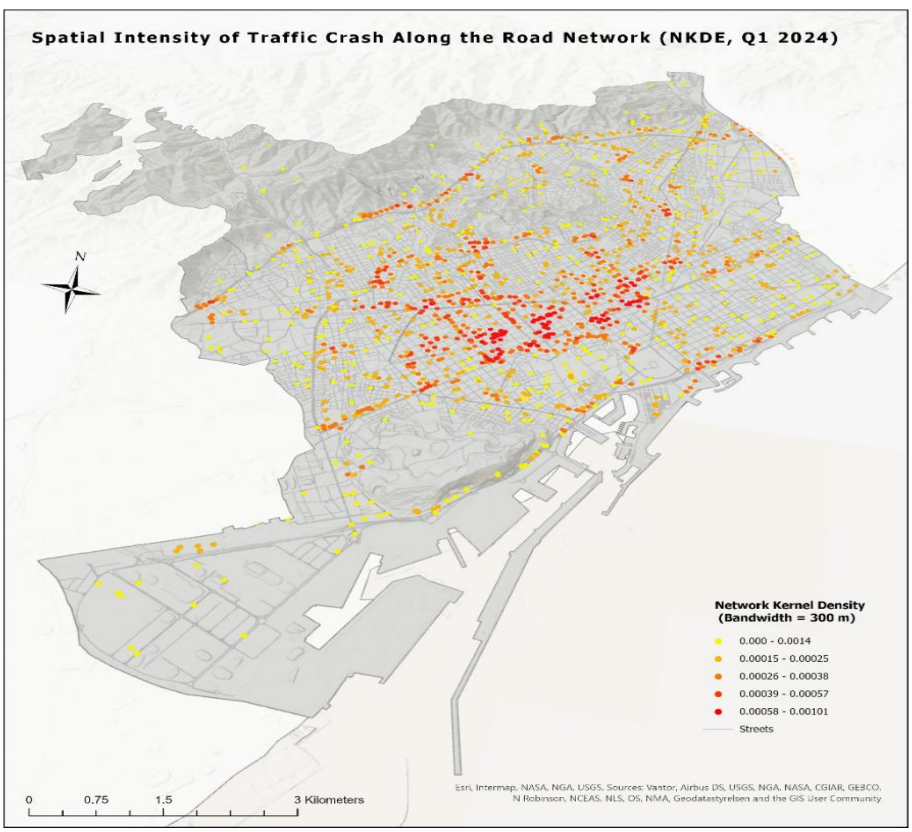

Figure 5.4: Spatial Intensity of Traffic Crash during first quarter of 2024

The clustering pattern is not randomly distributed but exhibits corridor oriented alignment along major routes and high connectivity intersections. Such alignment indicates that crash intensity is strongly associated with network centrality and traffic exposure rather than merely spatial proximity. Since NKDE expresses intensity per unit network length, these concentrations represent structurally embedded risk within the road hierarchy rather than simple accumulation of crash counts.

In contrast, outer areas display comparatively lower intensity values, corresponding to reduced intersection density, lower traffic volumes and less connected road networks. These differences between central and outer areas indicate that city structure and road connectivity affect crash risk distribution.

To evaluate the influence of bandwidth on crash data visualization, NKDE was produced using different bandwidth sizes. The 200 m bandwidth reveals more localized concentration patterns, emphasizing micro scale hotspots around specific intersections and short corridor segments (Figure 5.5). In contrast, the 300 m bandwidth produces a spatially continuous smoother and more intensity surface, where nearby high density segments merge into broader clusters.

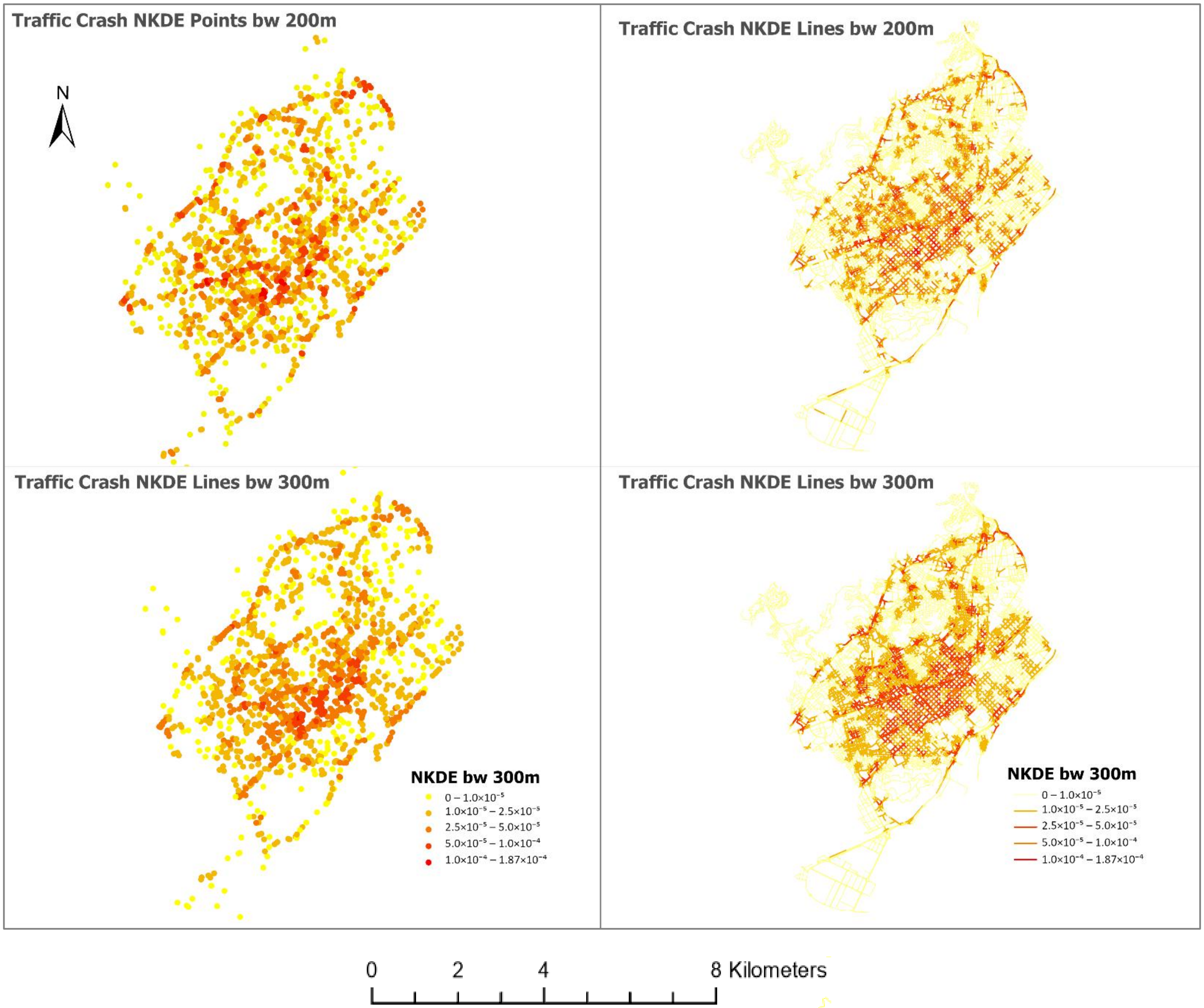

Figure 5.5: Spatial Intensity of Traffic Crash NKDE based on different bandwidth size

This increased smoothing reduces localized variability while preserving the dominant central concentration pattern. The persistence of high intensity zones across both bandwidths indicates that the observed clustering is structurally embedded within the urban network rather than an effected by kernel parameter selection. The different bandwidths therefore highlight complementary spatial scales of crash concentration, ranging from intersection level risk to corridor wide structural clustering.

5.4 Statistically Significant Hotspots

To evaluate whether the spatial concentrations observed in the NKDE surfaces represent statistically significant clustering rather than random variation, two complementary statistical procedures were applied. The local Getis–Ord Gi* hotspot statistic and a network constrained Monte Carlo randomization test (see Chapter 4 for methodological details). While the Gi* statistic identifies localized clusters of high infringement intensity at the street segment level, the Monte Carlo simulation provides a global assessment of whether the overall spatial formation deviates from a random network. The results of these analyses are presented below.

5.4.1 Getis–Ord Gi Local Hotspot Analysis

The Getis-Ord Gi* analysis identifies statistically significant local clusters of elevated traffic infringement intensity across the street network (Figure 5.4). In contrast to the NKDE surface, which represents continuous variations in density, the Gi* statistic detects locations where high values are spatially concentrated beyond expectations under a null hypothesis of local spatial randomness.

Significant hotspots are predominantly located within central areas. These clusters consist of adjacent street segments exhibiting consistently high infringement intensity at confidence levels of 90%, 95%, and 99%. The most prominent clusters ($z > 2.58$) occur along connected segments within the dense urban grid, indicating localized spatial dependence in infringement occurrence. The outer spaces contain comparatively few statistically significant hotspots and are largely classified as not significant.

The concentration of significant clusters in the central network indicate that enforcement is focused on areas instead of being randomly distributed. At the 95% confidence level, 1.76% of street segments were identified as significant hotspots, while only 0.49% remained significant at the stricter 99% confidence level. This indicates that high intensity clustering is spatially limited rather than network wide.

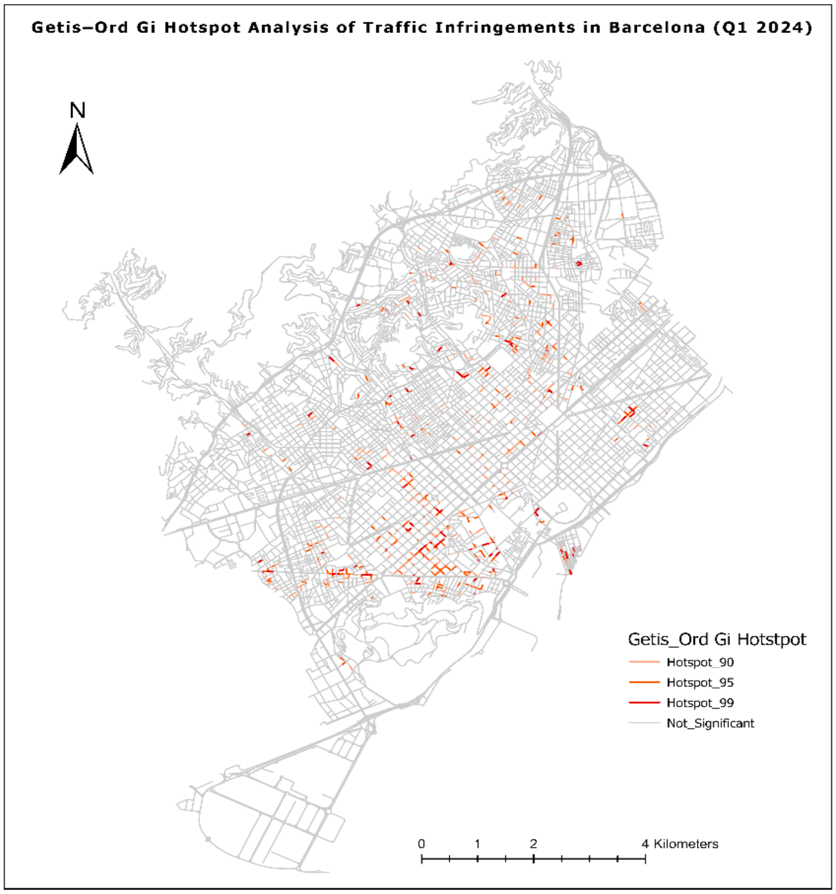

Figure 5.4: Getis -Ord Gi Hotspot map

The detection of significant high value clusters supports rejection of the null hypothesis of local spatial randomness. This confirms that infringement intensity displays positive local spatial autocorrelation among adjacent street segments. No statistically significant cold spots were detected. Although some segments show lower infringement intensity, these do not form spatially adjacent low value clusters but appear spatially dispersed.

Comparison with the NKDE surface reveals strong correspondence between areas of elevated density and Gi*-identified hotspots. Therefore, the high density areas in the NKDE map generally coincide with significant Gi* hotspots which indicate that clusters are real and not just caused by the smoothing process.

At the same time, the Gi* results distinguish between areas of moderate density and those demonstrating statistically robust clustering.

Thus, NKDE and Gi* provide complementary insights into the spatial structure of infringement intensity. The NKDE characterizes magnitude along the network, whereas Gi* confirms statistically significant spatial concentration.

5.4.2 Monte Carlo Randomization for Statistical Significance Assessment

The Monte Carlo simulation results complement the Gi* hotspot analysis by evaluating infringement intensity against a random, length controlled baseline. The total number of infringements was redistributed across street segments over 999 simulations. The allocation was proportional to segment length. This procedure generated an empirical null distribution that represent a spatially random process while controlling for network exposure.

The resulted map displayed in Figure 5.5, indicates that a distinct subset of segments exhibits statistically significant p-values ($p \leq 0.01$ and $0.01 < p \leq 0.05$), primarily concentrated within the central urban area. These segments demonstrate infringement intensities substantially exceeding those expected under a length weighted random allocation.

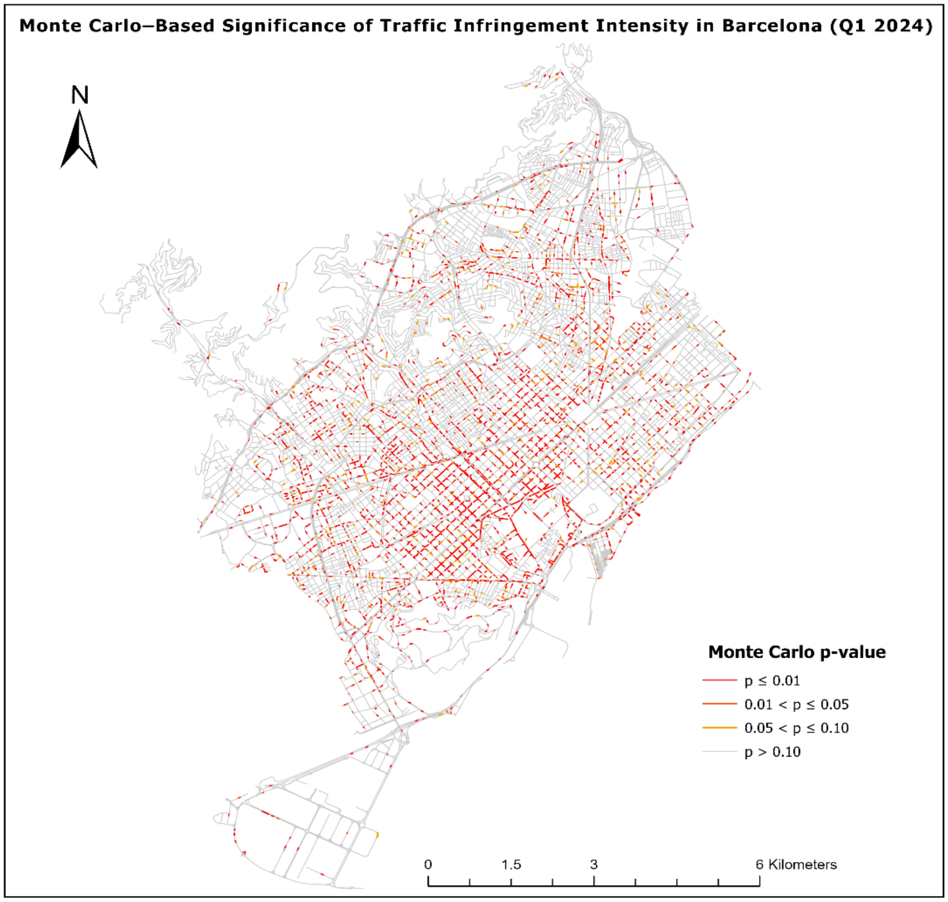

Figure 5.5: Monte Carlo Significance Intensity

The spatial configuration of significant segments is corridor oriented and centrally clustered rather than diffusely distributed. This indicate that infringement intensity cannot be explained solely by variation in network length or random processes.

When examined alongside the Getis–Ord Gi* results, a strong spatial correspondence observed. The street segments identified as Gi* hotspots are largely co-located with Monte Carlo significant segments. This convergence indicates that these locations show both local spatial autocorrelation, as detected by Gi*. They also show statistically significant deviation from a length-controlled random network process, as demonstrated by the Monte Carlo simulations. Instead of serving as alternative tests of the same hypothesis, the two approaches assess complementary dimensions of spatial structure.

Collectively, the Gi* and Monte Carlo analyses demonstrate that traffic infringement intensity in Barcelona is characterized by spatial concentration embedded within the highly connected central network.

5.5 Temporal Variation in Enforcement Patterns

To inspect whether traffic law enforcement reveals systematic temporal variation, the infringement dataset was disaggregated into distinct temporal subsets. These subtests include morning and evening periods as well as weekday and weekend intervals. This temporal stratification enables assessment of whether enforcement intensity remains spatially stable or experiences measurable shifts across different times of day and week.

For each temporal subset, NKDE was applied to identify changes in spatial concentration patterns along the road network. Through comparing the resulting intensity surfaces, it becomes possible to examine how enforcement hotspots reorganize in response to temporal fluctuations in traffic flow, mobility demand and urban activities.

This approach facilitates a spatiotemporal interpretation of enforcement practices which allow the identification of intensities in specific areas and time intervals. The results also help explain whether enforcement patterns are related to road network characteristics or temporal variations in traffic behavior.

5.5.1 Morning vs Evening Peak Patterns

The hourly distribution of traffic infringements reveals clear daily variation (Figure 5.6). Enforcement intensity increases sharply during the early morning hours which reaches to high levels between 06:00 am and 10:00 am. A second period of intensified activity occurs during the late afternoon and early evening, with infringement counts peak between approximately 16:00 and 20:00. In contrast, the late night and early morning hours exhibit very lower activity levels which show an off peak enforcement periods. These fluctuations confirm that infringement events are temporally structured rather than uniformly or randomly distributed throughout the day.

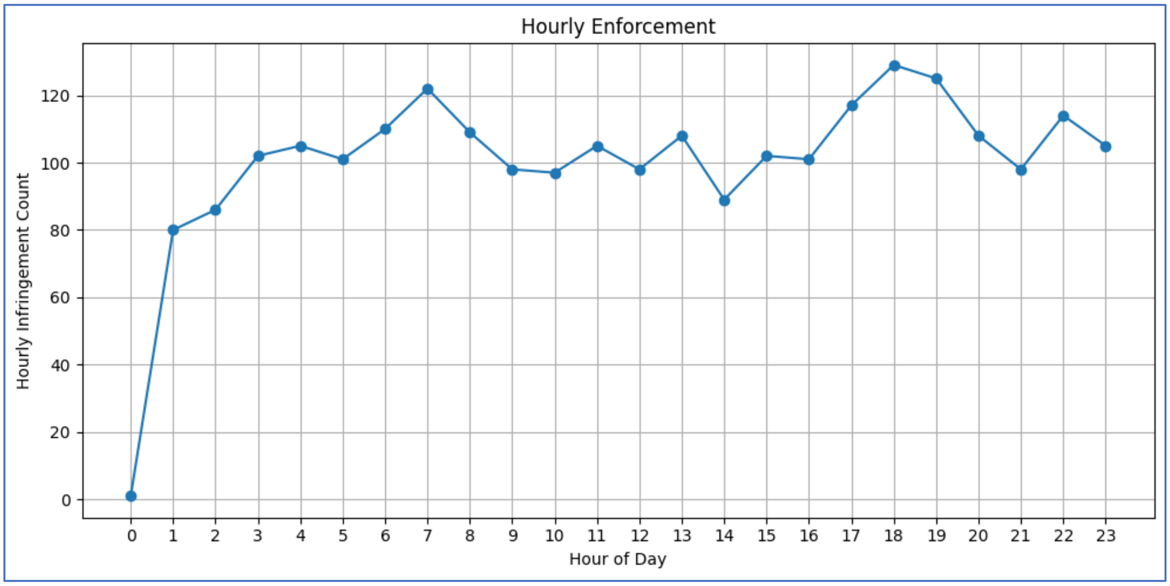

Figure 5.6: Hourly Enforcement distribution

In order to analyze the spatial temporal changes, the main infringement dataset was disaggregated into morning peak (07:00–10:00) and evening peak (17:00–20:00) intervals. The morning subset contains 42,484 records and evening subset includes 55,554 records. This temporal stratification enables assessment of whether increased enforcement volume corresponds to spatial concentration or redistribution across the network.

NKDE was applied using a consistent bandwidth to ensure comparability between different time intervals (Figure 5.7). The resulting intensity surfaces reveal distinct spatial formations. Morning enforcement displays more compact and spatially concentrated clusters. This pattern likely reflects morning travelling flows toward the city center, where high traffic volumes and dense intersections increase enforcement activity in central employment areas.

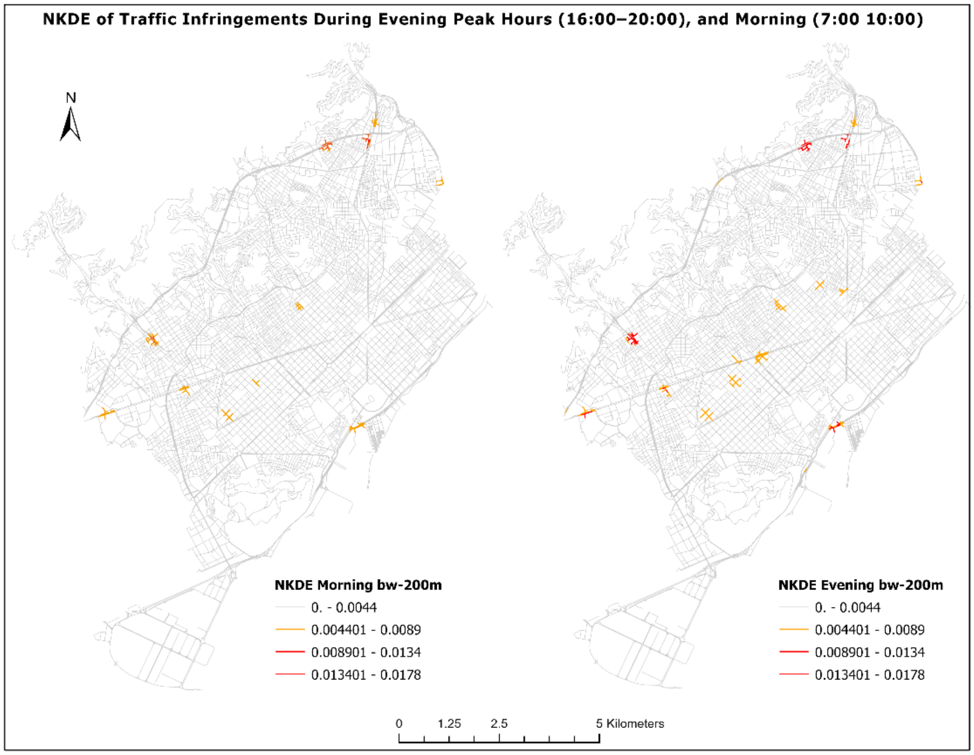

Figure 5.7: Traffic violations during evening and morning

Conversely, evening enforcement shows a broader and spatially scattered distribution. Although the total infringement counts are higher during this period, intensity is distributed across a wider set of corridors. This pattern reflects the end-of-day movement of traffic, when vehicles leaving work areas traffic spread across multiple road segments.

Several high-intensity locations remain consistent across both time periods. These stable hotspots represent important parts of Barcelona's transport network.

Overall, comparison demonstrates that traffic infringement patterns are formed by the interaction between land use structure and travel behavior. Morning peaks emphasize centralized junction, while evening peaks reflect spatial redistribution across the broader urban area. These findings underscore the importance of incorporating temporal stratification to evaluate enforcement within different time intervals.

5.5.2 Weekday vs Weekend Patterns

Figure 5.8 illustrates the hourly distribution of traffic violations across weekdays and weekends. As displayed the Infringement counts are consistently higher during weekdays throughout the 24 hour cycle which indicate the enforcement activity or exposure during standard working days. Despite differences in intensity, both temporal patterns show a similar daytime structure, with morning and late afternoon peaks and lower activity during late-night hours.

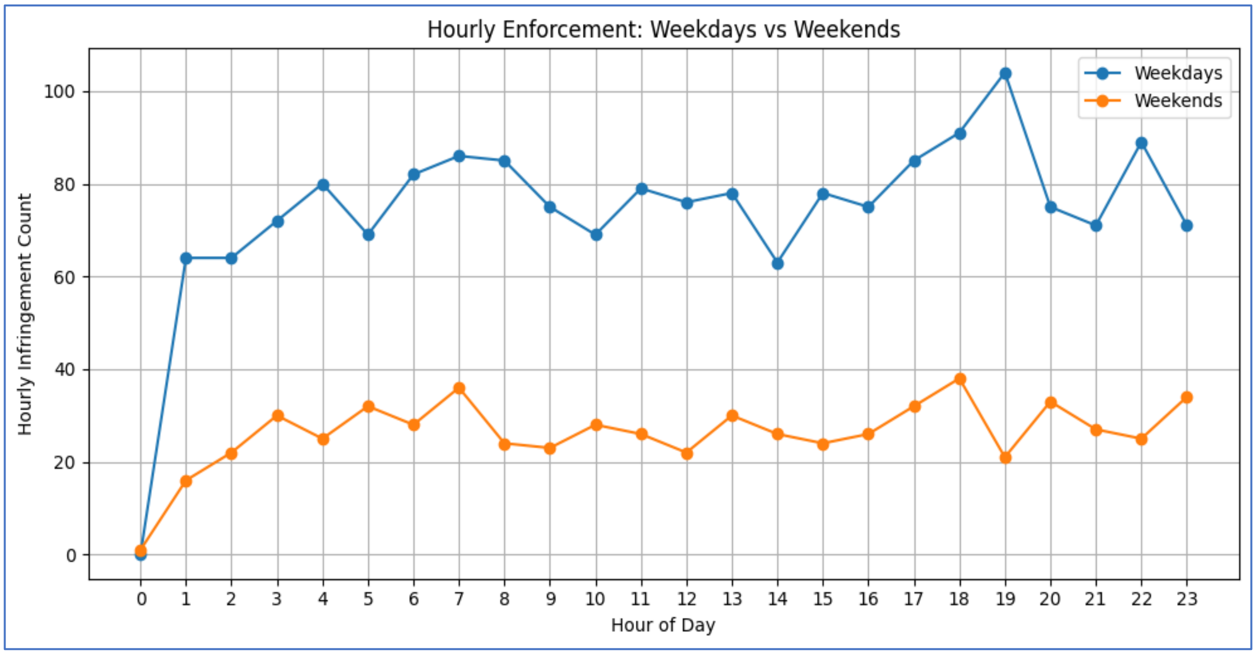

Figure 5.8: Hourly enforcement weekdays vs weekends

This parallel structure suggests that enforcement timing aligns with broader urban mobility cycles rather than being randomly distributed.

To evaluate if temporal differences in enforcement volume correspond to spatial restructuring, NKDE calculated separately for weekday and weekend datasets with same bandwidth and classification parameters. The resulting intensity surfaces reveal both persistent and shifting spatial forms.

As shown in Figure 5.9, the NKDE surfaces reveal clear spatial differentiation between weekday and weekend enforcement intensity. The weekday map displays a dense and spatially continuous cluster of high intensity segments concentrate in central area. These clusters form corridor oriented structures aligned with major routes and high connectivity intersection.

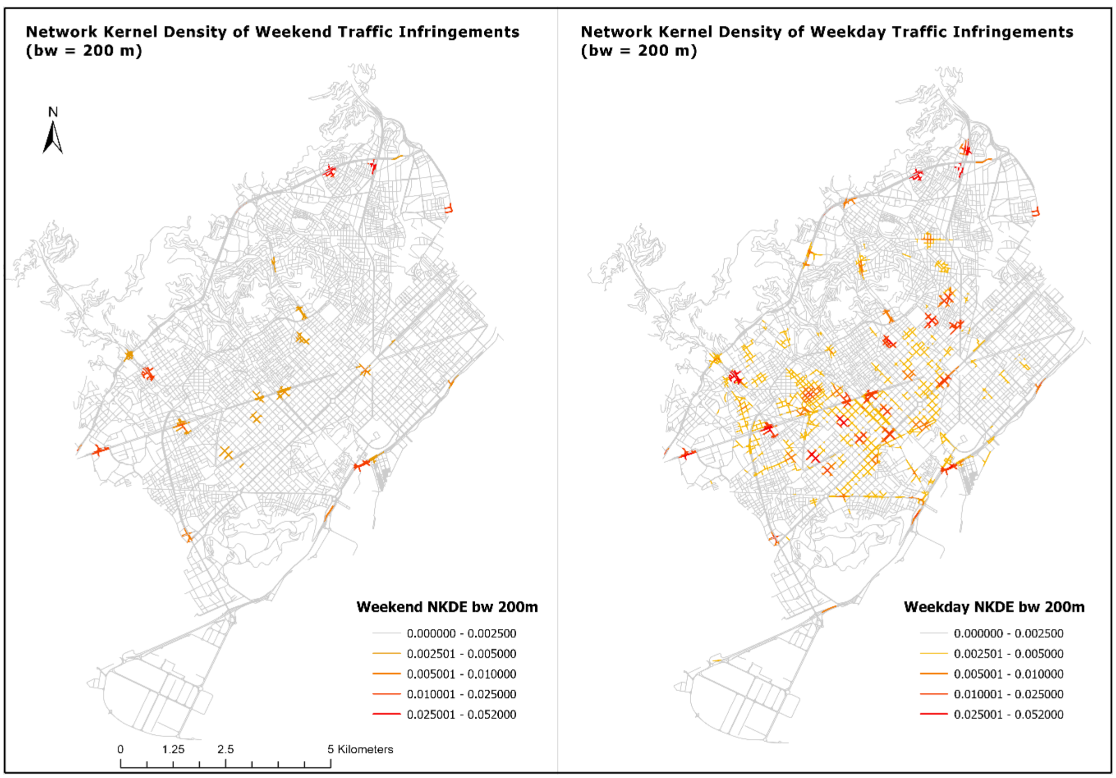

Figure 5.9: Weekend and Weekday infringements NKDE comparison

In contrast, the weekend NKDE surface displays considerably reduced intensity values and a scattered spatial formation. Although several central hotspots persist, the overall density surface appears spatially contracted, with fewer intensity nodes. This suggests that weekend enforcement activity following a similar spatial hierarchy but shows a reduced extent with less network wide.

Importantly, the persistence of central hotspots across both temporal categories indicates that enforcement intensity is structurally fixed within specific high centrality network segments. The main temporal difference is therefore not the location of hotspots, but the higher intensity observed during weekdays.

Although weekend activities are lower, the same major hotspots remain visible in both time periods. This suggests that enforcement concentration is shaped by road network structure and layout of the city.

Thus, this indicates that the spatial distribution of enforcement is mainly determined by the city's road network and urban structure.

5.6 Subgroup Differences by Violation Severity and Vehicle Type

To further refine the spatial interpretation of enforcement patterns, the main infringement dataset was divided according to violation severity and vehicle type. This breakdown permits assessment of whether observed hotspot structures are uniformly distributed across violation categories. Through analysis these derived if enforcement intensity reflects generalized spatial exposure or distinct risk profiles.

5.6.1 Minor vs Serious Violations

To enable a severity based analysis of infringement patterns, the main dataset was divided into two categories based on the variable SUBTYPE_FI that encodes legal and administrative severity of each recorded violation. Based on the official metadata, this variable differentiates violations based on their legal gravity and associated consequences. Specifically, records classified as CR correspond to minor violations, whereas records classified as CH represent serious or very serious violations. These categories reflect formal legal distinctions rather than spatial, contextual or behavioral characteristics.

Following two sub datasets were generated:

Minor Violations Dataset (CR): 134,711 records, containing all traffic violations classified as minor violations which associated with lower penalties and reduced legal consequences.

Serious Violations Dataset (CH): 101,095 records, including all traffic violations categorized as serious violations, that involving higher penalties and greater implications for road safety.

The hourly distribution reveals clear differences between severity categories. As shown in figure 5.10, minor violations exhibit a distinct daytime concentration with sharp increases starts around 08:00 and peaks occurring during administrative and enforcement hours (approximately 08:00–17:00). Counts decline significantly during late evening and early morning hours. In contrast, serious violations display a lower and temporally distributed shape. Although they also increase during daytime periods but remain comparatively dominant during early morning and late evening hours. This broader temporal dispersion suggests that serious violations are less constrained by administrative enforcement schedules. Hence, they may be associated with driving behavior occurring during full day cycle.

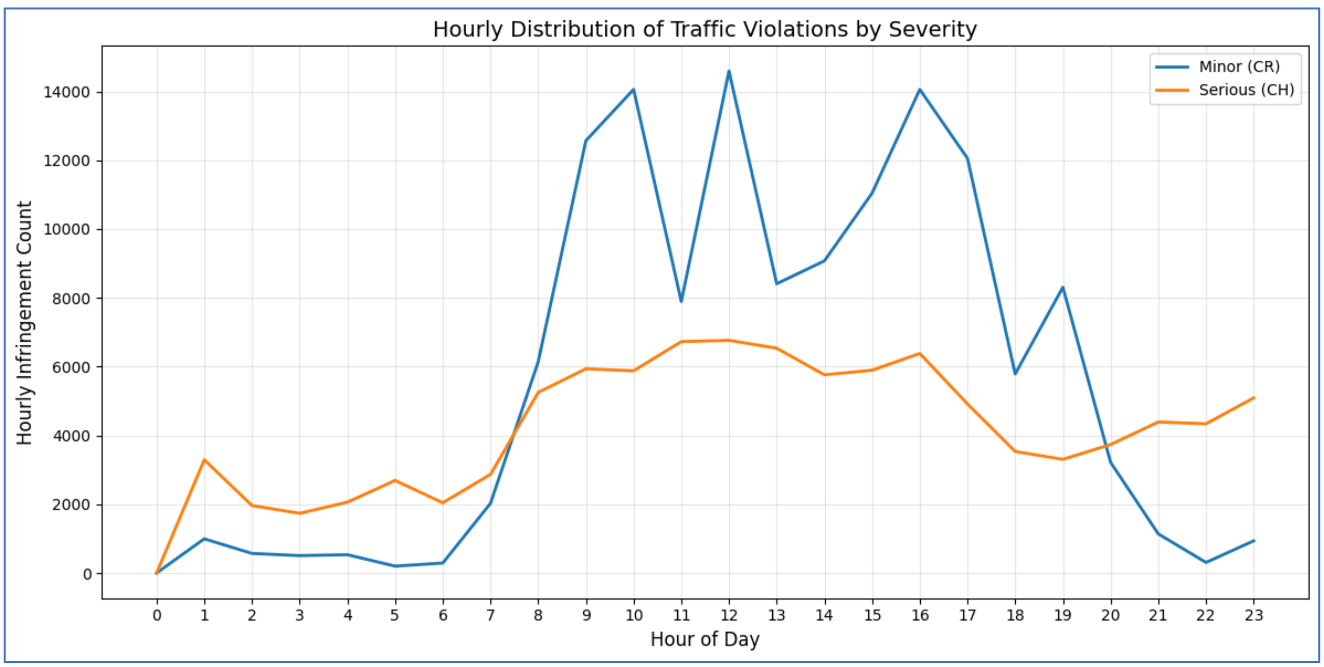

Figure 5.10: Hourly distribution of infringements during weekdays and weekends

To examine spatial differences between severity categories, the NKDE was calculated using a 200 m bandwidth. The spatial pattern of minor violations reveals a dense and relatively continuous concentration within the central urban area (Figure 5.11). High intensity segments form an interconnected cluster across the main roads and extend along major corridors.

The density gradually decreases toward outer areas, while moderate concentrations remain visible along primary transport routes. The spatial continuity aligns with the previously observed daytime concentration which support the interpretation that minor violations are closely associated with structured administrative enforcement.

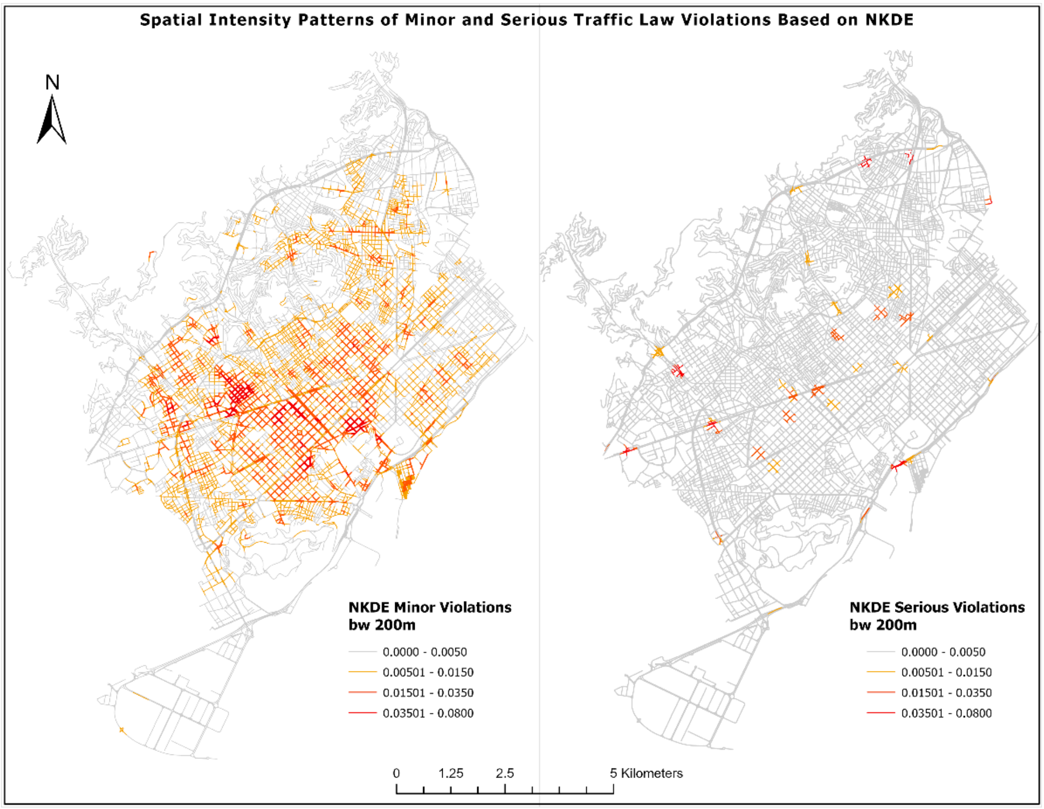

Figure 5.11: Minor and Serious traffic law violations NKDE

In contrast, serious violations display a more scattered and corridor oriented pattern. Instead of forming a continuous central cluster, serious violations appear as discrete hotspots concentrated along major roads and key intersections.

Comparatively, the NKDE results highlight two distinct spatial structures. Minor violations exhibit a centrally concentrated and continuous pattern consistent with routine regulatory monitoring. Serious violations, however, show localized and infrastructure linked clustering, suggesting a closer relationship to mobility intensity and risk conditions.

5.6.2 Vehicle Type Patterns

To further explore the temporal characteristics of traffic infringements, violations were analyzed based on vehicle type. The main categories include three most represented datasets of cars, motorcycles and trucks. Initially, hourly counts were combined to observe how infringement patterns vary across the daily cycle.

The resulted graph in Figure 5.12, reveal clear differences in the temporal distribution of violations among vehicle categories. Car related violations dominate the dataset and it shows higher counts throughout the day compared to motorcycles and trucks. Two peaks are visible. A morning peak around 07:00-08:00 and a second peak during the early evening period about 17:00-19:00.

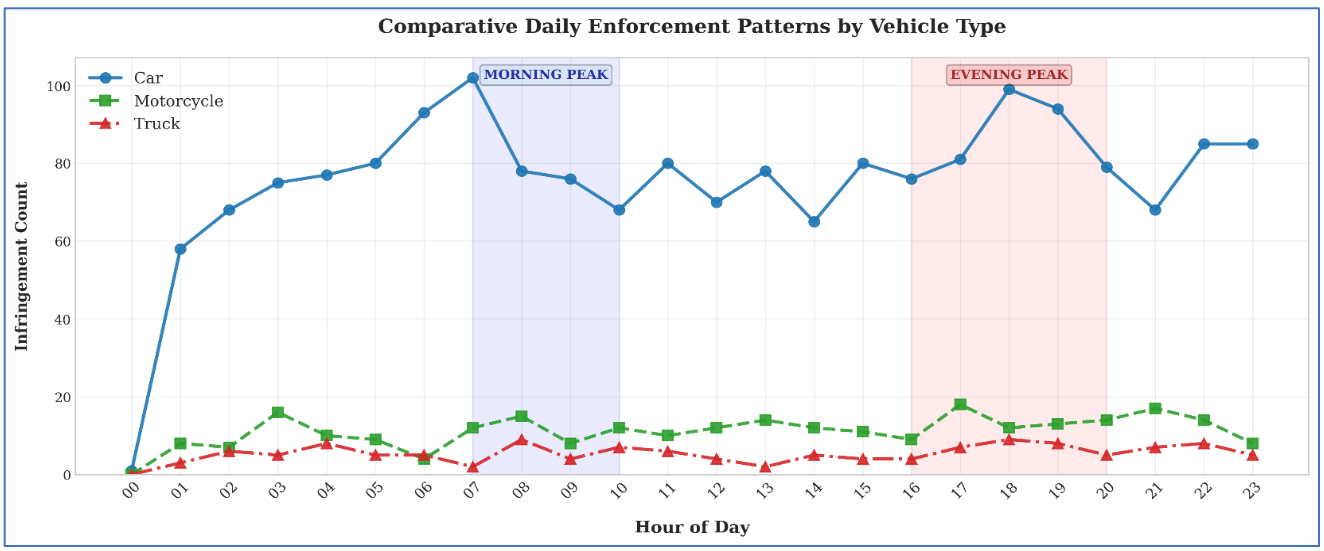

Figure 3 Daily Enforcement patterns by Vehicle type

These peaks match broadly with typical urban travelling periods which suggest that the higher volume of car traffic during these hours increases the likelihood of regulatory violations being recorded.

Motorcycle violations display a more moderate but still distinct temporal pattern. Counts gradually increase during the early morning hours and reach local highest during late afternoon and early evening periods around. Compared with cars, motorcycle violations appear more evenly distributed across the daytime hours with fewer variabilities.

Truck related violations occur at lower frequencies which reflect both the smaller presence of heavy vehicles within the urban traffic system.

Overall, the temporal distribution suggests that vehicle specific mobility patterns influence the timing of recorded traffic violations. Cars exhibit the strongest association with peak commuting hours, whereas motorcycles show a more gradual distribution across the day. Truck violations remain comparatively sparse but still demonstrate some alignment with broader traffic activity periods. These findings indicate that traffic enforcement and violation patterns differ across vehicle categories as well as on severity levels.

The NKDE was calculated along the road network using a bandwidth of 300 meters to identify segments with elevated concentrations of violations.

Since the raw NKDE values exhibited a highly skewed distribution with a small number of very high density segments and low density segments, a logarithmic transformation was applied prior to mapping. This transformation compresses extreme values and expands lower ranges to improve visual differentiation among density. The log transformed values therefore enhance cartographic readability while preserving the relative spatial structure of violation intensity.

The resulting maps displayed in Figure 13, reveal clear differences in the spatial concentration of violations across vehicle types. Car related violations exhibit the most extensive and continuous high density corridors especially in the central urban area and major routes.

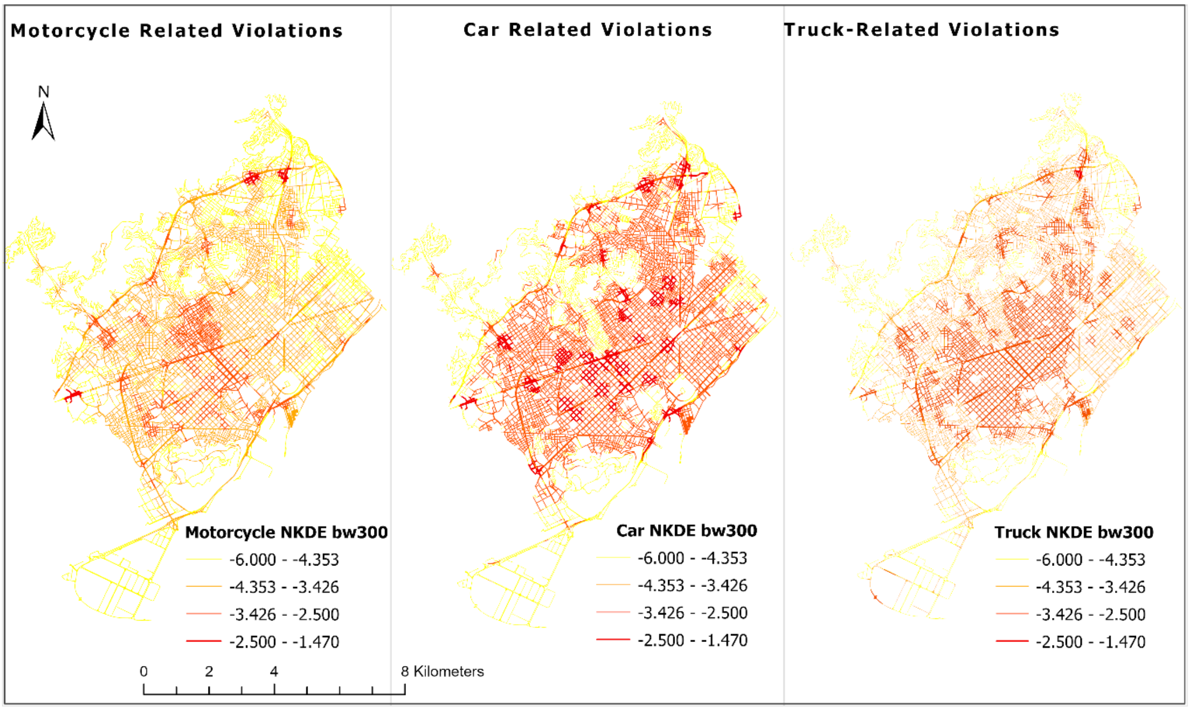

Figure 4.8: Vehicle types NKDE

Motorcycle violations display a moderately dispersed pattern with clusters occurring along several central corridors and secondary routes. Compared with car violations the spatial footprint is less continuous which suggest that motorcycle related violations are concentrated in specific mobility corridors rather than across the entire network.

Truck related violations show the most localized spatial patterns with relatively dispersed but distinct hotspots. This distribution likely reflects restricted circulation of heavy vehicles within dense urban areas.

When compared together with the temporal analysis, these spatial patterns provide a complementary understanding of infringement dynamics. The temporal graph demonstrates that different vehicle categories show distinct hourly activity profiles, while the NKDE maps reveal that these violations are also spatially differentiated. Cars dominate both temporally and spatially, motorcycles show intermediate scattering and truck violations remain comparatively localized.

Therefore, the temporal and spatial analyses indicate that traffic violations are structured by both mobility patterns and vehicle types. That shows the importance of considering vehicle categories when analyzing urban traffic enforcement dynamics.

5.7 Comparative Synthesis of Spatial Patterns

The preceding analyses reveal a clear spatial temporal structure in the distribution of traffic law enforcement across Barcelona’s road network. Although the district level exploratory analysis identifies broad variations in infringement density, the network based analyses provide a more detailed perspective on how traffic violations concentrate along roads.

Results from the NKDE show that traffic violation events are unevenly distributed which form a linear clusters along main roads and highly connected intersections especially in central districts. These concentrations are further supported by the Getis–Ord Gi* hotspot analysis and Monte Carlo randomization tests. This confirm that several of these clusters represent statistically significant hotspots rather than random spatial occurrences.

Temporal analysis indicates that these spatial patterns correspond with systematic daily and weekly times in enforcement activity. Higher infringement counts occur during weekday particularly in the morning and late afternoon, while lower levels are observed during weekends and late night hours. Although the overall temporal pattern remains consistent but the spatial extent and intensity of hotspots vary across time periods.

Subgroup analyses further reveal differences associated with violation severity and vehicle type. Minor violations tend to be more spatially dispersed across the urban grid, however serious violations exhibit more localized clustering. Similarly, Car related violations dominate both spatially and temporally, while motorcycle and truck violations occur less frequently and show more selective clusters.

Overall, the spatial, temporal and subgroup analyses reveal clear patterns in traffic violations across Barcelona. These patterns are influenced by the structure of the road network, daily traffic cycles, enforcement practices and vehicle-specific behavior.

6. Discussion

The previous chapter presented the observed results of the spatial temporal analysis of urban mobility infringement enforcement. As chapter 5 focused on describing the observed patterns in the dataset, the present chapter interprets these findings within academic literature. In particular, the discussion asses how the identified spatial concentrations, temporal dynamics and modal differences in enforcement relate to previous research on traffic enforcement. By linking the results to existing studies, this chapter aims to emphasize the contribution of the research and reflect on the methodological inferences of the outcomes.

6.1 Discussion of Spatial-Temporal Enforcement Patterns

This research explored spatial and temporal patterns of enforcement related to urban mobility infringements using GIS based analytical methods. Based on an infringement dataset, the research inspected how enforcement activities are distributed across space, time and vehicle types. The primary objective was to explore how spatial temporal analysis can contribute to a better understanding of enforcement changes in urban area.

The results presented in Chapter 5 shown several notable patterns. The spatial analysis identified areas with higher concentrations of enforcement activity, while temporal analysis indicated variations in enforcement intensity across different time's intervals.

In addition, differences between transport modes and violation categories suggested that enforcement practices may not be uniformly distributed but instead reflect specific spatial and operational priorities. Building on these findings, this chapter interprets the results and relate them with urban mobility literature.

Lee et al. (2025) highlighted the importance of spatial analytical approaches to identify enforcement hotspots, understand traffic violation patterns that can help informed interventions.

6.2 Interpretation of spatial patterns

The spatial analysis shown several clusters of enforcement activity within specific areas of the study region. These hotspots indicate that enforcement actions are not evenly distributed across space but instead concentrate in particular urban zones. Similar spatial clustering has been identified in previous studies which assess the traffic violations and enforcement patterns. For example, Li et al (2020) used spatio-temporal kernel density estimation to study traffic violations from automated enforcement systems. The results showed that violations clustered at specific urban intersections instead of being evenly spread across the road network. These hotspots frequently occurred at busy intersections characterized by high traffic volumes and complex vehicle movements.

Likewise, Lee et al. (2025) identified significant spatial clustering through study of Driving Under the Influence (DUI) related incidents in urban roads. Their results suggest that enforcement activities tend to concentrate along major road corridors and intersections.

The spatial distribution observed in analysis also suggests that enforcement activities are concentrated in central urban areas characterized by intensive mobility activity. This pattern aligns with findings from previous research on traffic safety and regulatory monitoring. For instance, Ma et al. (2021) demonstrated that traffic accidents exhibit significant spatial clustering within urban environments and identified high risk locations for targeted safety interventions.

Similarly, a research studied the built environment and indicates that areas with dense street networks and high land use intensity experience higher crash densities (Ling et al., 2025). Central urban districts typically contain a concentration of commercial activities, public transport nodes and mixed land uses. Therefore, the concentration of enforcement activity in these areas may reflect the prioritization by authorities to manage locations with higher mobility demand.

Areas with dense transport infrastructure and highly connected road networks often experience complex mobility flow that can increase violations and enforcement activity. The results of this investigation are generally consistent with previous research but provide additional insight by analyzing enforcement activity across space, time, and different types of mobility violations.

6.3 Temporal enforcement dynamics

The temporal analysis results displayed a clear variations in enforcement activity across different times of the day and days of the week. Enforcement actions were not evenly distributed over time but instead exhibited identifiable peaks during specific periods. Previous research has also revealed that traffic incidents and violations are more common during periods of heavy traffic and travel activity (Haile et al., 2025). Studies using automated traffic enforcement data also show that traffic violations are more common at certain times and locations due to mobility patterns (Li et al., 2026). Overall, these findings suggest that enforcement activities may be aligned with periods of intensified urban movement when the likelihood of violations is higher.

Further temporal differentiation emerges when comparing weekday and weekend patterns. Weekdays are typically characterized by structured travelling flows associated with employment, education and service activities which result high traffic volumes across urban corridors.

Empirical research on traffic safety patterns supports this interpretation which demonstrate that crash occurrences and traffic incidents often increase during weekday mobility Haile et al.(2025). Therefore, enforcement agencies frequently concentrate monitoring activities during these periods to maximize visibility and restriction. In this context, the observed weekday dominance in enforcement activity may therefore represent an operational response to predictable mobility demand.

At a finer temporal scale, the hourly distribution of enforcement activities reveals clear daytime patterns. The results show two major peaks in enforcement intensity a morning peak and late afternoon. These periods correspond closely with daily travelling cycles. Studies show that travel demand typically peaks in the morning and evening because of traveling to work and schools (Gao & Levinson, 2024). In addition, time geography studies stated that daily schedules and time limits strongly influence when and where people travel in urban areas (Mahmoudi et al., 2019). As a result, traffic interactions and exposure to potential violations increase during these peak mobility periods.

A research using traffic and mobility data also showed that violations and enforcement often cluster in similar time periods (Li et al., 2020). Therefore, the temporal concentration of enforcement during commuting hours likely reflects both the mobility times and response of their monitoring.

6.4 Modal and Violation Specific Differentiation

The spatial analysis further reveals large variation in enforcement patterns across different transport modes. The NKDE maps indicate that Car related violations exhibit the most extensive spatial distribution across the urban road network. In contrast, Motorcycle related violations appear more spatially concentrated, forming localized hotspots particularly within dense urban. Truck related traffic violations display a more limited spatial clusters primarily aligned along arterial roads. These forms suggest that enforcement activity is not uniformly distributed across transport modes but instead reflects the dissimilar mobility patterns.

Accordingly, violations involving load vehicles tend to be spatially concentrated along key routes and access points. Previous research in traffic safety has similarly underlined that different vehicle types interact with road infrastructure differently because of variances in size, maneuverability and operational functions within the transport system (Walton et al., 2013; Robbins et al., 2018). These modal characteristics can influence both traffic interaction dynamics and the spatial distribution of traffic violations.

A further differentiation emerges when comparing the spatial patterns of minor and serious violations. A traffic safety research has demonstrated that different types of violations and crash risks are often linked to specific environmental and behavioral conditions within the road network (Yang & Huemer, 2022). Therefore, the spatial contrast between minor and serious violations may reflect the differing mechanisms through everyday driving behaviors.

Traffic safety research shows that different types of traffic violations and crash risks are often related to specific road, environmental and driving conditions (Yang & Huemer, 2022). Therefore, the spatial differences between minor and serious violations may reflect different driving behaviors.

The traffic enforcement patterns are influenced by both transport mode and violation. Different vehicle types such as cars, motorcycles and trucks interact differently with urban infrastructure that leads to separate spatial patterns of violations and enforcements. These findings highlight the need for adaptive and data-driven enforcement strategies that consider modal diversity and behavioral differences.

6.5 Methodological implications

The application of GIS based spatial analysis played a central role in identifying and interpreting the spatial distribution of enforcement activities in current study. Through employing spatial analytical techniques such as NKDE, it was possible to visualize and quantify the geographic concentration of traffic violations. Traditional descriptive statistics indicate overall frequencies of violations but they cannot reveal where within the urban environment these events are concentrated. GIS based approaches therefore provide a valuable methodological framework to observe the spatial organization of enforcement activities.

The investigation of both spatial and temporal variation lead to identify how enforcement patterns evolve across different intervals.

Hence, GIS visualization tools help translate complex spatial data into practical insights for urban mobility management.

6.6 Limitations

One important limitation of current study is the temporal scope of the dataset used for analysis which cover only the first three months of 2024. Accordingly, the patterns identified in the spatial temporal analysis should be interpreted as indicative but not a full representation of long term enforcement dynamics. Since the urban mobility patterns often vary across seasons due to weather conditions, tourism activity or changing travel behavior throughout the year. Thus, enforcement patterns observed during this limited time frame may not fully capture seasonal variations in mobility.

A further limitation concern is the nature of enforcement data itself. The dataset used in this work reflects recorded enforcement actions but not total number of all violations that may occur within the road network. Enforcement records therefore represent only those violations that were detected and officially documented by authorities. As a result, the spatial distribution of enforcement events may partly reflect operational priorities, resource allocation and monitoring strategies.

Despite mentioned limitations, this present study provides valuable insights into the spatial temporal structure of enforcement activity within an urban mobility system.

Future research could extend this analysis by incorporating long-time enforcement data, additional traffic exposure indicators and complementary datasets. Hence, integrating these additional data sources would allow researchers to better evaluate the relationship between enforcement activity, mobility demand and infrastructural factors.

7. Conclusions and Future Research

This chapter summarizes the key findings of the study and highlights its main contributions to research on traffic law enforcement and urban mobility. It reflects the implications of results for policy and practice particularly in the context of data driven urban safety strategies.

7.1 Summary of Key Findings

The current study inspected the spatial, temporal and modal distribution of traffic law enforcement in Barcelona using an integrated geospatial analytical framework. The study used network-constrained NKDE, Getis–Ord Gi* hotspot analysis and Monte Carlo simulation to analyze traffic infringement enforcement patterns. The aim was to identify statistically significant spatial clustering and temporal patterns.

The analysis was based on a geocoded dataset of more than 260,000 traffic infringement records. The outcomes indicate that traffic infringement events in Barcelona are not randomly distributed across the urban street network. Instead, they form clearly identifiable spatial concentrations along specific raods and intersections within the city. Network kernel density estimation revealed continuous linear clusters of infringement intensity along roads which are highly connected.

The statistical hotspot analysis further confirmed the presence of localized clusters of high infringement intensity.

The temporal analysis revealed that enforcement intensity also follows systematic daily and weekly variations. Higher levels of infringement events occur during weekday peak periods, particularly during the morning and evening commuting hours. In contrast, lower levels of enforcement activity are observed during weekends and late night periods.

The study also identified clear differences across vehicle categories and violation types. Car related violations dominate the dataset both spatially and temporally which reflect the central role of private automobiles in Barcelona’s mobility system. Motorcycle related violations exhibit a more dispersed pattern, while truck related violations display the most localized distribution access routes. These modal differences indicate that enforcement patterns are influenced not only by the spatial structure of the road network but also by vehicle specific mobility constraints.

The results indicate that traffic infringement patterns in Barcelona are shaped by road network, traffic demand and enforcement practices. The combined spatial and temporal analyses help explain how traffic enforcement operates within the urban mobility system.

7.2 Evaluation of Hypotheses

This section evaluates the hypotheses introduced in Chapter 3 based on results (Chapter 5) and their interpretation (Chapter 6).

H1: Traffic enforcement exhibits significant spatial clustering across urban areas. The NKDE and Getis-Ord Gi* analyses identify statistically significant clusters of enforcement particularly in central areas. Monte Carlo simulation confirms that these patterns deviate from spatial randomness. H1 is therefore accepted.

H2: Traffic enforcement follows identifiable temporal patterns related to daily and weekly cycles. The temporal analysis reveals variation in enforcement intensity with clear peaks during weekday morning and evening periods but lower activity at night and weekends. These results indicate consistent temporal structuring aligned with traffic demand. Accordingly, H2 is accepted.

H3: Traffic enforcement patterns differ by vehicle type and violation severity. Subgroup analyses demonstrate distinct spatial distributions across vehicle types and violation categories. The Cars showing widespread coverage, Trucks concentrated along specific corridors and Motorcycles more dispersed. Differences between minor and serious violations further support this variation. Thus, H3 is accepted.

7.3 Research Contributions

This research contributes to the growing body of literature on spatial analysis of traffic enforcement and urban mobility governance. Its contributions can be understood in methodological and policy oriented terms.

From a methodological perspective, the study demonstrates the value of integrating multiple spatial analytical techniques to examine enforcement patterns. NKDE enables the visualization of infringement intensity along the street network, while the Getis–Ord Gi* statistic identifies statistically significant clusters of high values. The addition of Monte Carlo simulation further strengthens the inferential accuracy of the analysis. Collectively, these methods create a complementary analytical approach that improves the reliability of hotspot detection within urban road networks.

A second contribution relates to the analysis of open government data. Although many cities have begun publishing detailed enforcement records through open data initiatives, such datasets remain underutilized in spatial traffic research. The current study demonstrates how large scale open enforcement datasets can be systematically analyzed using geospatial techniques to reveal meaningful patterns in urban mobility governance.

The study also provides insights into the spatial and temporal organization of traffic law enforcement in Barcelona. Whereas previous research has observed traffic crashes or mobility patterns in the city, fewer studies have focused specifically on the spatial distribution of enforcement.

Finally, the research contributes to policy oriented discussions on data driven traffic management. Through identifying statistically significant enforcement hotspots and temporal activity cycles, the study provides evidence that can support more efficient enforcement strategies.

7.4 Directions for Future Research

Building on the findings and limitations of current research, several possibilities for future research could further advance the spatial analysis of traffic law enforcement.

First, using enforcement data from multiple years would help identify seasonal patterns, long-term trends and changes in enforcement strategies. It could also reveal whether enforcement hotspots remain stable or shift because of policy changes, infrastructure developments or broader mobility changes.

Second, future studies could use traffic indicators such as traffic volume, mobility flows, or vehicle-kilometer data. This would make it possible to compare enforcement intensity with actual traffic activity and identify whether enforcement is focused on areas with higher traffic demand or safety risk.

Finally, future research could explore the equity implications of traffic enforcement. Incorporating socio-economic and demographic data would enable the assessment of potential spatial disparities in enforcement intensity across neighborhoods or mobility groups.

Overall, current study demonstrates the value of spatial analytical approaches for understanding traffic law enforcement within complex urban mobility systems. As well as it underscore the importance of considering network structure, mobility demand, and modal characteristics when evaluating enforcement outcomes that can support evidence based traffic safety policies.

Statement on the Use of Generative AI:

Generative AI tools were used in a limited capacity for minor code debugging, grammar clarification and sentence refinement to improve clarity and readability. All analytical methods, spatial analysis, interpretations, and content were independently developed, verified, and written by the author.

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Appendix:

Appendix A – Street Network Preparation

```
import geopandas as gpd

# Adding unique identifier to each street segment
streets["edge_id"] = streets.index.astype(str)

# Export processed street network
streets.to_file("streets_with_edgeid.shp")
```

Appendix B – Infringement Data Pre-processing

```
import pandas as pd

# Load infringement dataset
infringements = pd.read_csv("infringements.csv")

# Remove records without spatial coordinates
infr_clean = infringements.dropna(subset=['Longitud_WGS84', 'Latitud_WGS84'])

# Remove remaining missing values
infr_final = infr_clean.dropna()
```

Appendix C – GIS Preparation

All spatial datasets (street network and infringement points) were reprojected to a common coordinate reference system:
ETRS89 / UTM Zone 31N (EPSG:25831)

- Geometry validation was applied to correct invalid features in both line and point datasets.
- The street network was checked for topological consistency, including:
    - removal of duplicate geometries
    - correction of disconnected segments
    - verification of network continuity

Appendix D: NKDE

```
library(sf)
library(spNetwork)
library(dplyr)
```

```r
# Load street network and event points
streets <- st_read("streets.shp") %>%
  st_transform(25831)

points <- st_read("points.shp") %>%
  st_transform(25831)

# Lixelization of street network
lixels <- lixelize_lines(streets, 100)
samples <- lines_center(lixels)

# Run NKDE
dens <- nkde(
  lines = streets,
  events = points,
  w = rep(1, nrow(points)),
  samples = samples,
  kernel_name = "gaussian",
  bw = 200,
  method = "simple"
)

# Attaching density values to network
samples$nkde <- dens
```

Appendix E: Log Transformation of NKDE Values

To reduce skewness in some NKDE distribution and improve visualization, a logarithmic transformation was applied:

$Y = \log10 (x+\epsilon)$

Where x is the NKDE value and ϵ is a small constant to avoid undefined values.