Title

Tackling Traffic Complexity: Characterizing Regional and Citywide Transportation Dynamics Using Data Analytics, Machine Learning, and HPC Simulations

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Tackling Traffic Complexity: Characterizing Regional and Citywide Transportation Dynamics Using Data Analytics, Machine Learning, and HPC Simulations

By

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Abstract

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The ongoing urbanization process is swiftly giving rise to megaregions, reshaping the urban landscape. Travel constitutes a vital aspect of urban life; hence, a comprehensive understanding of traffic dynamics is crucial for the efficient management of cities. Traffic dynamics refer to the patterns of movement exhibited by people and vehicles within a transportation system. These dynamics are typically characterized in terms of flow and speed, providing crucial insights into the functioning of the urban transportation system.

Traffic simulators are extensively used to analyze traffic dynamics in cities and regions. However, many traffic simulators used in regional studies have limitations. One primary limitation is the substantial data and computational requirements necessary to model a large urban region with high fidelity and speed. To tackle this challenge in traffic simulators, many researchers reduce the size of the road network, including only major arterials and highways; model a subset of the population; and/or aggregate travel demand to a smaller subset of network nodes, aiming to obtain rough estimates of travel volumes. However, the downsizing of the road network and the reduction/consolidation of demand lead to alterations in the characteristics and performance of the network. This approach can result in highly inaccurate predictions that fail to capture the actual dynamics and behavior of traffic. It can provide misleading information to agencies regarding the necessary investments for constructing, maintaining, or improving their roadway infrastructure, as well as decisions related to traffic management and incident response plans.

To address these gaps, this dissertation provides a detailed characterization of large-scale regional traffic dynamics across diverse scenarios using a high-performance traffic simulator. It contributes to and leverages a scalable high-performance mesoscopic traffic simulation platform named Mobiliti, which incorporates various routing strategies to model real-world

traffic conditions with high fidelity and speed. In the case of San Francisco Bay Area, Mobiliti can simulate 19 million vehicle trips on a road network with approximately 0.5 million nodes and 1 million links, representing 7 million drivers and 4 million truck trips in less than three minutes. Subsequently, using data analytics and machine learning models, we identify traffic patterns and characterize cities based on transportation-oriented typologies for large metropolitan regions.

Leveraging Mobiliti alongside real-world data sources, we delve into various facets of regional traffic dynamics, covering both novel and critical areas. Our investigation began by examining dynamic routing, a prevalent feature introduced by the widespread adoption of navigation apps. This feature introduces an additional layer of traffic control, thereby altering traffic dynamics on streets. Through modeling the varying penetrations of dynamic routing, we quantified its effects on the San Francisco Bay Area using metrics such as Vehicle Miles Traveled (VMT), Vehicle Hours of Delay (VHD), affected trips, and its impact on local roads, among others. Next, we recognized that different types of traffic routing, for example, prioritizing time savings versus prioritizing fuel efficiency, influence traffic dynamics in distinct ways. These dynamics, in turn, shape our cities and significantly impact quality of life. Consequently, we developed a framework to analyze these complex dynamics. We evaluated the impact of different routing strategies across multiple dimensions, examining their effects on neighborhoods, safety, environment, and more. Thirdly, network resilience is a critical factor in the San Francisco Bay Area, known for its interconnected bridges. Incidents in this region have the potential to disrupt multiple cities, impacting productivity and energy efficiency. Therefore, we focused on examining the vulnerability of the transportation system to such events and the cascading effects they may cause. A deeper understanding of these dynamics can assist in effective event response planning. The final two studies focus on cities within metropolitan regions. We begin by analyzing street network structures of cities and then proceed to incorporate additional transportation dimensions such as travel demand, traffic flow, and infrastructure. By employing clustering techniques, we identify city typologies and their respective characteristics. This analysis offers us the opportunity to reflect on past urban development efforts, learn from one another, and envision our future city-building objectives.

In total, the specific contributions of this dissertation are:

1. Analyzed the effects of dynamic routing and its varying penetration rates across a vast metropolitan region using large-scale discrete event simulations, demonstrating its substantial influence on mobility metrics at a regional scale. Previous studies were constrained by geographic scale and a limited number of simulation runs, thus failing to capture the full impacts of dynamic routing.

2. Developed a novel multi-themed analytical framework called the Socially-Aware Evaluation Framework for Transportation (SAEF), aiding in comprehending how traffic

routing and resulting dynamics impact cities within a region. Our framework's indicators are carefully chosen to detect system changes when routing strategies are altered, with a focus on neighborhood-related indicators, often overlooked in existing frameworks.

3. Enhanced the evaluation of large-scale network disruptions by modeling dynamic route choices for travelers within a full-scale urban network, encompassing an entire day's demand. Our method more realistically captures drivers' behavior during incidents and we are able to capture the full impacts of incidents at scale, thus enabling the creation of better traffic management and response strategies.

4. Created city typologies for all cities within a metropolitan region based on street network structure, which can provide valuable insights into how drivers experience a city based on its street layout. To aid in this classification, we introduced a new metric for categorizing intersections that distinguishes between various types of 3-way and 4-way intersections based on geometric angles. By incorporating this geometric metric alongside existing centrality metrics, we have achieved better differentiation for improved typology generation, capturing the nuances between grid and other street typologies more effectively.

5. Developed transportation-oriented city typologies based on various dimensions including traffic flow, trip demand, multi-modal network, land use, and road network. These typologies serve as a foundation for facilitating the effective exchange of policies and resources, relying on a thorough understanding of traffic characteristics. We integrated metrics related to trip demand and traffic flow alongside commonly used metrics from road network, multi-modal network, and land use. This integration is crucial for capturing the travel behavior and traffic dynamics of cities, enabling the generation of meaningful and comprehensive typologies.

Each of the items mentioned above is described in more detail in the following paragraphs.

In the second chapter, we examined dynamic routing and its impact on large urban areas using the Mobiliti traffic simulator. Over the last few decades, navigation apps have introduced a new level of traffic control and warranting study as they become pervasive and dictate street traffic flows. Previous work on dynamic routing has been constrained by limited geographic scale and a small number of simulation experiment runs, often requiring hours to complete a single simulation. This limitation poses a bottleneck for running multiple simulations and testing various what-if scenarios to identify the full range of rerouting impacts. We address this gap by utilizing high-performance parallel computing, large urban scale simulator Mobiliti, which can run a single simulation for the entire San Francisco Bay area in less than 10 minutes. We ran multiple simulations with varying penetration rates, revealing diminishing benefits of rerouting after a 70% penetration rate. We also found that dynamic rerouting effectively reallocates vehicle flows from heavily utilized highways and arterials to less congested neighborhood links, reducing overall system delay. Interestingly, the increased traffic volume on local roads does not always lead to congestion, as many links do not reach congested levels despite the increased flow. In summary, our analysis demonstrates, for the first time, the effects of varying penetration rates on traffic dynamics at a regional scale.

In the third chapter, we present an analytical framework called Socially- Aware Evaluation Framework for Transportation (SAEF), which assists in understanding how traffic routing and the resultant dynamics affect cities across a region across multiple dimensions. With the proliferation of real-time navigation routing apps, traffic dynamics in urban environments have changed, resulting in undesired effects that compromise safety and neighborhood health. Therefore, understanding these disparities in traffic distribution across various dimensions is crucial for decision-makers. While previous studies have created frameworks to assess the effects of wide-ranging transportation infrastructure changes or the adoption of smart city technologies, none have established a framework with indicators specific enough to capture the impacts of various traffic routing strategies on cities. Furthermore, existing frameworks and metrics lack translatability to identify the impacts of routing strategies, as crucial dimensions like safety or neighborhood considerations are not adequately addressed. Therefore in this work, our first contribution is developing a framework with a set of themes and indicators that can capture the impact of traffic routing holistically. We identified relevant indicators from the literature, organizing them into four themes: neighborhood, safety, mobility, and environment. When necessary, we developed new methodologies to calculate these indicators. A second contribution is the application of SAEF framework to four cities in the Bay area in the context of three different routing strategies - user equilibrium travel time, system optimal travel time, and system optimal fuel. The four cities were compared to understand how city structure and urban form play a role in the distribution of traffic dynamics. The results demonstrate that many neighborhood impacts, such as traffic load on residential streets and around minority schools, degraded with the system-optimal travel time and fuel routing in comparison to the user-equilibrium travel time routing. The findings also show that all routing strategies subject the city's disadvantaged neighborhoods to disproportionate traffic exposure. With the widespread adoption of navigation apps, our intent with this work is to provide an evaluation framework that enables reflection on the consequences of traffic routing, allowing city planners to recognize the trade-offs and potential unintended consequences.

In the fourth chapter, we offer a set of evaluation tools designed to measure the impact of significant transportation disruptions on a regional scale. We illustrate the application of these tools through a case study involving the closure of the Richmond-San Rafael Bridge in the San Francisco Bay Area. Evaluating the dynamics of transportation networks in the context of events can inform disaster plans and aid in traffic management strategies in preparation for or during an event. Existing research on road network disruptions often relies on short time frames and small-scale models, largely due to computational limitations that hinder the widespread adoption of large-scale urban simulation models. Consequently, smaller-scale micro-simulation models are commonly preferred for designing response plans, typically targeting selected highways and major arterials in close proximity to incidents. However, these studies face three key limitations. Firstly, they often rely on user-equilibrium assumptions for route choice, which fail to adequately reflect realistic driver behavior during incidents. Secondly, they use reduced road network representations due to computational constraints, typically focusing on small areas surrounding closures. Thirdly, they frequently extrapolate findings from peak periods to estimate daily impacts, potentially overestimating congestion due to differences in traffic dynamics between peak and non-peak periods. To address these gaps, our study employs a large-scale, mesoscopic simulation model with dynamic routing capability. This model enables us to simulate a full-scale urban network with an entire day's demand, allowing for a comprehensive assessment of the regional traffic impact of the incident. Our findings indicate that the region experienced an additional 14,000 vehicle hours of delay and 600,000 vehicle miles due to the bridge closure. Furthermore, the median traffic volume on neighborhood streets in San Francisco, Vallejo, and San Rafael increased by more than 10%, highlighting the role of local roads in accommodating the traffic overflow, a factor often overlooked in prior studies. With large-scale modeling of a critical network disruption using dynamic rerouting capability, complete road network, and full demand, we provide valuable insights into the response dynamics of this specific event. In doing so, we demonstrate the value of such regional analyses to incident and disaster planning.

In the fifth chapter, we developed typologies to classify cities within a metropolitan area according to their street network characteristics. Spatial networks such as streets and transit lines influence urban dynamics and travel behavior. Analysing these patterns can also help identify how drivers experience city streets and understand the unique characteristics and challenges present in each urban environment. While previous studies have investigated global network patterns for cities, they have often overlooked detailed characterizations within a single large urban region. Additionally, most existing research uses metrics like degree, centrality, orientation etc., and misses the nuances of street networks at the intersection level, such as geometric angles formed by links at intersections, which could offer a more refined feature for characterization. To address these gaps, this study examines 94 cities in the San Francisco Bay Area, taking into account diverse road network features. We introduce a novel metric for classifying intersections, distinguishing between various types of 3-way, and 4-way intersections based on the angles formed at the intersections. Through the application of clustering techniques in machine learning, we have identified three distinct typologies - grid, orthogonal, and organic cities - within San Francisco Bay Area. Gridded cities are distinguished by their dense network of right-angled four-way and three-way intersections. These cities exhibit a compact layout with smaller link lengths and slower traffic speeds. On the other hand, orthogonal cities exhibit a street network configuration characterized by right-angled three-way intersections and longer street lengths. Organic cities represent a third typology, characterized by their irregular and non-grid-like street network. These cities feature long links with numerous dead ends and winding, circuitous roads. Our findings indicate that the integration of the new metric has improved our ability to distinguish between different types of cities, complementing the existing metrics. In gridded cities, the introduction of the new metric enhances the recognition of grid patterns by explicitly considering 90-degree intersection angles. Conversely, for non-gridded cities, a notable advancement is the ability to differentiate between various types of degree 3 nodes (3-way intersections). While many cities have a significant number of degree 3 nodes, the arrangement of these intersections can vary greatly due to angle variations, resulting in either 90 degree T intersections or non-T intersections. Our study showcases the effectiveness of the new metric in capturing these distinctions, facilitating the classification of cities with a high proportion of T intersections into orthogonal cities and those with non-T intersections into organic cities. The significance of this differentiation extends to how drivers navigate and experience intersections and streets within cities. Based on the angles, turns, and curves of the road network, driving experiences vary significantly. Therefore, understanding these nuances is crucial for optimizing traffic flow, enhancing road safety, and improving overall driving experiences for motorists. Finally, the typologies generated could offer valuable support for city planners and policymakers in crafting a range of practical strategies tailored to the complexities of each city's road network, covering aspects such as evacuation plans, traffic signage placements, and traffic signal control.

In the sixth chapter, we expanded upon our previous city characterization work focused on network structure by incorporating multiple transportation dimensions. As cities evolve and face shared challenges, the development of city typologies, rooted in a comprehensive understanding of traffic characteristics, becomes crucial for facilitating the effective exchange of policies and resources among them. Prior work on transportation based city typologies often fails to provide characterizations specific to a single extensive urban area, as it predominantly focuses on cities globally. Furthermore, these studies frequently overlook essential dimensions such as trip demand and traffic flow in their characterizations, despite their significant impact on street network behavior and traffic dynamics. Therefore in this study, we develop a transportation-focused characterization for all cities within a large urban region, specifically the San Francisco Bay Area, California. We incorporate over 40 metrics across five transportation dimensions: road network, trip demand, traffic flow, multi-modal network, and land use. Using factor analysis and unsupervised machine learning clustering methods, we identified eight distinct typologies for the Bay Area: Live Work; Job and Activity Magnets; Anchor Cities; Multi-modal; Hyper-connected; Low-density residential; Medium-density Residential; Mixed-use residential. The results revealed that many clusters were characterized by features from travel demand and traffic flow dimensions, thus signifying their importance in typology generation. These typologies can serve as a basis to create discourse among Bay Area cities and determine if, through success/failure experiences, common strategies can be formed.

In total, the analytical framework and methods outlined in this dissertation provide detailed and nuanced insights into regional traffic dynamics, surpassing existing literature. By utilizing and contributing to the Mobiliti simulator, we modeled large urban areas with high fidelity and speed, enabling the testing of multiple "what if"scenarios for large metropolitan regions. Our investigation of dynamic routing and its varying penetration rate in Chapter 2 represents the first large-scale regional study examining the impact of real-time traffic routing. Furthermore, the SAEF framework presented in Chapter 3 of this dissertation represents the first analytical framework that captures the impact of traffic routing holistically. With the widespread adoption of navigation apps, this framework enables reflection on the consequences of traffic routing, allowing city planners to recognize the trade-offs and potential unintended consequences. The large-scale network disruption evaluated in Chapter 4 provides a suite of analytical tools for assessing disruptions at both regional and local levels. These tools enable the creation of enhanced traffic management and response strategies by capturing driver behavior more realistically during incidents. The typologies developed in Chapters 5 and 6 provide a comprehensive understanding of cities in a region, considering both network structure and overall transportation dimensions. The new metric introduced in Chapter 5 aids in quantifying the network more precisely, while the comprehensive use of various metrics from different transportation dimensions, particularly trip demand and traffic flow, facilitates a more thorough characterization of cities in Chapter 6. The identified typologies can catalyze dialogue among San Francisco Bay Area cities, facilitating the exploration of common strategies derived from shared experiences of success or failure. Ultimately, the findings presented in this dissertation contribute not only to enriching academic discourse on transportation dynamics but also carry practical implications for policymakers. They furnish invaluable guidance for crafting more effective and nuanced traffic management strategies for cities and large metropolitan regions, thereby shaping the future of urban mobility with precision and foresight.

To
Amma, Achachen & Johnny

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Chapter 1

Introduction

Growing up in India, I witnessed firsthand the essential role transportation systems play in improving people's lives. Public transit is often the sole means for most individuals to access employment opportunities and support their families. Hence the transportation policies and investments made by decision-makers significantly and directly impact people's quality of life. Unfortunately, due to various limitations, these decisions are often based on a partial understanding of transportation systems and travel behavior. This became especially evident during my time at work, where I was involved in decision making for the Smart Cities Project — an extensive urban transformation initiative led by the Government of India. This experience ignited my passion to delve deeper into understanding transportation systems and using data to make informed decisions in this critical field.

Coming to Berkeley exposed me to a wealth of new ideas and the latest innovations in the field of transportation. It was also a period of significant transformation in the transportation sector, marked by the accumulation of vast amounts of data and the emergence of new technologies such as electric, autonomous, and shared technologies, reshaping the landscape. During my master's program at UC Berkeley, I became actively involved with the Smart Cities Research Center, where I found myself deeply engrossed in the Big Data Solutions for Mobility project. This project aimed to harness big data and high-performance computing to develop a scalable, rapid traffic simulator capable of testing various traffic scenarios and informing the design of effective traffic management strategies. The potential of this innovative simulator was immense; it allowed for the testing of multiple traffic scenarios, analysis of traffic dynamics at scale, and execution of numerous simulations within a short timeframe, revolutionizing conventional approaches. Moreover, the value of this work extended beyond academic research; it held considerable value for policymakers, city officials, and transportation authorities. Deeply inspired by this project, I resolved to continue research and deepen my understanding of complex traffic dynamics and transportation systems.

1.1 Motivation

The ongoing urbanization process is swiftly giving rise to megaregions, reshaping the urban landscape. Travel constitutes a vital aspect of urban life; hence, a comprehensive understanding of traffic dynamics is crucial for the efficient management of cities. Traffic dynamics refer to the patterns of movement exhibited by people and vehicles within a transportation system. These dynamics are typically characterized in terms of flow and speed, providing crucial insights into the functioning of the urban transportation system.

Traffic simulators are extensively used to analyze traffic dynamics in cities and regions. However, many traffic simulators used in regional studies have limitations. One primary limitation is the substantial data and computational requirements necessary to model a large urban region with high fidelity and speed. To tackle this challenge in traffic simulators, many researchers reduce the size of the road network, including only major arterials and highways; model a subset of the population; and/or aggregate travel demand to a smaller subset of network nodes, aiming to obtain rough estimates of travel volumes. However, the downsizing of the road network and the reduction/consolidation of demand lead to alterations in the characteristics and performance of the network. This approach can result in highly inaccurate predictions that fail to capture the actual dynamics and behavior of traffic. It can provide misleading information to agencies regarding the necessary investments for constructing, maintaining, or improving their roadway infrastructure, as well as decisions related to traffic management and incident response plans.

1.2 Research Objectives

To address these gaps, this dissertation provides a detailed characterization of large-scale regional traffic dynamics across diverse scenarios using a high-performance traffic simulator. It contributes to and leverages a scalable high-performance mesoscopic traffic simulation platform named Mobiliti, which incorporates various routing strategies to model real-world traffic conditions with high fidelity and speed. In the case of San Francisco Bay Area, Mobiliti can simulate 19 million vehicle trips on a road network with approximately 0.5 million nodes and 1 million links, representing 7 million drivers and 4 million truck trips in less than three minutes. Subsequently, using data analytics and machine learning models, we identify traffic patterns and characterize cities based on transportation-oriented typologies for large metropolitan regions.

The research objectives of this dissertation are to:

1. Analyze the effects of dynamic routing and its varying penetration rates at regional scale with high fidelity.

2. Develop a multi-themed analytical framework to aid in comprehending how traffic routing and resulting dynamics impact cities.

3. Enhance the evaluation of large-scale network disruptions by modeling dynamic route choices of drivers, with a full-scale urban network, encompassing an entire day's demand.

4. Create city typologies for all cities within a metropolitan region based on street network structure accounting for the nuances in intersection geometry.

5. Create transportation-based city typologies that encompass multiple transportation dimensions, such as traffic flow, demand, infrastructure, and network, to generate categorizations for all cities in a metropolitan region.

1.3 Dynamic Traffic Routing

Dynamic routing provided by navigation apps serves as active traffic managers changing street traffic dynamics. The introduction of these new active traffic managers in the last decade makes it more difficult for researchers and government transportation agencies to understand and predict the dynamics of congested transportation systems. Traffic simulation is a key capability for these organizations to analyze different scenarios and predict the potential impacts of different infrastructure changes, policies, or control strategies. However, the complexity of transportation systems makes them extremely difficult to simulate at the urban scale. As such, little is known about how to control and actively manage large-scale road networks in the presence of significant congestion, particularly with active management now being implemented by different agents, such as smartphone apps and traffic centers.

To model traffic flow patterns on road networks, there are a variety of mathematical and simulation-based methods available. The traffic assignment models formulated by [90] are classical mathematical models with many extended versions considering different problem assumptions and settings. Simulation models primarily use non-equilibrium route choice principles such as first shortest path, to determine link flows [14, 84]. Some simulation models also use traffic assignment as their route choice principle. The simulation models complement traffic assignment, which is one of the essential tools that planners use for estimating congestion. With a reliable origin-destination demand matrix, an accurate traffic assignment generates optimized traffic-state predictions [84]. While equilibrium models have been very popular in the past due to mathematical clarity, their main drawback is the inability to capture the congestion-dependent evolution of a driver's route [54]. This limitation is overcome with non-equilibrium models that allow for modeling dynamic route guidance and unexpected events such as incidents or evacuation strategies [14].

In the area of dynamic re-routing, research by [64] showed how proactive dynamic rerouting could reduce average travel time for congested road networks using the SUMO micro simulator on a medium-sized area of London (3,002 links and 332 nodes with 954 vehicles) [114] gave a theoretical analysis of the dynamics and stability of equilibrium with travelers that reroute depending on cost difference, and demonstrated their results on some small networks (up to 31 nodes and 40 links with three OD pairs). Similarly, [103] provides a theoretical treatment of distributed multi-agent route selection problem with incentives, with numerical examples of their approach on the Sioux Falls road network (24 nodes). In [100], the authors utilize SUMO and OMNeT++ to model an area of Brooklyn with 380 nodes and 474 links, with a traffic demand of 2,500 vehicles. Their approach is similar to ours (albeit on a smaller network) in that they utilize a distributed cloud-based vehicle control system, where sensors detect congestion, and routes are suggested to avoid the congestion. In [55], the authors utilize a combination of SUMO, Veins, and OMNeT++ tools to analyze the impact of rerouting on a 2×2 grid map (9 nodes, 24 links). In [80], the authors describe a vanpool scheduler architecture for dynamic rerouting. They evaluate their approach on a network of the Munich city center, where the focus is more on responding to stochastic vanpool requests rather than dynamic congestion effects. In [59] they investigate the information comply model to simulate how drivers can react to information about an event and evaluated their approach on a network with approximately 1,000 links. There has also been related work in the area of route selection in the context of dynamic traffic assignment (e.g., [12]). Dynamic traffic assignment approaches typically model converged dynamic driver behavior adapted to daily congestion patterns, rather than more reactive dynamic rerouting scenarios that explore how traffic can respond to unexpected events. However, all the aforementioned studies are conducted on small regions using small networks and demand, or they use toy examples to demonstrate the effects. No previous studies have been conducted at a regional scale.

In **Chapter 2**, we leverage high-performance parallel discrete event simulator Mobiliti [25] to simulate the effect of dynamic rerouting on large road networks (on the order of hundreds of thousands to millions of links) with tens of millions of vehicle trips per day. Subsequently, we analyze the effects of varying penetration rates of dynamic routing on traffic flows and congestion using metrics such as VMT, VHD, and fuel consumption, as well as their effects on local roads.

1.4 Traffic Routing Impact Evaluation Framework

Traffic flows in urban environments are heavily influenced by real-time routing provided by various independent navigation systems (e.g., Google Maps, Waze, Apple Maps) [92, 46]. Studies indicate that over 55% of drivers in the US use navigation apps daily [78, 98]. Historically, transportation management primarily relied on infrastructure and policy-based interventions, including traffic lights, speed limits, variable message signs, HOV lanes, and tolls. However, the widespread adoption of mobile phones and route guidance systems has introduced a new layer of control, wherein network activity can be significantly influenced by routing instructions provided by these navigation systems. Unlike traditional infrastructure controls, these systems operate independently, often leading to unintended traffic dynamics that may compromise safety and public health in affected neighborhoods [68]. Hence, it is imperative to investigate their impacts across various dimensions influencing urban life and comprehend the associated trade-offs.

We conducted a thorough review of transportation literature to identify frameworks and indicators suitable for assessing the impacts of traffic routing strategies on cities. Given the absence of dedicated frameworks tailored for routing, we examined general frameworks within the transportation domain and evaluated their applicability for routing impact assessment [75, 15]. European Commission's CITYkeys [5], HASTA [58], International Standards Organization (ISO), the European Committee for Standardization, and the British Standards Institution (BSI) frameworks provide metrics to assess the impact of new or existing transportation infrastructure, smart city technologies, etc. However, we found that existing frameworks tend to have broader contexts, considering the entirety of transportation infrastructure (e.g., transportation infrastructure cost, electric fleet mix, or transit usage) or the entirety of smart cities (e.g., technology adoption rate or percentage of smart signals). A few frameworks have delved into more complex aspects, such as how different indicators interact reciprocally, what benefits they generate, or how they affect citizens' quality of life. Moreover, the existing indicators are not specific enough to capture factors related to the impact of routing strategies on cities, such as the share of traffic in neighborhoods or traffic impacts near schools. While safety and neighborhood aspects are discussed in some metrics, they are primarily qualitative and subjective. Key challenges revolve around selecting suitable evaluation methodologies to provide urban value and outcomes that address a city's objectives.

Therefore, in **Chapter 3**, we developed a holistic framework of metrics aimed at understanding how traffic routing and their resultant dynamics impact city metrics, with the intent of avoiding unintended consequences and adhering to city objectives. Our framework, called the Socially-Aware Evaluation Framework for Transportation (SAEF)[60], is an evaluation framework comprising multiple measures related to urban performance, such as safety, mobility, and neighborhood congestion. The selected metrics can be evaluated for cities of various sizes and at the urban scale. The framework is designed to enable decision-makers to assess typical routing strategies and evaluate their potential impact on different aspects of a city.

1.5 Evaluation of Large Scale Network Disruptions

With the increasing occurrence of natural and man-made disasters in urban environments, understanding the impacts of major disruptive events is extremely important for evaluating a city's resilience. Transportation networks in cities are fundamental to disaster planning as they may either be part or the entirety of the event (e.g., bridge collapse); they may reflect the dramatic reactions to the event (e.g., major congestion in a hurricane evacuation); or it may play a part in the management of the event (e.g., using both directions of a highway to increase traffic flow out of the path of a hurricane). As such, evaluating the dynamics of transportation networks in the context of events can inform disaster plans and aid in traffic management strategies in preparation for or during an event.

Traffic simulators have been used in the past to model network disruptions and provide management strategies. However, existing work on road network disruptions typically employs short time frames and small-scale network models. Large-scale urban simulation models have been primarily absent in disaster management literature and practice due to their computational challenges. Instead, small-scale micro-simulation models are commonly used to design a deployable response plan, such as modifying signal timings and ramp metering plans, for a few highways and major arterials in the vicinity of the incident [72].

With regards to network disruption modeling, many simulation models employ the user equilibrium assumption to simulate travelers' route choices following a disaster [6, 111]. The route choice principles used in these studies encompass dynamic or stochastic user equilibrium. While equilibrium models have been very popular in the past due to mathematical clarity, their main drawback is the inability to capture the congestion-dependent evolution of a driver's route. Dynamic traffic assignment (DTA) addresses this by capturing the dynamic diffusion of traffic flow under time-varying demands in a stochastic network [12, 6, 91]. However, DTA approaches typically model converged dynamics adapted to daily congestion patterns, rather than more reactive dynamic rerouting scenarios that explore how traffic can respond to unexpected events. The assumption that people have perfect knowledge of the environment in which they operate is not reasonable in the event of sudden disruptions [40]. This limitation is overcome in simulation models with dynamic routing mechanisms that allow for modeling route guidance dynamics and unexpected events such as incidents or evacuation strategies [11, 14, 54, 24, 84, 108]. Specific transportation operations applications like major network disruptions and evacuations require non-equilibrium models [24, 116] to realistically capture the traffic dynamics.

Furthermore, large-scale traffic simulations can often result in substantial computational requirements, as they involve loading a significant number of trips, often numbering in the millions, onto an expansive road network comprising millions of links and nodes. The most common strategy employed to overcome this challenge is to a) limit the analysis area to a small region around the incident and/or b) reduce the size of the road network to include only highways and major arterials [111, 6]. However, in the case of a major network disruption impacting multiple cities and populations, restricting the analysis region will not adequately capture the complete traffic impact of the incident [10]. Additionally, reducing the road network can overestimate highway congestion patterns and miss capturing the impacts on throughways and local streets. Therefore, in our study, by using a large-scale urban simulator that runs on high-performance computing, we model a large region around the closure with a complete road network representation to understand the full impact of the bridge closure.

Due to a lack of behavioral data and models associated with disruptions, most simulation studies in the literature consider the ODT trip demand as fixed for the bridge open and closed simulations, without accounting for travel behavior changes except for route choice. Studies examining the behavioral impacts of network disruptions have used surveys and statistical models to evaluate them [116, 33, 49, 106]. These studies are conducted for disruptions with long-time horizons, and impacts are assessed days or months after the incident rather than on the day of closure [116, 49, 33]. They report changes in route choice, trip cancellations, shifts in departure time, and changes in travel modes as the main behavioral changes depending on the type and duration of the incident. It is also evident from these studies that route choice changes are the primary behavioral response to incidents, followed by changes in departure time shifts and trip cancellations. We already account for route changes through dynamic rerouting in our simulations. As for the departure time shifts and trip cancellations, which require an extensive behavioral survey beyond the scope of this study, we conducted a sensitivity analysis to assess the impacts of behavioral changes due to the incident.

To summarize, previous studies assessing the traffic impacts from network disruptions have three main limitations. Firstly, they employ user-equilibrium assumptions to model route choice, which cannot realistically capture the reactive driver behavior during incidents. Secondly, due to computational limitations, most previous studies use reduced road network representation and limit the study region to a small area around closure. Thirdly, all the previous analyses were conducted for a few hours in the morning or evening peak period and then extrapolated to the whole day to get the daily impacts. This could lead to overestimating the congestion as the dynamics in peak and non-peak periods are very different. Additionally, most studies assume Origin-Destination-Trip (ODT) demand remains unchanged during closures, failing to account for potential driver behavioral changes. Thus, to evaluate a highly congested regional network disruption consisting of many links and intersections, an advanced traffic simulation model with high computational efficiency is required to capture relevant traffic dynamics.

Therefore, in **Chapter 4**, our study utilizes Mobiliti, a large-scale mesoscopic simulation model with dynamic routing capability, capable of simulating a full-scale urban network with an entire day's demand, to assess the regional traffic impact of the incident [61]. We analyze the impacts of the incident at both regional and local levels and also conduct a sensitivity analysis to capture behavioral changes resulting from the incident.

1.6 City Typologies based on Network Structure

The road network serves as the backbone of any city, providing essential connections between different parts of the urban landscape. The structure and connectivity of streets influence how drivers experience the city as they navigate the streets and intersections, thereby affecting traffic flow, behavior, and the overall dynamics of the city. For example, a gridded layout with small links and multiple intersections tends to result in lower speeds, whereas organic cities with long link lengths often experience higher speeds. Additionally, the types of intersections in a street network significantly influence driving experience, congestion propagation, and changes in traffic dynamics. Thus, analyzing cities based on their street layouts offers valuable insights for formulating effective traffic management strategies, particularly in large urban areas. Moreover, this understanding can foster collaboration among cities within a broader urban region. By characterizing each city, it becomes feasible to devise strategies that are not only efficient but also attuned to the distinctive features of each layout, thereby optimizing the overall functionality of the urban landscape.

Over the last two decades, there has been a substantial body of research in network science, focusing on the development of metrics to delineate and understand networks [65, 88, 110, 18, 51]. In the context of transportation networks, there has been an emphasis on classifying cities based on both network topology and geometric features [17, 13, 94, 32]. Despite this, a gap persists in the investigation of geometric metrics that can characterize network structure. Specifically, limited attention has been given to quantifying patterns at intersections based on the geometric angles formed. These intersection patterns, particularly at 3-way and 4-way intersections, exhibit variations that contribute to distinct intersection configurations, resulting in different road network structures. Explicitly accounting for these intersection patterns promises the generation of better, more accurate, and representative typologies. Furthermore, the majority of the existing literature is dedicated to the characterization of cities worldwide, enabling the recognition of overarching trends and patterns. However, to derive practical insights and effectively apply these insights to the realm of planning and design, it is crucial to perform clustering at a regional level.

In **Chapter 5**, we characterized cities in the expansive urban region of the San Francisco Bay Area, encompassing of over 90 cities. Through the application of various topological and geometric measures, we establish distinct typologies for cities based on their network structure. Additionally, we introduce a novel metric to identify node patterns linked to three-way and four-way intersection types. Subsequently, we develop two clustering models: a baseline employing existing metrics and an enhanced model integrating additional measures. Our analysis entails a thorough comparison and contrast of cities within these two models, emphasizing the effectiveness of the new metric in delineating city structures. Lastly, we provide a discussion on how these classifications can inform effective transportation management strategies.

1.7 Transportation based City Typologies

City typologies have captured the interest of urban planners since the late 20th century. Cities embody a complex blend of features, encompassing street networks, land use patterns, demographics, and various economic and environmental factors. This intricate mix shapes and confines a city's transportation dynamics, resulting in a unique spatial logic for each urban setting. As a result, traffic policies and strategies effective in one city may not translate universally or prove successful elsewhere. Establishing city typologies, founded on a deep comprehension of traffic features, becomes essential for facilitating the exchange of policies and resources among cities. As cities evolve and confront shared challenges, the dissemination of knowledge rooted in underlying transportation features becomes increasingly crucial for sustainable development and efficient resource utilization.

Cities can be depicted in various ways, offering different representations based on the researcher's objectives [63, 95]. Examining the network structure can reveal information about the connectivity of streets and how drivers experience the city. Analyzing activities and land use can indicate the city's vibrancy and how land use has shaped its urban form.

Considering all factors related to transportation demand and supply provides yet another perspective. The latter is our topic of interest.

In the field of transportation research, numerous studies focus on understanding the network structure of cities, while only a limited few delve into exploring the multifaceted dimensions that influence transportation within urban areas. A considerable body of literature categorizes cities based on their street networks, utilizing metrics derived from geometry and topology [17, 51, 18, 32, 94, 13]. For example, [17] used four features—average node degree, orientation order, median street length, and average street circuit—to classify 100 cities globally into three primary and eight subsidiary categories. When compared to cities in other regions of the world, they discovered that American cities had a more pronounced grid-like layout. By analyzing the geometric characteristics and four centrality metrics, [94] divided cities into two groups according to whether or not there were major geographical restrictions. [13] employed both topological and geometric properties to classify 80 cities into distinct categories such as gridiron, long link, organic, hybrid, and mixed cities. Using four node centrality metrics, [32] categorized 18 cities into three categories: self-organized, model, and planned. They show that using different centralities makes it possible to extract useful structural features from networks.

Moreover, many investigations have delved into urban forms and their impact on travel demand, particularly regarding mode choice behavior [102, 71, 48, 9, 41, 86, 20]. Additional studies have taken a focused approach to categorizing cities, considering factors such as energy consumption[93], global status, and political and economic considerations [67]. [85] classified Latin American cities based on indicators of the socioeconomic urban environment, utilizing factor analysis and finite mixture modeling to establish typologies, resulting in five distinct classifications primarily distinguished by education, employment, and gender-specific labor participation.

In addition to typologies based solely on network structure and urban form, a few studies have developed classifications considering multiple dimensions of transportation. For instance, [73] categorized 331 cities into 12 typologies based on economic, demographic, urban form, mobility, and environmental indicators, grouping them into six categories: Auto, BusTransit, Congested, Hybrid, MetroBike, and MassTransit. They used factor analysis and hierarchical clustering in their analysis. The investigation addressed the dimension of trip demand by incorporating mode share as a feature, while for analyzing traffic flow, congestion served as a metric. In their study, [79] classified 73,057 census tracts in the US, first creating microtypes and then establishing geotypes at the county level. They used factor analysis and CLARA clustering algorithm. For the trip demand dimension, the study approximated travel demand determinants using population density, job type, job density, and proportion of trips by distance. In examining the traffic flow dimension, the study utilized truck volume as a metric; however, it did not encompass flow or speed data for automobiles or other modes of transport. In a recent study, [82] utilized supervised machine learning techniques to predict a city's typology by extracting data from Wikipedia pages via natural language processing. They developed a logistic regression model trained on a sparse set of five features acquired through text matching from Wikipedia. Their classification categorized 2000 cities into four classes: congestion, auto-heavy, transit-heavy, and bike-friendly cities.

While some research has extended beyond network topology to include indicators such as economics, demography, and employment in city classification, a limitation exists in explicitly integrating metrics on trip demand and traffic flow characteristics to formulate transportation-oriented typologies for cities. In many cases, researchers have confined their analysis to a limited number of metrics due to data scarcity. A comprehensive set of metrics pertaining to traffic flow and trip demand dimensions is notably absent from current city characterizations. This integration is pivotal for capturing the complete spectrum of travel behavior and traffic dynamics within cities, facilitating the development of meaningful and comprehensive typologies. Furthermore, no studies have undertaken a comprehensive examination of cities within a large metropolitan region, as data availability may be limited to only the top cities in the world.

In **Chapter 6**, we proposed a new transportation-based typology that incorporates detailed trip demand and traffic flow data to enrich city typologies, specifically focusing on contiguous cities within a metropolitan region. By integrating trip demand characteristics such as trip purpose and mode share, along with traffic flow metrics like VMT (Vehicle Miles Traveled) and VHD (Vehicle Hours Delay), with traditional demand drivers like land use, a more comprehensive understanding of urban transportation systems can be achieved. Furthermore, unlike previous studies that examine cities globally, our research focuses on cities in the large metropolitan region of the San Francisco Bay Area, encompassing over 90 cities. Examining cities within a large urban region allows for the development of typologies conducive to meaningful collaborations. These integrated typologies facilitates optimized transportation planning and policy-making, ultimately leading to improved mobility outcomes and sustainable urban development.

1.8 Dissertation Outline

In this section, I outline my research objectives, review existing literature, identify their limitations, and discuss the potential problems resulting from these limitations. Subsequently, in the following chapters, I elaborate on how my research addresses these identified limitations.

This dissertation is structured as follows: Chapter 2 presents a concise overview of the Mobiliti simulator and explores the effects of varying dynamic routing penetration rates on large urban areas. Chapter 3 introduces the SAEF framework designed to assess the influence of different routing strategies on urban environments. Chapter 4 delves into the analysis of large-scale network disruptions. Chapter 5 focuses on characterizing cities based on network structure. Chapter 6 discusses the generation of transportation-focused typologies for cities in the San Francisco Bay Area. Finally, in Chapter 7, I summarize the accomplishments and outline future steps.

Chapter 2

Impact of Dynamic Routing on Metropolitan-scale Traffic Systems

2.1 Introduction

Transportation systems are undergoing a profound transformation driven by the integration of emerging technologies, such as enhanced connectivity and automation. These advancements necessitate more sophisticated control mechanisms to ensure efficient operation in terms of energy consumption, mobility, and productivity. Although simulating large-scale, high-fidelity transportation systems can offer insights, it remains a formidable challenge. This is primarily due to the computational demands associated with processing vast numbers of events and the complex, nonlinear interactions among system components and travelers.

To address these challenges, the Smart Cities Research Center at UC Berkeley, in collaboration with Lawrence Berkeley National Lab, has developed Mobiliti, a cutting-edge, high-performance traffic simulator tailored for large-scale mobility applications. Mobiliti is an agent-based scalable parallel discrete event simulation platform that runs on Lawrence Berkeley National Laboratory's NERSC computer. It instantiates millions of network nodes, links, and vehicle agents to simulate the movement of the population through the road network and provide estimates of the associated congestion, energy use, and productivity loss. Fleet compositions of both statically and dynamically routed agents provide a mechanism for simulating the dynamic response of vehicles under congestion, thus providing insights into the emergent dynamics associated with driver rerouting. Our results show excellent computational performance scalability on multiple compute nodes for a scenario involving 60% dynamically-routed agents, simulating $\tilde{1}9$ million trip legs over a road network with $0\tilde{.}5$ million nodes and $\tilde{1}$ million links, representing 7 million drivers and 4 million truck trips, processing 4.5 billion events in less than three minutes.

I had the privilege of being part of the Mobiliti development team since its early stages, contributing significantly to road network modeling, travel demand analysis, simulation validation, and various traffic analytics. For readers interested in exploring the technical details of the traffic simulator further, additional information can be found at [25, 26].

Leveraging Mobiliti, we explored various aspects of regional traffic dynamics, encompassing novel and critical areas. This chapter discusses the examination of dynamic routing, a prevalent feature introduced by the ubiquitous use of navigation apps, which adds an additional level of traffic control, altering traffic dynamics on streets. By modeling the varying penetrations of dynamic routing, we quantified its effects on the San Francisco Bay Area using metrics such as VMT, VHD, trips affected, and impact on local roads, among others. This chapter constitutes a section of the published paper [25], focusing on the experiment, analysis, and validation, which represents my primary contribution.

2.2 Dynamic Routing

Active traffic management strategies using changeable message signs or broadcast media are regularly used by traffic management centers to present alternate routes to drivers when abnormal events occur on the roadways. Shifting traffic onto alternate routes maximizes the efficiency and capacity of the network and increases safety by reducing secondary vehicle accidents due to unexpected congestion. With highways, parallel corridors that handle the rerouted traffic must be available with adequate capacity for rerouting to be successful. This requires traffic centers, with humans in the loop, to assess the situation, have knowledge of the parallel routes via predefined control strategies, and implement an active control plan. In the past five years, smartphone navigation apps have gained popularity and serve a similar role. These applications use their current understanding of congestion to compute new routes in which the travel time is shorter for the user of the device. The congestion information is generated by aggregating the speeds and locations of all of the devices that the app is monitoring. A road congestion estimate is created using road network information and other traffic information, such as historical traffic information, and combined with the current user's destination. If the projected congestion of the user's current route significantly impacts their expected travel time, the app may suggest a new route to the user with a shorter travel time. As such, these navigation applications are also serving as active traffic managers.

The introduction of these new active traffic managers makes it more difficult for researchers and government transportation agencies to understand and predict the dynamics of congested transportation systems. Traffic simulation is a key capability for these organizations to analyze different scenarios and predict the potential impacts of different infrastructure changes, policies, or control strategies. However, the complexity of transportation systems makes them extremely difficult to simulate at the urban scale. As such, little is known about how to control and actively manage large-scale road networks in the presence of significant congestion, particularly with the active management now being implemented by different agents, such as smartphone apps and traffic centers. We do know that providing information about congested states and having a variety of sources provide new travel routes will likely create unpredictable patterns and dynamic variation. Control strategies implemented through traffic management can include infrastructure modifications such as signal-phase-timing adjustments of signals to redirect traffic and expedite congestion mitigation. These control decisions are determined by estimating the impact of the rerouting action. To-date, these do not include rerouting that occurs as a result of drivers following an app's routing information. This was made evident when during an evacuation event, drivers were venturing into dangerous situations with routes that were not informed by road closures associated with the event [22].

In the last two decades, transportation network simulation has increased in popularity for emulating driving behaviors, predicting traffic dynamics, and predicting impacts of control strategies. Applied models can broadly be categorized into both equilibrium models, often referred to as traffic assignment models, and non-equilibrium models, often referred to as simulation models [14, 84]. The simulation models complement traffic assignment, which is one of the essential tools that planners use for estimating congestion. With a reliable origin-destination demand matrix, an accurate traffic assignment generates optimized traffic-state predictions [84]. While equilibrium models have been very popular in the past due to mathematical clarity, their main drawback is the inability to capture the congestion-dependent evolution of a driver's route [54]. This limitation is overcome with non-equilibrium models that allow for modeling route guidance dynamics and unexpected events such as incidents or evacuation strategies [14].

Hence, to forecast emergent traffic dynamics resulting from congestion-dependent rerouting and unforeseen incidents, we employ the Mobiliti traffic simulator equipped with dynamic routing penetrations. By adjusting the penetrations, we can effectively gauge the diverse effects of mobility alterations induced by these rerouted traffic scenarios. In the upcoming sections of this chapter, we detail the experimental setup of Mobiliti, examine the simulated impacts of varying dynamic rerouting penetration rates on various transportation system metrics, and conclude with a validation of the simulation results against real-world data sources.

2.3 Experimental Set Up

For this study, we use a San Francisco Bay Area map derived from a HERE Technologies [47] map consisting of 450,000 nodes and 1 million links covering areas from Santa Rosa, Napa, and Vacaville to the north, to San Jose to the south, and Oakland, Hayward, Fremont, and Livermore to the east. The trip demand is initialized from an input file with 19 million trip legs (origin/destination pairs) based on disaggregate simulated trip records from the San Francisco County Transportation Authority (SFCTA) SF CHAMP 6.1 model [87]. Each trip leg is specified with origin and destination travel analysis zones (chosen from 40,000 micro-analysis zones) and a start time. Since our simulator models each individual vehicle traversing from link to link at discrete times, we chose specific origin and destination nodes within the given Traffic Analysis Zones (TAZs). We weighted each node by its nearby population density derived from the Global Human Settlement (GHS) database [39] to avoid choosing nodes that are in very sparsely populated regions of the map, which would unrealistically send traffic to remote areas. We also avoided selecting freeway or ramp nodes as origins or destinations.

Figure 2.1(left) shows the temporal profile of the SFCTA demand model's trip legs during the simulated model day. Our simulation runs a single model day, and the figure shows on the y-axis the number of trips that start in each hour of the day. The number of trip legs per hour varies from very low in the early morning hours to very high during late afternoon rush hour. Since trip lengths can vary considerably, by weighing each trip by its length, Figure 2.1(right) shows the total vehicle miles traveled (VMT) by start time, which is defined as the sum of the total trip distance over all trips that start in each hour of the day. This figure illustrates the time-varying magnitude of the total load on the road network.

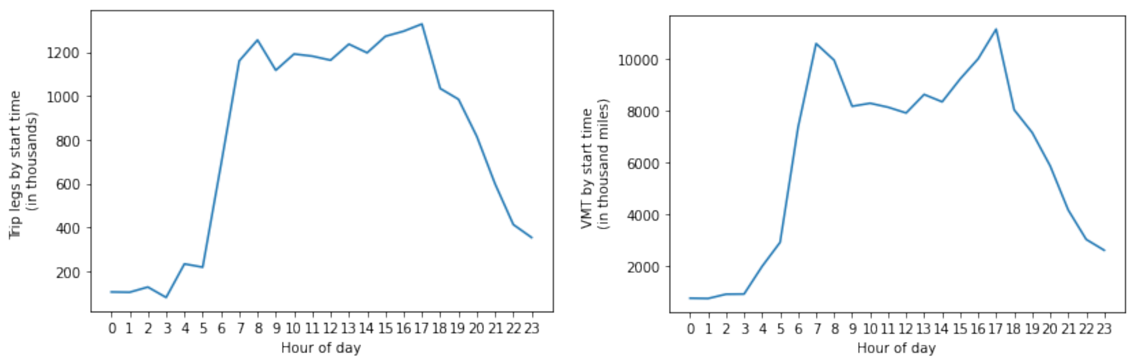


Figure 2.1: These figures give a temporal profile of how demand evolves through the simulated day. The left figure shows the total number of trip legs starting at different times of the day. The right figure shows the total VMT summed over trips that start at different times of day.

2.4 Analysis

Impact of dynamic rerouting on system metrics

To understand the effect of rerouting penetration, we enabled dynamic rerouting for varying percentages of vehicle trip legs for the entire Bay Area. We chose to study a range of penetration rates from 0% to 100% at 10% increments. Figure 2.2 illustrates the impact of enabling dynamic rerouting for 100% vehicle trips for the entire metropolitan-scale system simulated. The difference between baseline and 100% rerouting case is that the former uses static shortest path routes based on free speed traversal times, whereas the latter uses dynamic routes computed by the vehicle controllers based on their knowledge of the current traffic congestion patterns. In Figure 2.2, blue links handle a lesser number of vehicle traversals when 100% dynamic rerouting is enabled, while the red links handle a greater number.

The figure shows how the traffic is rerouted away from certain links to reduce congestion (blue), while other links end up handling higher traffic (red).

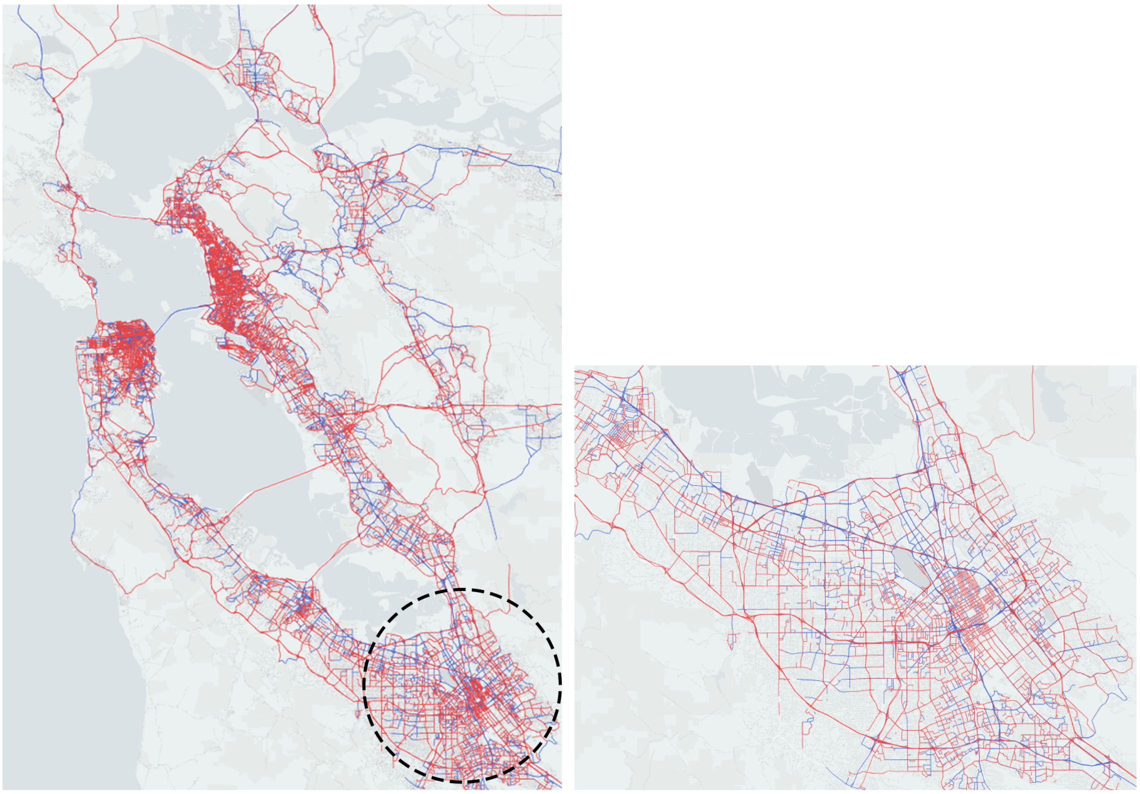


Figure 2.2: The figures show the system-wide impact on the number of vehicle link traversals from enabling dynamic rerouting (baseline versus 100% penetration) for Bay Area (left) and San Jose city (right). Red or blue represents an increase or decrease in vehicle traversal count for a day.

Figure 2.3 shows how the reroutes are temporally distributed throughout the simulation day, illustrating that almost 80% of the rerouting occurs during the morning and evening rush hours when the demand is the highest. The distribution of reroutes is heavily influenced by the temporal distribution of trip legs in the demand model input (Figure 2.1). As can be seen in Figure 2.1(right), there is a peak in the total vehicle miles traveled (VMT) in the morning (7 am to 10 am) and the evening rush hours (3:30 pm to 6:30 pm). Because the level of demand during rush hours is the highest, we see corresponding peaks in the number of reroutes. Further, it must be noted that penetration rate indicates the number of trip legs allowed to reroute, but not all reroutable trip legs actually reroute. Table 2.1 indicates the percentage of trip legs rerouted as a percentage of allowed reroutable legs. At higher penetration rates, the percentage decreases even though the actual number of reroutes is higher, since not many trip legs engage in any relevant congestion and hence do not reroute.

Furthermore, among the trips that do reroute, the number of *reroutes per trip* remains small, with 99.9% of trips rerouting three times or fewer in the 100% penetration scenario.

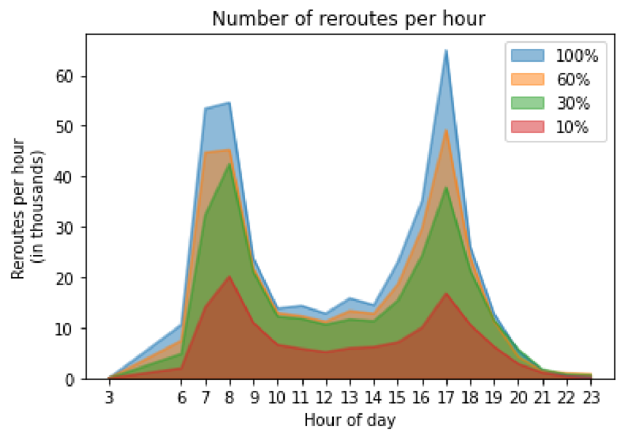


Figure 2.3: The figure gives a temporal profile of the rate of dynamic vehicle reroutes for a day. Sharp increases in reroutes can be seen in the morning and evening peak hours.

Table 2.1: Share of Rerouted Trip Legs

Penetration rate (%)	**Trip legs reroutable** (in thousands)	**Trip legs rerouted** (in thousands)	**Percentage rerouted** (%)
10	1,900	130	7
20	3,800	221	6
30	5,700	274	5
40	7,600	291	4
50	9,500	301	3
60	11,400	317	3
70	13,300	329	2
80	15,200	340	2
90	17,100	355	2
100	19,000	374	2

Using the delay and fuel model described in our previous work [26], we can make impact estimates for dynamic rerouting penetration rates. Figure 2.4 exhibits the system level vehicle hours of delay (VHD) and the number of reroutes for different penetration levels, and Table 2.2 shows the system level vehicle miles traveled (VMT) and fuel consumption resulting from the dynamic rerouting. As the penetration rate increases, the delay reduces without any significant change in VMT. The minimum system delay is incurred with 100% penetration rate. However, if we look at the "knee of the curve" for VHD, the return starts

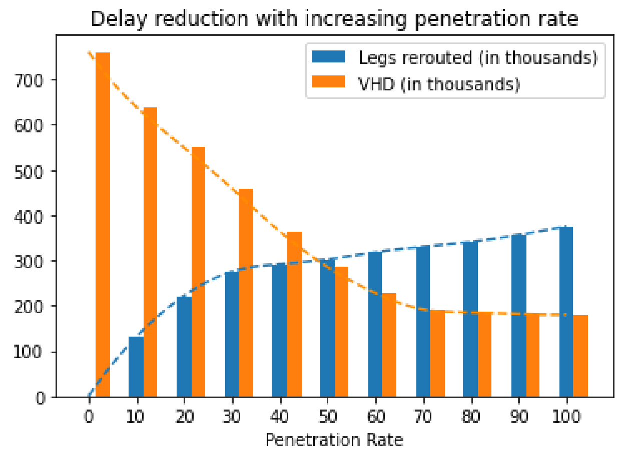


Figure 2.4: The figure shows the system wide vehicle hours of delay (VHD) and the number of trip legs rerouted from varying dynamic rerouting penetration rates. As the penetration rate increases, the overall system delay reduces. If we look at the elbow of the VHD curve, after 70% penetration rate the returns start diminishing.

diminishing after 70% penetration. On average, a rerouted trip saves 16 minutes in travel time with no additional trip distance with 100% penetration rate compared to baseline as shown in Figure 2.5 (left).

Table 2.2: VMT and Fuel Consumption

Penetration rate	**Vehicle Miles Traveled** (in thousand miles)	**Fuel** (in thousand gallons)
0%	146,847	5,906
10%	146,783	5,903
20%	146,707	5,899
30%	146,652	5,894
40%	146,605	5,891
50%	146,572	5,888
60%	146,546	5,886
70%	146,537	5,884
80%	146,517	5,883
90%	146,505	5,882
100%	146,490	5,882

We observe that dynamic rerouting effectively rearranges the vehicle flows from high-utilized highways and arterials to low-utilized neighborhood links to reduce the overall system delay. We analyze these effects by investigating the rearrangement of the traffic flow

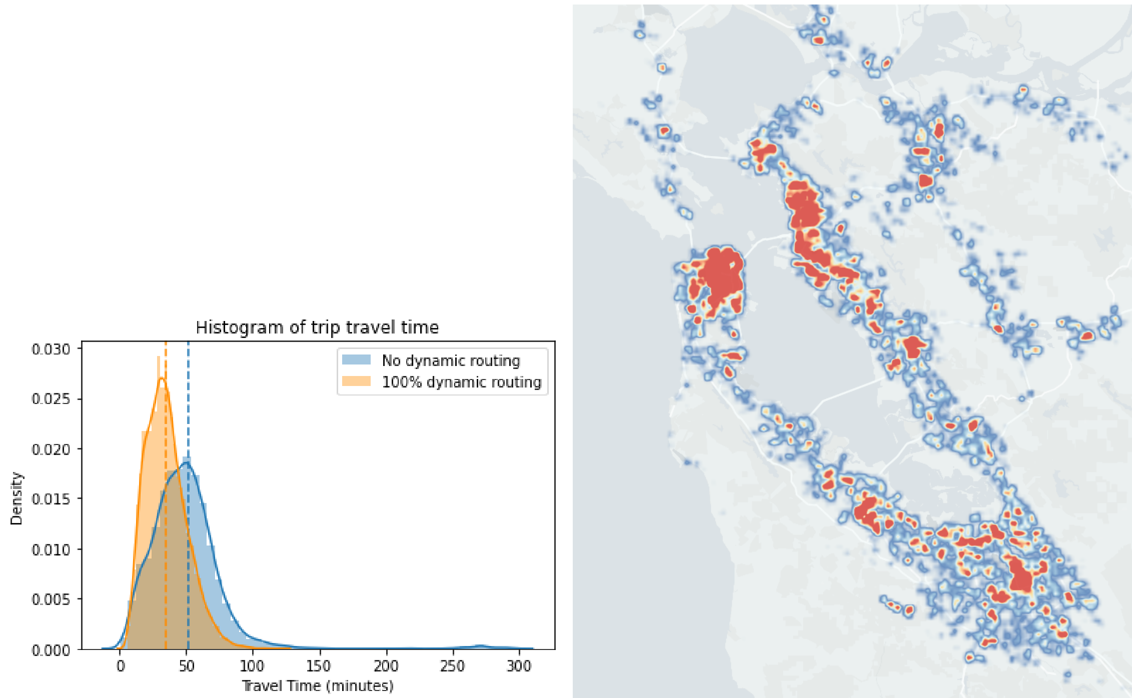


Figure 2.5: (Left) The figure shows the distribution of the travel times for trip legs. The mean travel time per trip leg with 100% dynamic routing is 35 minutes, and without dynamic routing is 51 minutes, as shown by the corresponding orange and blue vertical lines. (Right) The figure shows the heat map of areas with the highest congestion (volume over capacity more than 0.75) with increased vehicle counts due to dynamic rerouting in the morning rush hour for functional class 5 links. Red indicates high congestion, and blue represents low congestion.

by functional classification of links. We maintain the definitions of functional class roads as defined by HERE Technologies [47]. Specifically, functional classes are hierarchical classifications of roads according to speed, importance, and connectivity. A road can be one of five functional classes defined in Table 2.3.

Table 2.3: Functional Road Classes

Functional class	**Definition**
1	Allows high volume, maximum speed traffic movement
2	Allows high volume, high speed traffic movement
3	Provides high volume of traffic movement
4	Provides high volume of traffic movement at moderate speeds between neighborhoods
5	Local roads with volume and traffic movement below the level of any functional class

By examining the traffic flow by *functional class* (FC) with 100% dynamic rerouting penetration, we observe that traffic shifts from FC 2 and 3 to FC 4 and 5. This significantly reduces highway delays while increasing traffic on FC 5 in the morning and evening peaks. It is also interesting to note that the increased traffic volume on FC 5 does not always cause congestion in those links, as many links do not reach congested levels with the increased flow. Specifically, 7000 kilometers of FC 5 links received additional traffic flow with 100% dynamic rerouting, of which 75% received fewer than six additional vehicles during the morning peak.

Of the FC 5 links with increased traffic volume, 440 kilometers are congested with a volume-over-capacity ratio higher than 0.75. Spatial analysis of the congestion shows that the cities of San Francisco, San Jose, Berkeley, Oakland, and Fremont are the most affected by the increased traffic on the local roads (Figure 2.5 (right)). The local roads (FC 5) in these cities have a mean increase of 70 vehicles during the morning peak. Finally, of the 440 kilometers of congested road network in the morning peak, 110 kilometers reflects *new* congestion created due to dynamic rerouting on the local roads. These roads would arguably be some of the most negatively impacted areas by high dynamic rerouting penetrations.

Finally, we present the results of user equilibrium (UE) traffic assignment in Table 2.4 for comparison. Compared with the system metrics for dynamic rerouting with a 100% penetration rate, we can see that VHD is nearly half, fuel consumption is slightly higher, and VMT is slightly lower in user equilibrium. Since the user equilibrium is a steady-state solution computed through iterative optimization, it results in routes with lower delays than the more reactive dynamic rerouting approach. However, in reality, the user equilibrium state is never actually achieved, and hence congestion is underestimated in the user equilibrium traffic assignment.

Table 2.4: User Equilibrium Traffic Assignment:System Metrics

	Vehicle Miles Traveled (in thousand miles)	**Vehicle Hours of Delay** (in thousand hours)	**Fuel** (in thousand gallons)
User Equilibrium	146,051	90	5,915

Validation

Validation was performed for the simulation runs with different penetration rates to test the effectiveness of representing the real-world traffic environment. We conducted a three-stage validation procedure using multiple data sources. Our results show that the simulation with 60% dynamic rerouting is the closest to representing real-world traffic. We have only included the validation for this penetration rate here for brevity. Our results are consistent with multiple surveys stating that the percentage of Americans having smartphones who uses online maps or navigation services daily ranges from 55% to 65% [78, 38, 98].

Stage 1 of the validation procedure involves comparing the traffic flows or counts between the simulation and real world data. This includes checking a) traffic counts for eight corridor links in San Jose city, b) average daily traffic (ADT) counts for four main bridges in the Bay

Area, and c) traffic flows for all major highways in the Bay area. The traffic count for each link was compared against the field data for the entire day in 15 minutes increments. The field data for city roads and highways were collected from the city of San Jose, and the Caltrans Performance Measurement System (PeMS) website [34] respectively for the year 2019. Each corridor provided information regarding traffic volumes by time of the day and direction. Since PeMS data is prone to measurement error, data from multiple weekdays in April and May 2019 were averaged to get a typical day value. A coefficient of determination R-squared (R^2) of 0.7, which is typically used as a satisfactory criterion for link count checks, is used as the threshold. Figure 2.6 shows R^2 values for the eight corridors under consideration. The modeled corridors are closely matched with the field data, with the lowest R^2 value observed being 0.76 for Zanker road.

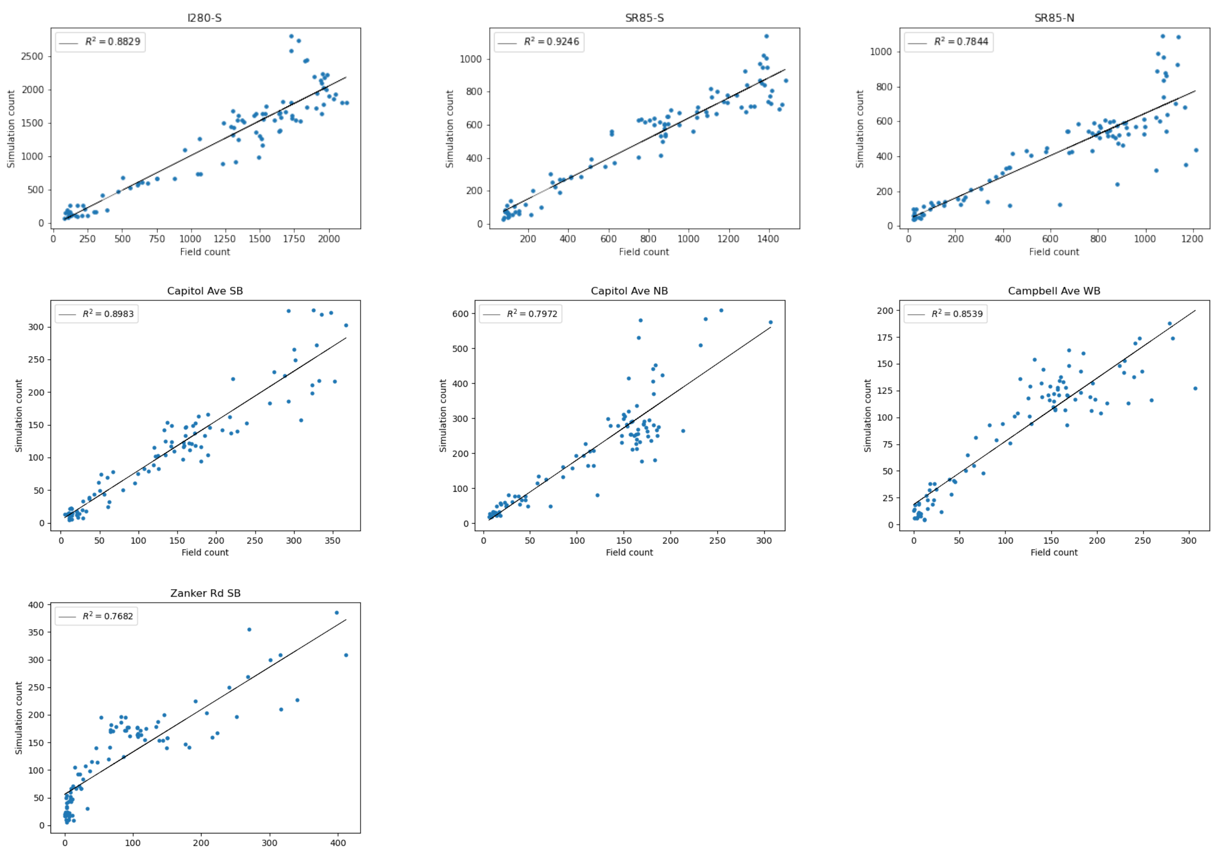


Figure 2.6: The figure shows the validation of traffic counts in 15-minute increments for links in different functional classes. All links have satisfactory R^2 of greater than 0.7.

Additionally, ADT for four main bridges in the Bay Area in both directions is shown in Table 2.5. The field data were obtained from the Caltrans website [34] for the year 2019.

The target error was ±25%, and seven of the eight links met this criterion. We believe that the high relative error for the Golden Gate Bridge northbound (NB) count is due to the Caltrans field count not accurately representing the actual bridge count. The discrepancy is due to the sensor placement **after** a major exit, which results in a significant percentage of bridge traffic not being counted by the sensor.

Table 2.5: Average Daily Traffic (ADT) Comparison

Sl No	**Bridge**	**Field Count**	**Simulation Count**	**Relative Error (%)**
1	I-580 Richmond San Rafael Bridge EB	56182	51551	-8%
2	I-580 Richmond San Rafael Bridge WB	41597	52131	25%
3	I-80 Bay Bridge EB	132000	148105	12%
4	I-80 Bay Bridge WB	131861	139993	6%
5	US-101 Golden Gate Bridge NB	32212*	63730	98%
6	US-101 Golden Gate Bridge SB	74526	70020	-6%
7	CA-92 San Mateo Bridge EB	56510	53684	-5%
8	CA-92 San Mateo Bridge WB	62597	50199	-20%

* Golden Gate Bridge northbound (NB) link's closest PeMS sensor is located after an off ramp and hence the field count does not reflect the full bridge traffic count.

Next, we evaluated R^2 for all links with a corresponding PeMS sensor in Bay Area. We were able to match 2061 links with mainline sensors and the resulting R^2 distribution is shown in Figure 2.7(left). Of the total matched links, 72% have R^2 greater than 0.7, and 5% have lower than 0.4 (Figure 2.7(right)).

Stage 2 in the validation procedure compares simulation speed with a) Uber Movement data for San Francisco city streets and b) PeMS speed data for Bay Area highways. For Uber Movement, speed data for the San Francisco region for quarter four, 2019 is obtained from the website [101] . Links from Uber network were matched to Mobiliti links for a total of 139,495 links (20% of total). The speeds were compared from 8 am to 9 am for different speed limits. Figure 2.8 shows the average speeds from Mobiliti and Uber across all speed limits. The speed distributions from both links with 60 mph and 70 mph speed limit is shown in the second row.

Next, we compared highway links with PeMS speed profiles for the 2061 matched links. Figure 2.9 shows the difference in speeds between simulation and PeMS at 9 am and 3 pm for a weekday. Most links are within ±20 mph difference. Further, R^2 values were evaluated for all links to understand the time series trends. Figure 2.10 shows a time series comparison

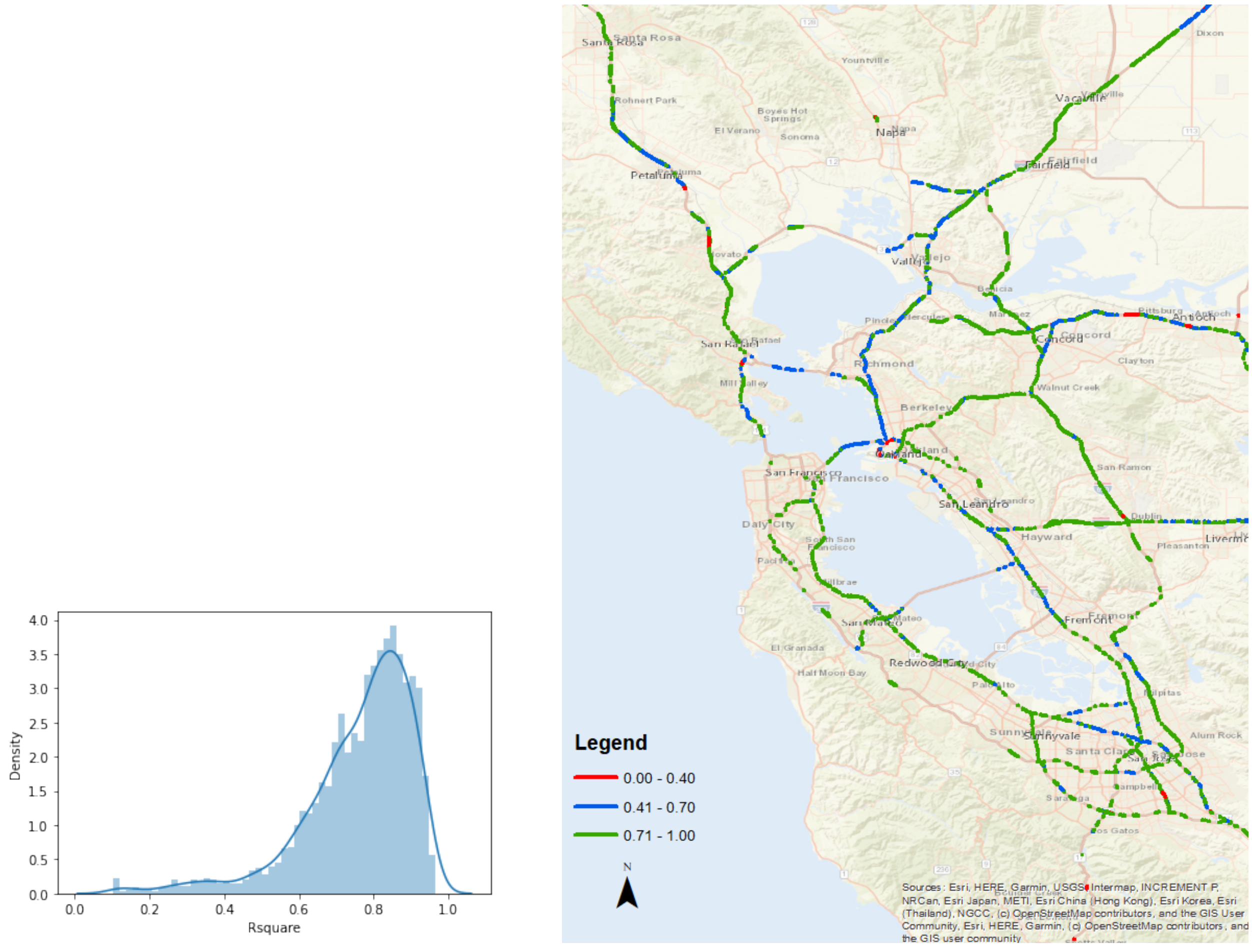


Figure 2.7: Validation metrics for highway link flows compared to PeMS sensors are shown. (Left) Distribution of R^2 values for the highway links is shown in the figure. It follows a left skewed normal distribution with mean 0.75 and standard deviation 0.15. (Right) The map shows the spatial distribution of R^2 values of flows for the links.

for six highway links. Of the total, 55% of highway links have R^2 greater than 0.4. We plan to improve the speed models to reflect time series trends closer to real-world data in the future.

Stage 3 is system-level comparisons, network validation, and error checking. Model visualization is used to check for unusual activities in traffic flows and odd roadway network attributes. Error checking and model verification consist of smaller tasks such as checks for link geometry and connectivity, link speeds, and ramp and intersection geometry. Since our travel demand data was obtained from SFCTA, which conducts its validation, we did not conduct additional behavior checks. We conducted system metric checks for VMT and total demand and validated them against the 2017 Environmental Impact Report for the Bay

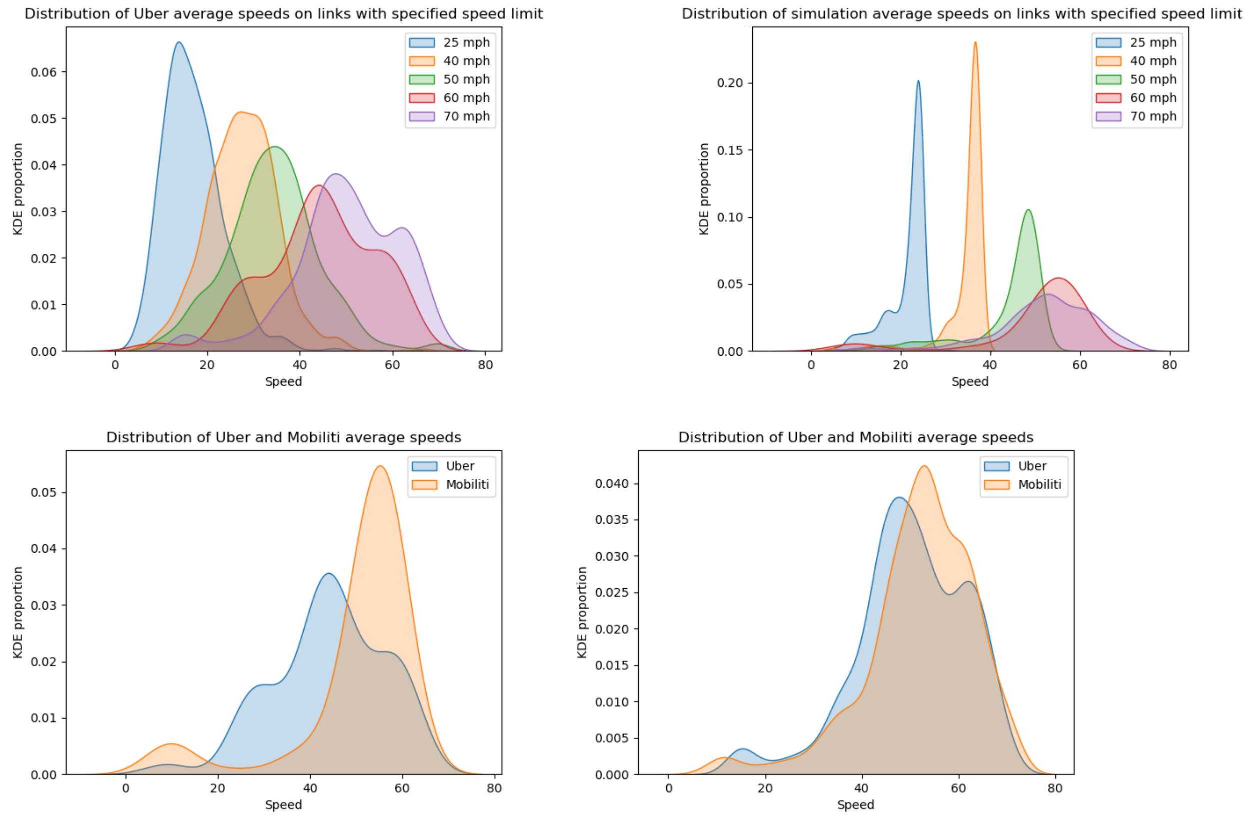


Figure 2.8: Average Uber (left) and Mobiliti (right) speeds across all speed limits from 8 am to 9 am in shown in the first row. The second row shows the kernel density plots comparing both speed distributions at 60 mph (left) and 70 mph (right).

Area [36] in Table 2.6.

Table 2.6: System Level Metrics

Metric	Simulation	Field Data	Relative Error(%)
VMT	146,546,360	158,406,800	-7
Daily Trips	19,167,301	21,227,800	-10

2.5 Conclusion

Vehicles are rapidly gaining the ability to utilize up-to-date road congestion information to reroute their paths during trips through smartphone navigation apps. In this chapter, we

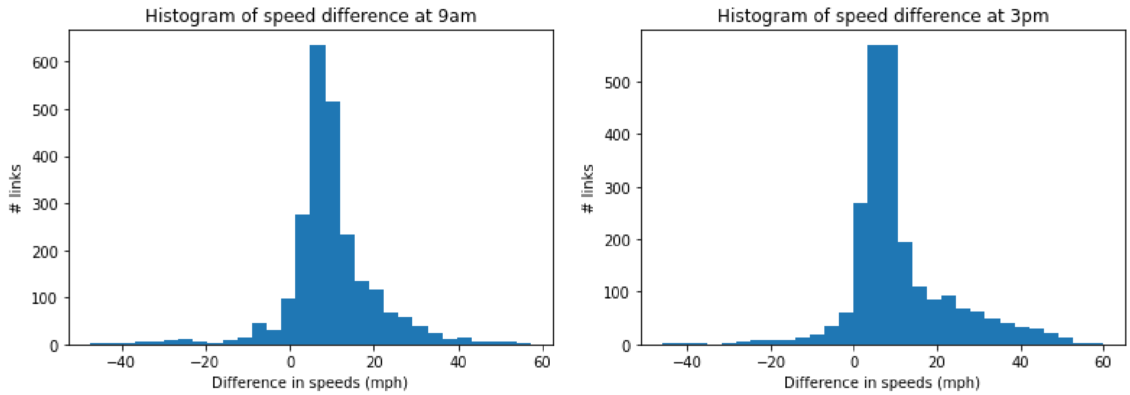


Figure 2.9: The figure shows the histogram of the speed difference between simulation and PeMS at 9am and 3pm for highways in the Bay Area.

presented an analysis of system-level impacts by varying the dynamic rerouting penetration rate at 10% increments and examining the varying effects on different functional classes and geographical regions using the Mobiliti simulator. Our results indicate diminishing benefits of rerouting after reaching a 70% penetration rate. We found that dynamic rerouting effectively reallocates vehicle flows from heavily utilized highways and arterials to less congested neighborhood links, thereby reducing overall system delay. Interestingly, the increased traffic volume on local roads does not always lead to congestion, as many links do not reach congested levels despite the increased flow. Finally, we present a validation of the simulation results compared to real-world data sources.

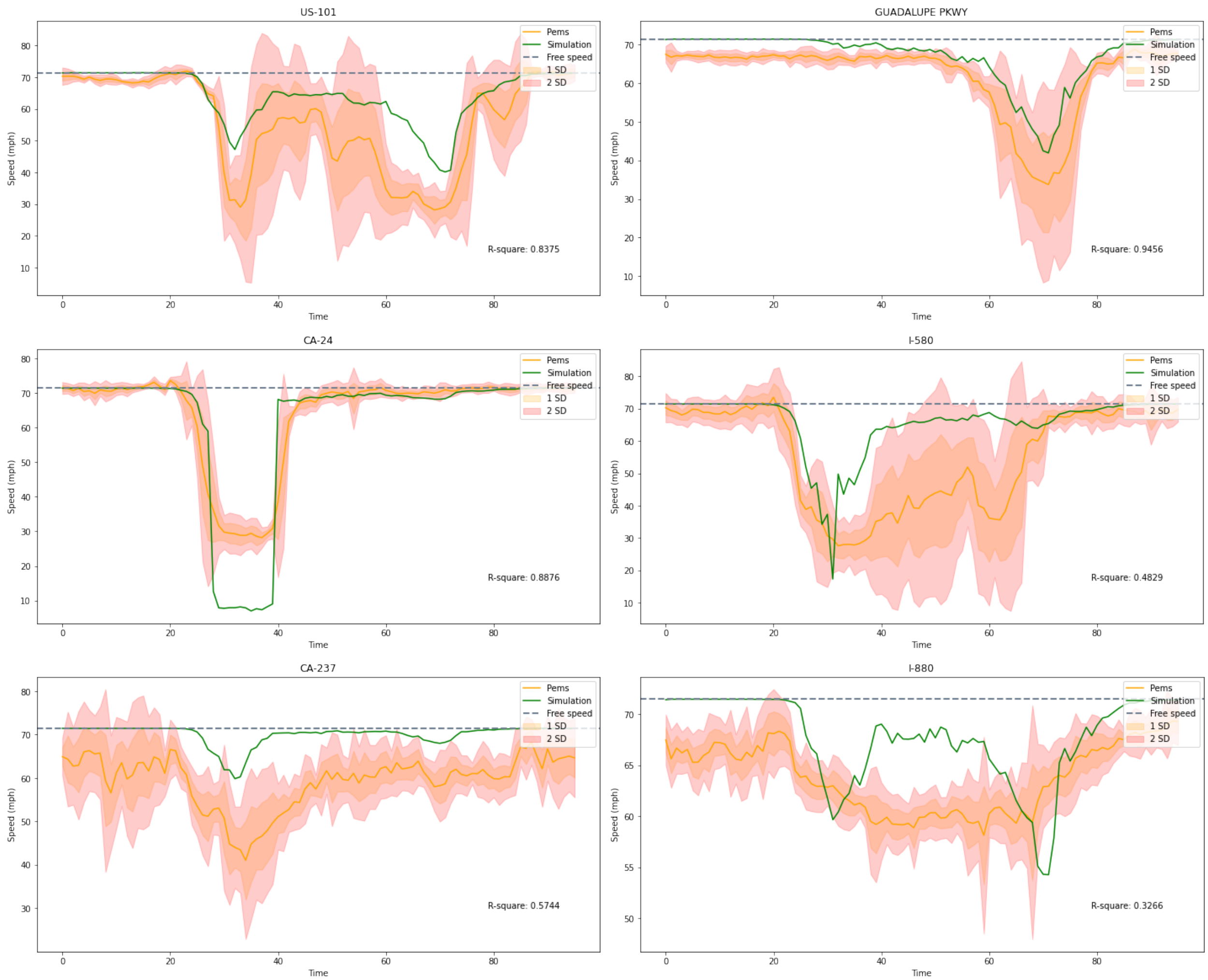


Figure 2.10: The figures show the simulation and PeMS speed profile for highways. The yellow line represents the average weekday values from PeMS. The first and second standard deviation bands are also shown. The green line represents the simulation speed for a typical day.

Chapter 3

Socially-Aware Evaluation Framework for Transportation

Abstract

Technological advancements are rapidly changing traffic management in cities. Navigation applications, in particular, have impacted cities in many ways by rerouting traffic. As different routing strategies distribute traffic differently, understanding these disparities across multiple city-relevant dimensions is extremely important for decision-makers. We develop a multi-themed framework called Socially- Aware Evaluation Framework for Transportation (SAEF), which assists in understanding how traffic routing and the resultant dynamics affect cities. The framework is presented for four Bay Area cities, for which we compare three routing strategies - user equilibrium travel time, system optimal travel time, and system optimal fuel. The results demonstrate that many neighborhood impacts, such as traffic load on residential streets and around minority schools, degraded with the system-optimal travel time and fuel routing in comparison to the user-equilibrium travel time routing. The findings also show that all routing strategies subject the city's disadvantaged neighborhoods to disproportionate traffic exposure. Our intent with this work is to provide an evaluation framework that enables reflection on the consequences of traffic routing and management strategies, allowing city planners to recognize the trade-offs and potential unintended consequences.

3.1 Introduction

Massive adoption of mobile devices and cloud-based applications have created new mechanisms for understanding how people move in urban environments. This new mobility data, along with data generated by city infrastructure, will provide cities with a more detailed view of traffic dynamics and allow them to play a more active role in managing urban performance. In addition, emerging connected and automated technologies promise to create more efficient solutions for city management. For example, the promise of autonomous and connected vehicle fleets in smart cities may provide the possibility of optimal traffic management through mass control of vehicle routes. These technologies will augment current mechanisms for traffic management in cities, e.g., traffic lights, variable message signs, HOV lanes, and tolls.

Traffic flows in urban environments are currently heavily influenced by real-time routing provided by various independent navigation systems (e.g, Google maps, Waze, Apple maps) [46, 92], with up to 60% of drivers using them daily [78, 98]. These systems add another level of control that is not in coordination with existing infrastructure control. This has created undesired traffic dynamics, driven mainly by real-time route guidance systems, that often compromise safety and health in the neighborhoods affected [68].

In this paper, our goal is to develop a holistic framework of metrics that will assist in understanding how routing strategies and their resultant traffic dynamics impact city metrics, with the intent of avoiding unintended consequences and adhering to city objectives. Our framework, called *Socially- Aware Evaluation Framework for Transportation - SAEF*, is an evaluation framework with multiple measures related to urban performance, such as safety, mobility, and neighborhood congestion. The selected metrics can be evaluated for cities of various sizes and at the urban scale. The framework is designed to allow decision-makers to assess typical routing strategies and evaluate the potential impact on different aspects of a city. For illustrative purposes, we present the framework for four cities in the Bay Area. The routing strategies we evaluate are (1) user equilibrium in which travel time for each user is optimized, (2) system optimal travel time, and (3) system optimal fuel use. The impact of these optimization strategies on the Bay Area is generated using results from a mesoscopic simulation platform called Mobiliti [26] that implements a Quasi Dynamic Traffic Assignment (QDTA) [27]. The QDTA algorithm partitions the day into 15-minute intervals and performs a static traffic assignment for each interval, including trip accounting that allows for residual traffic from the previous time interval. Although the framework was developed with the primary objective of evaluating the impact of traffic routing strategies, it may also be used as an evaluation tool for a wider array of transportation projects, such as infrastructure changes, connected traffic signals, and traffic management projects.

The remainder of the paper is organized as follows. In Section 2, a background of the existing transportation frameworks is provided. The design of our framework and indicators are presented in Section 3; the study methods, results, and interpretation is elucidated in Section 4. Finally, the conclusions are discussed in Section 5, along with possible directions for future work.

3.2 Literature Review

Traffic Routing in Cities

There has been much previous work in the area of transportation modeling, and traffic route choices [44, 81, 115]. Understanding the distribution of traffic on local road networks gained popularity in the past decade with route guidance systems rerouting traffic differently than before [3, 7, 77]. Most route guidance systems aim to provide a user with the least travel time route [69]. This might mean taking people off the highway to local streets to save a few minutes of travel time [52]. Some services provide routes to users that minimize fuel consumption. This could mean traveling at a consistent speed and thus preferring certain roads that maintain that speed limit [8, 4]. Studies evaluating the impacts of navigation systems model app-based and non-app-based users differently to understand the resulting congestion patterns [62, 21]. Most of them model a corridor or a small network with varying percentages of app users to show the increase in congestion as app users increase by using metrics like traffic flow, distance, and average marginal regret. Ahmed and Hesham modeled eco-routing as a feedback user equilibrium model for downtown LA and measured the outcome in terms of fuel consumption and congestion levels [37]. It could be seen from the previous studies that different strategies have different impacts across the city network in terms of time and distance. However, no previous studies have explored the impacts of routing holistically on multiple city dimensions other than time, distance, or fuel.

Evaluation Frameworks in Transportation

We conducted an extensive review of transportation literature to identify frameworks or indicators that can be used to assess the impacts of traffic routing strategies on cities. Due to the lack of specific frameworks designed for routing, we reviewed the general frameworks in the transportation domain and assessed their usability for routing impact evaluation. European Commission's CITYkeys framework developed a set of city performance measures at the city level, and project level [5]. The framework was focused on five major themes: people, planet, prosperity, governance, and propagation. Out of the 116 key performance indicators, the ones concerning transportation were in car waiting time, reduction in traffic accidents, quality of public transportation, improved access to vehicle sharing solutions, extended bike route network, reduced exposure to noise pollution, and reduction in annual energy consumption. HASTA framework measures sustainability for a transportation project based on three economic, environmental, and social dimensions and six sustainability indicator groups for Swedish cities [58]. They came up with a total of 83 indicators. Additionally, considerable work is ongoing through the International Standards Organization (ISO), European Committee for Standardization, and BSI to establish proper standards in smart urban development project evaluation. ISO 37122:2019 provides a framework for a resilient city with 19 themes and multiple indicators for each theme. The transportation theme has 14 indicators, primarily focusing on real-time technology, electric fleet, and integrated payment systems (ISO 37122:2019). In addition to the frameworks, there is a vast literature on transportation indicators used to evaluate new projects. Specific to smart cities and transportation, Orlowski and Romanowska developed a set of smart mobility indicators that encompass the following domains: technical infrastructure, information infrastructure, mobility methods, and vehicles used for this purpose and legislation with 108 metrics [75]. Benevolo et al. (2016) investigated the role of ICT in supporting smart mobility actions, influencing their impact on the citizens' quality of life, and on the public value created for the city as a whole [15]. They provided an action taxonomy considering three aspects of smart mobility actors aiming to investigate the role of ICT in improving the citizens' quality of life and the public value created for the city as a whole.

Existing frameworks tend to have broader contexts by considering the entirety of transportation infrastructure (for example, transportation infrastructure cost, electric fleet mix, or transit usage) or the entirety of smart cities (for example, technology adoption rate or percentage of smart signals). A few frameworks have reasoned on more complex aspects, such as how different indicators interact reciprocally, what benefits they generate how they affect citizens' quality of life. Moreover, the existing indicators are not specific enough to capture factors related to the impact of routing strategies on cities, such as the share of traffic in neighborhoods or traffic impacts near schools. While the aspects of safety and neighborhood are discussed in some metrics, they are primarily qualitative and subjective. Key challenges are centered on selecting suitable evaluation methodologies to provide urban value and outcomes that address a city's objectives. With this focus, our first contribution is developing a framework with a set of themes and indicators that relate to the impact of traffic routing holistically. In order to properly address the interactions between the different aspects of a city and traffic, a systemic approach is adopted. We identified relevant indicators from the literature, grouped them into relevant themes, and developed new methodologies when needed to calculate these indicators. This comprehensive set of indicators and methods will help understand how routing strategies and the resulting traffic dynamics affect cities and provide a mechanism to recognize the trade-offs involved. A second contribution is the application of our SAEF framework to four cities in the Bay area in the context of three different routing strategies. This helps us understand how city structure and urban form play a role in traffic dynamics. A discussion is provided both from a city level and a cross-city comparison. To the best of our knowledge, this is the first time a multi-theme, holistic evaluation has been used to identify the impacts of vehicle routing strategies for a large-scale network with cross-city comparisons.

3.3 Socially- Aware Evaluation Framework for Transportation

Framework Design

To explore the city level impacts of various routing strategies, we develop a holistic framework called **Socially- Aware Evaluation Framework for Transportation - SAEF**. We define the term 'socially-aware' to include four complementary themes of neighborhood, safety, mobility, and environment that encompass the multitudes of traffic impacts on cities (Figure 3.1). In order to capture socially relevant aspects of these impacts, we create themes and indicators beyond traffic congestion measurement and thus reference our framework as socially-aware. The themes are assembled from a set of city performance indicators grounded in literature [74, 99, 58]. Each theme identifies factors that are likely key concerns for that theme. For example, accidents are a concern when considering safety, similarly, emissions are a concern when considering environmental quality. Based on these factors, we defined indicators/metrics (Figure 3.2) that could be derived from real world or simulated data. These indicators were culled from a thorough review of literature from domestic and international journals, city policies, and international organizations related to transportation. A list of over 100 indicators with a wide range of scale and use was identified. A manageable set of indicators that we assessed as significant and measurable were created for each theme. Identified indicators should also be able to capture the differences in the system when routing strategies are varied. This resulted in 24 indicators: 9 were selected as reflections of neighborhood quality, 6 for safety, 5 for mobility, and 4 for environment quality. This framework can then provide a basis for the following:

- comparing indicators as a function of specific traffic management strategies,
- attaching weights to the metrics that reflect planning objectives,
- stressing the relationship between policy goals and intended city-level impact, and
- monitoring progress towards long-term policy goals.

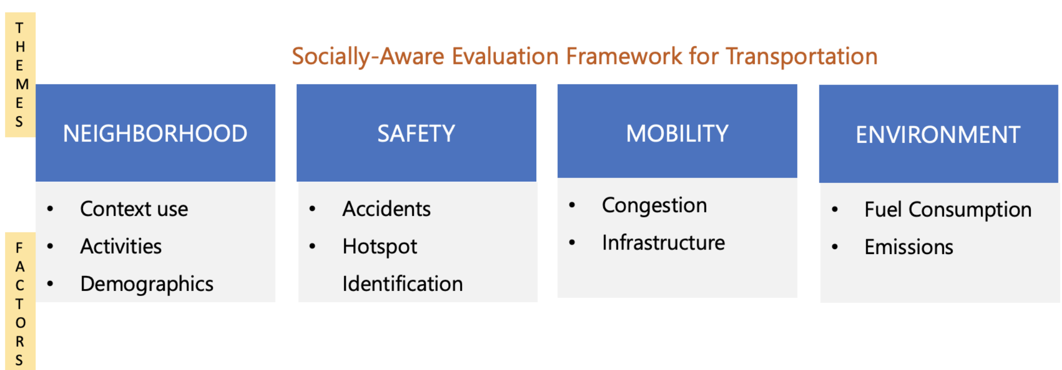


Figure 3.1: Themes in the framework

Operationalizing the Framework

Operationalizing the framework is the key to its usability for city managers. SAEF provides a set of measurable indicators in the context of a broad framework. It provides a mechanism for prioritizing the city's objectives with an understanding of the trade-offs that must be

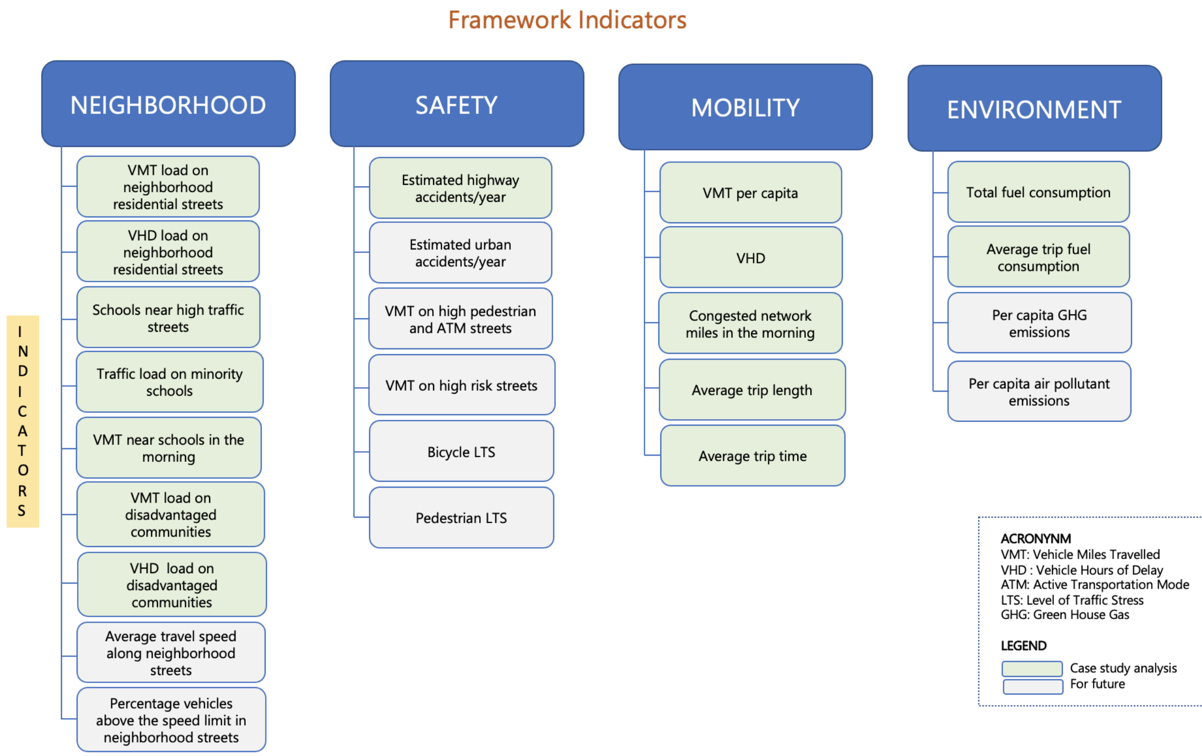


Figure 3.2: Indicators for each theme

made to achieve certain objectives. For example, if a traffic management strategy attempts to reduce fuel consumption, it may result in more vehicles traveling through neighborhoods. City planners can then determine whether the reduced emissions are a higher priority than the likely safety costs of higher traffic flows on neighborhood streets. They can choose specific themes from the framework based on their objectives and values and evaluate them in the context of proposed traffic management strategies.

Each indicator is detailed in Appendix 3.5, including a description, the unit of measurement, and spatial/temporal levels. The indicators are structured in spatial and temporal dimensions. The spatial dimension is partitioned into the individual, community, and city levels (Figure 3.3). There are two temporal dimensions - peak hours or an entire day - based on the indicator relevance. The list of indicators is not intended to be exhaustive. It can be revised as new information becomes accessible.

The following section addresses how to quantify the indicators. Once the indicators are quantified, the decision-makers can weigh them to generate an aggregate score for decision-making. The weighting should reflect the goals of the city and rationalize the values of the indicators. An alternative method is visualizing the indicators in the context of various strategies for comparison.

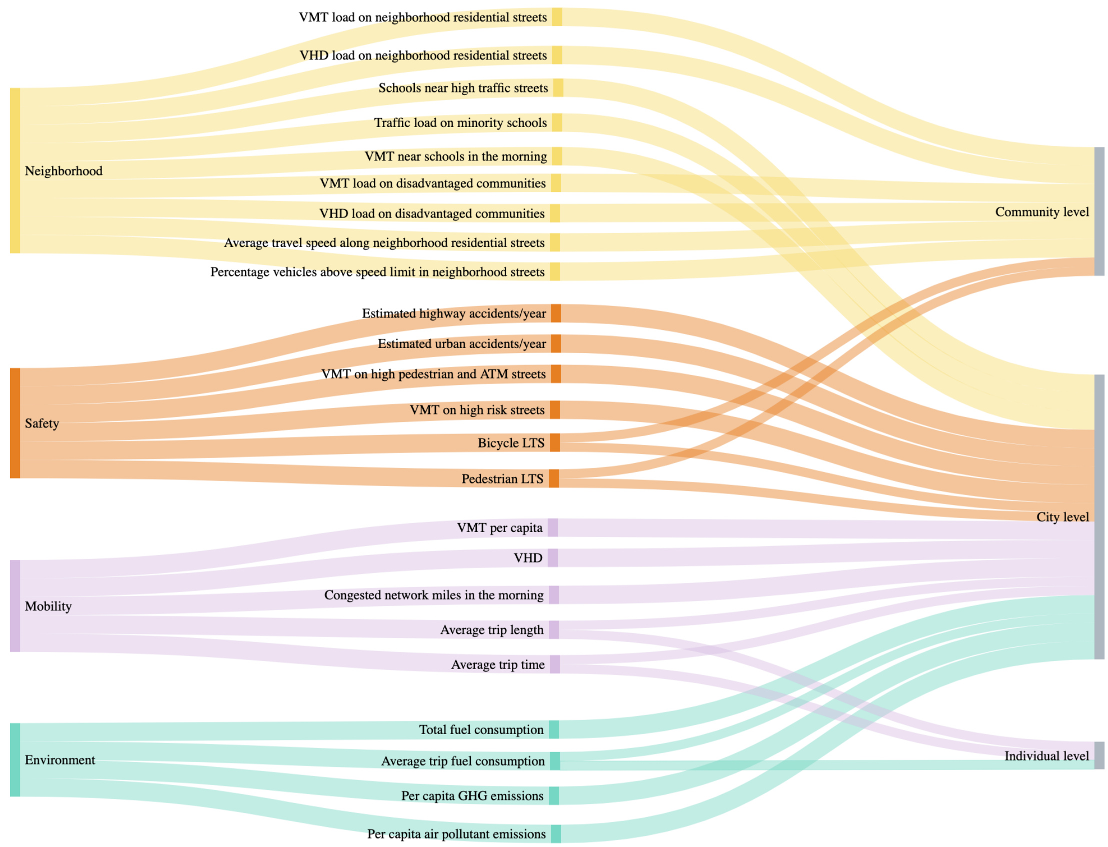


Figure 3.3: SAEF Indicators and their spatial levels.

3.4 Application of the Framework

Traffic Simulation

To evaluate the impacts of various routing strategies, we use the results from an agent-based traffic simulator Mobiliti [26, 25]. Mobiliti is a mesoscopic urban-scale transportation simulation platform that implements parallel discrete event simulation on high-performance computers at Lawrence Berkeley National lab. We employ Mobiliti as it can simulate the entire San Francisco Bay Area in under 15 minutes, allowing us to simulate multiple traffic route optimizations. The transportation network for the Bay Area has over 1 million links and 0.5 million nodes. The trip demand is defined by a travel demand model, which for the Bay Area is the SFCTA CHAMP 6 [87]. Mobiliti provides three optimization methods based on standard traffic assignment algorithms. Specifically, it implements a Quasi-Dynamic Traffic Assignment (QDTA) [27] followed by a discrete event simulation. The main components of the simulator are detailed in Figure 3.4. For a given demand, route choice is generated in the QDTA step based on the seminal Wadrop's principles of user equilibrium or system optimal [105]. The optimization objectives are travel time or fuel (refer to Appendix 3.5 for the specific objective functions). QDTA divides the analysis period into small time steps (15 minutes) and uses a sequence of static traffic assignment steps to obtain an optimized route assignment for each time step. Route truncation and residual demand mechanism are included to address the fact that some trip legs cannot be finished in a single analysis time step and need to be split across multiple steps. The route truncation operation estimates the intermediate stop location a trip can reach within the interval. For long trips, the intermediate stop location may differ from the trip destination, and the remaining leg of the trip will enter the next time step as the residual demand. Determining an intermediate stop relies on knowing each link's travel time (or other general costs), which is a function of the link flow assigned to the network during that time interval. Then network loading is conducted in the simulation step. The outputs of the simulation are flows, speeds, and fuel consumption for every link at 15-minute intervals, in addition to the trip leg metrics like travel time and distance and the routes of every trip.

We studied three optimization scenarios: (1) user equilibrium travel time (UET), (2) system optimal travel time (SOT), and (3) system optimal fuel (SOF). The typical optimization for trip level shortest travel time (UET) is compared against the system optimal strategies. The embedded complexity of transportation networks naturally requires trade-offs when optimizing for different objectives. Our goal with the framework is to provide context for understanding the trade-offs. The results are examined for four cities: San Jose, San Francisco, Oakland, and Concord. These cities were selected to represent different-sized conurbations, relevant to their population and geographical area. Figure 3.5 shows all Bay area cities with the chosen four case study cities highlighted.

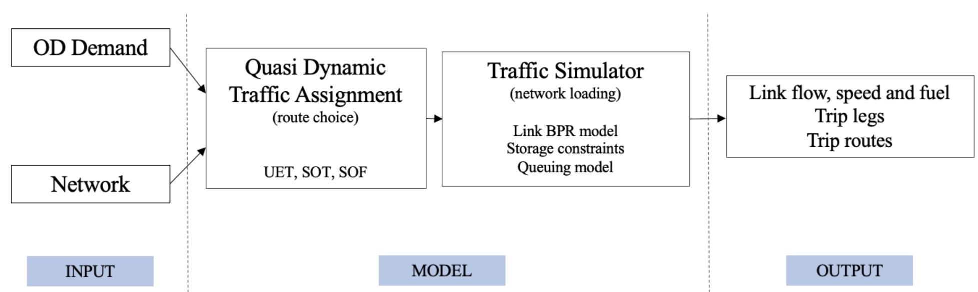


Figure 3.4: Mobiliti simulation framework

Network Typologies

Flow distribution on roads will differ based on how the system is optimized. Hence, understanding traffic flow distribution on road types is relevant for impact elevation. Traditionally,

Table 3.1: Case Study Cities

City	Area (sq.mile)	Population	Population density (person/sq.mile)	Trips per capita
San Jose	185	1,021,795	5,524	3.1
San Francisco	49	874,961	17,847	2.2
Oakland	58	425,097	7,333	2.7
Concord	31	129,183	4,105	3.5

road classification systems are based on mobility, and access for vehicular use [42]. This study seeks to incorporate the local context of streets, including how vehicular traffic dynamics impact localized populations. To this end, we created a road classification scheme based on the principles of USDOT complete street guidelines [31]. Complete streets provide guidelines for the design and operation of streets to enable safe use and support the mobility of all citizens. Adoption of these guidelines is underway in a variety of cities. For example, San Francisco has classified their street based on land use characteristics, transportation roles, and special characteristics (e.g., downtown residential streets, downtown commercial streets, mixed-use streets, etc.). This resulted in 16 classes designed using extensive community surveys and manual labeling. Similarly, San Jose classified streets into eight types based on a street's primary function, and adjacent land use context. Because we wish to compare our indicators across all Bay Area cities, we created an alternative classification scheme based on parcel-level zoning data and street functional classes. This classification scheme, of 8 types, allowed us to then partition and develop improved metrics that will help evaluate the themes of our framework.

Our classification uses the Mobiliti road network, which was derived from a professional map from HERE Technologies [47]. The HERE technologies map includes definitions of five functional class roads defined in Appendix 3.5 Table 3.4. For identifying the transport context, links are classified into three types - highways, throughways, and neighborhood streets. These are based on the functional classification and speeds: highways group higher functional class links of 1, 2, and 3 with speeds greater than 50 mph, throughways group rest of class 3 and 4 links that carry greater volumes and higher speeds of vehicle traffic, and neighborhood streets group class 5 links with lower speeds and volumes. For identifying land use context, we use the parcel level zoning data obtained from Metropolitan Transportation Commission (MTC). There are 1,956,207 parcels in the analysis region grouped into either of the five land uses - residential, commercial, industrial, public-semi public, and others. For each link, the side use is determined based on the zoning of the adjacent parcels. If the link is associated with more than one parcel, the use of the largest parcel is assigned to the link. Based on the transport and land use context for each link, 8 street types are established. This classification composition for Bay Area streets is shown in Figure 3.6. Appendix 3.5 Table 3.5 details the network lengths associated with the classification. While slightly coarser than a more detailed partitioning, the classification does not involve the complexity of surveys

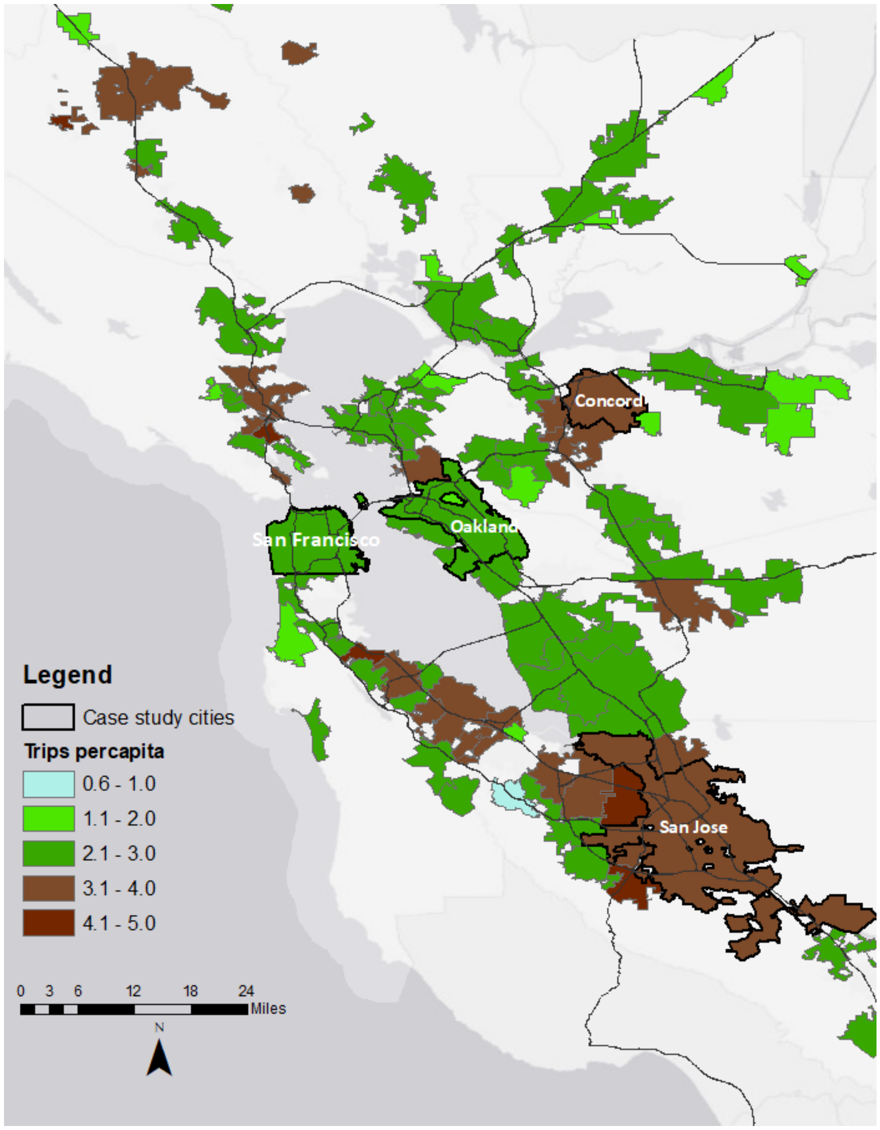


Figure 3.5: Bay area cities colored by percapita trips.

and manual labeling and can still provide a good understanding of the network typologies. Figure 3.7 shows the resulting context based link classification for the four cities of interest.

Methods for Quantifying Indicators

Quantifying the indicators described in the framework can be accomplished by using existing models, developing new models, and accessing city data, e.g., zoning use, numbers of accidents, traffic flow and speeds from highway and city detectors, and locations of schools. For

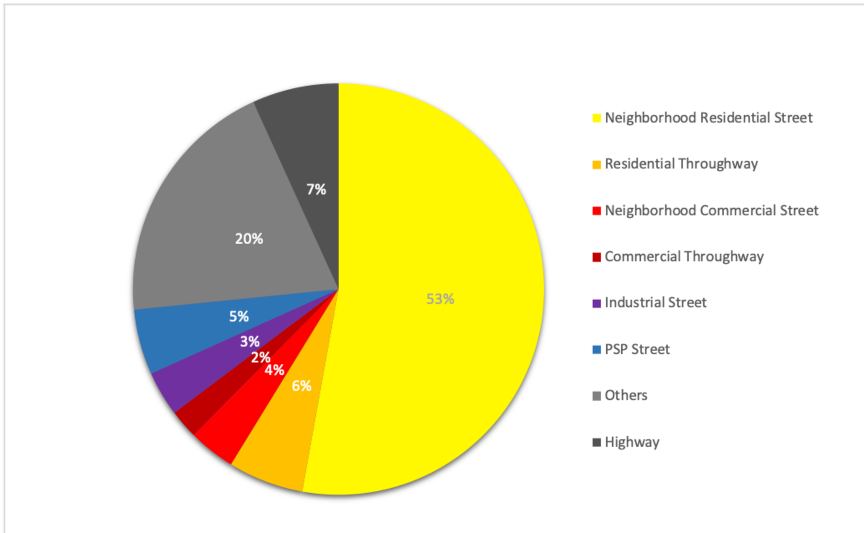


Figure 3.6: Network typologies for Bay Area. Neighborhood residential streets constitute the highest share, followed by highways. Individual cities reflect similar partitioning.

our initial approach, we chose to confine our attention to developing the broad framework discussed in the previous section and examine a subset of indicators. A list of indicators evaluated for our case study cities and their corresponding method for evaluation is provided in Table 3.2. The Mobiliti simulation results for each optimization scenario described in the previous section provided link level and trip level traffic values for our evaluations.

Table 3.2: Methods used to evaluate indicators

Theme	Indicator	Method
Neighborhood	VMT load on neighborhood residential streets, VHD load on neighborhood residential streets	Section 3.4, 3.4
	Schools near high traffic streets, Traffic load on minority schools, VMT near schools in the morning	Section 3.4
	VMT load on disadvantaged communities, VHD load on disadvantaged communities	Section 3.4
Safety	Estimated highway accidents/year	Section 3.4
Mobility	VMT per capita, VHD, Congested network miles in the morning, Average trip length, Average trip time	Section 3.4
Environment	Total fuel consumption, Average trip fuel consumption	Section 3.4

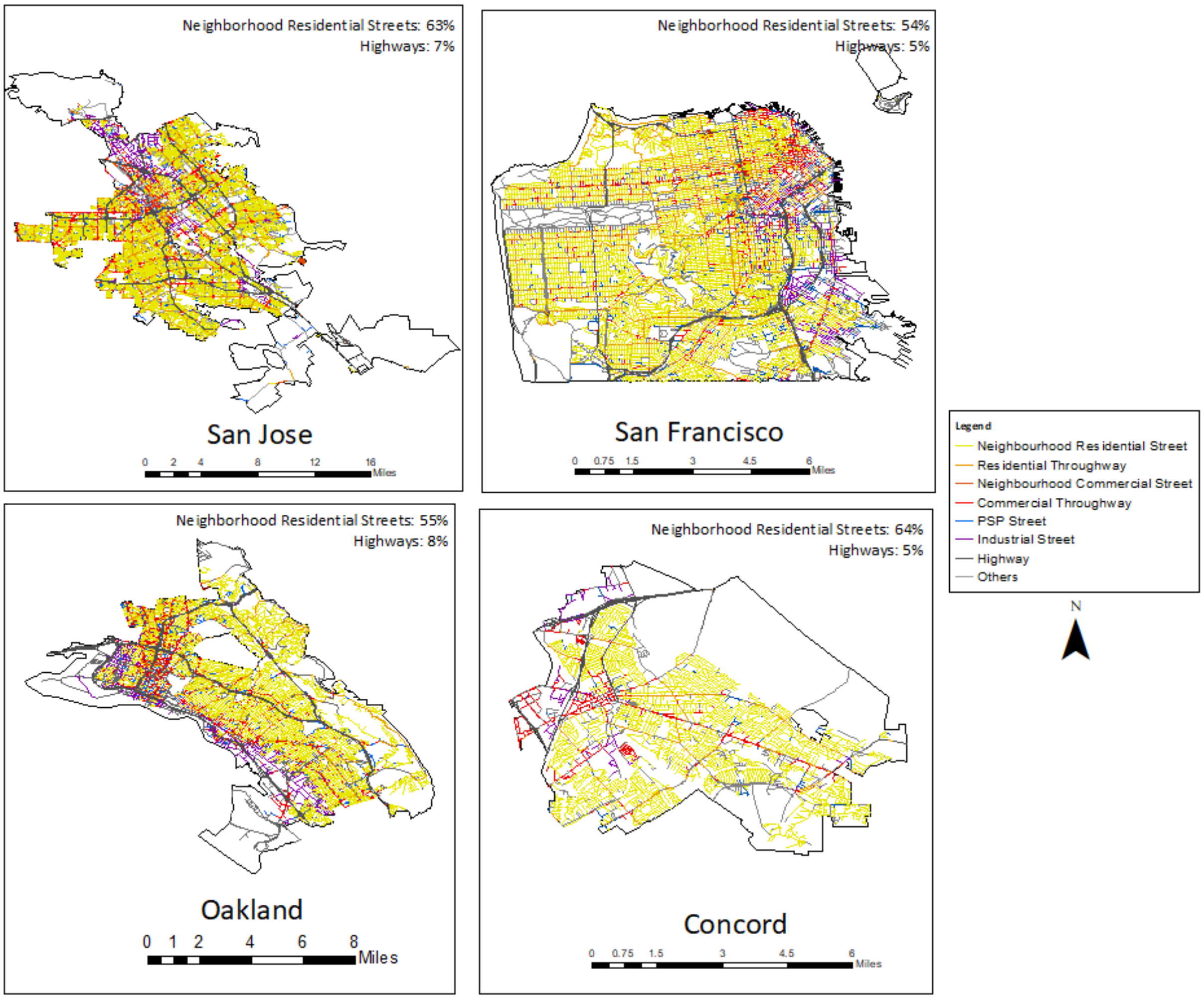


Figure 3.7: Network typologies for Oakland, San Jose, San Francisco, and Concord. Oakland has the highest percentage of highways, and Concord has the highest percentage of neighborhood residential streets.

Neighborhood Indicators

VMT and VHD load are the metrics used to evaluate the effect of traffic routing on neighborhood residential streets. After identifying the neighborhood typology described in the previous section, we calculate the VMT or VHD load as a proportion of VMT or VHD on the neighborhood residential streets divided by the proportion of network in neighborhood residential streets.

Impact near schools is another indicator of the neighborhood theme. Exposure to traffic-related air pollutants has been associated with various adverse long-term and short-term health effects. Long term traffic-related air pollution can cause breathing and mental health problems, and in the short term, increased traffic flow near schools pose accident risk and congestion around schools. Previous studies have demonstrated that it is preferable to locate schools in areas with higher percentages of local roads in order to reduce exposure to air pollutants [112]. However, vehicle route optimizations may have diverted traffic to local roads and inadvertently changed the predicted exposure levels. We examine these impacts by a) identifying high and medium-traffic flow links around schools and b) estimating the increased vehicular traffic during morning school hours. We further examine the load borne by minority schools in traffic exposure.

School data on the location and characteristics of 1849 public schools in the Bay Area, grades pre-kindergarten through 12, was obtained from Elementary/Secondary Information System (ElSi), which is a web application of the National Centre for Education Statistics (NCES) using data from the Common Core of Data (CCD) for the year 2018-2019. We evaluated roads within a 250m radius of each school [56]. Studies suggest that Average Daily Traffic (ADT) greater than 50,000 creates high exposure to traffic emissions, and between 25,000 to 50,000 is considered medium exposure [43, 107]. For all links in the buffer of each school, ADT counts were calculated to determine if these thresholds were exceeded. In addition, we identify the effects of increased traffic flow during the morning 7-8 am hours when children are likely to be present by calculating the vehicle miles traveled (VMT) for the same links in the 250m buffer. To identify the impact on minority schools, we classified the schools by socio-economic indicators. A school is defined as a minority school if the majority (75% or higher) of students in the school belong to a minority race (Black, Hispanic, Asian/Pacific Islander, or American Indian/Alaska Native). The traffic load on minority schools is calculated as the proportion of minority schools impacted by traffic divided by the proportion of minority schools in a city.

Disadvantaged communities often bear disproportionate impacts of traffic exposure. We quantify these impacts using the VMT and VHD load on these communities. To evaluate this, we identify disadvantaged communities from the Metropolitan Transportation Commission's (MTC) communities of concern classification from 2020. MTC's Communities of Concern (COC) is based on 2014 - 2018 American Community Survey (ACS) 5-year tract-level data. The COC definition is based on eight disadvantage factors and respective thresholds. The factors are the minority, low income, limited English proficiency, zero vehicle households, senior citizens, people with disability, single-parent families, and severely rent-burdened households. All census tracts with concern classes categorized as high, higher, and highest are considered part of our disadvantaged group (Figure 3.8). We then calculated the VMT and VHD load on disadvantaged communities, similar to the neighborhood residential street load equation. The VMT/VHD load on disadvantaged communities is defined as a ratio of the proportion of VMT/VHD on streets in the disadvantaged communities to the proportion of network miles in these disadvantaged communities.

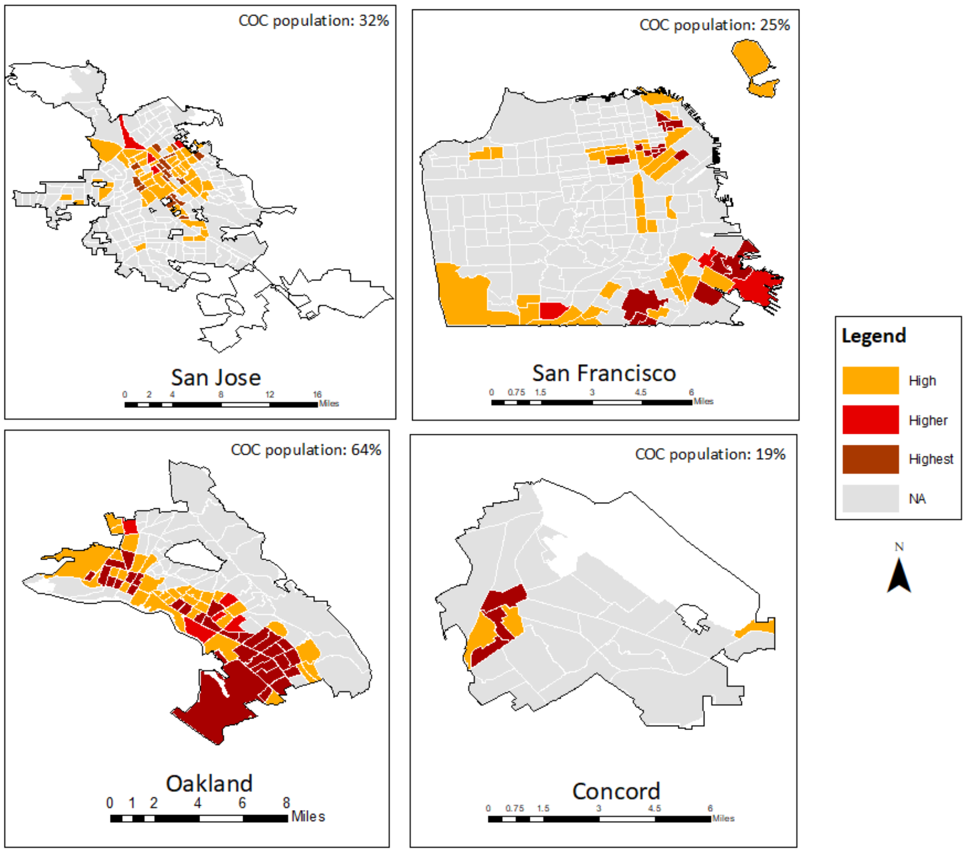


Figure 3.8: Theme Neighborhood: Communities of Concern census tracts in the case study cities. Oakland has the highest percentage of population living in these census tracts and Concord the least.

Safety Indicators

Estimating the accidents for highways and local roads is based on factors like traffic flow, road geometry, and road type [83]. For the state of California, Caltrans has developed safety performance functions (SPF) to estimate the occurrence of accidents on highways [89]. The safety performance function calculates the estimated number of accidents per year on a road segment as a function of average daily traffic (ADT) and the length of the road. We use the Type 1 SPF, which is specified as:

$$\lambda_i = \alpha + ln(length)_i + \beta ln(ADT)_i \tag{3.1}$$

where: λ is the estimated number of accidents per year, ADT is the Average daily traffic. The model parameters estimated using the Caltrans Performance Measurement System (PeMS) data are described in Appendix 3.5.

Estimating urban road accidents is another indicator of the safety theme. However, we did not include this in the subset of indicators evaluated for the case study cities as it requires a detailed urban accident model estimation. Estimating this complex model is out of the scope of this paper. Further, it requires more granular data like road geometric elements, pavement condition variables, and intersection details, which are currently unavailable to us. If the data becomes available, we will incorporate this in future studies.

Mobility and Environment Indicators

Mobility indicators used in the framework include key system performance metrics, e.g., vehicle miles traveled per capita (VMT), vehicle hours of delay (VHD), congested urban VMT, and trip level metrics, e.g., average trip distance and time. VMT is typically a system performance measure reported for overall analysis. It is calculated as the vehicle flow on a link multiplied by the link lengths. VHD is the delay per vehicle for a given segment multiplied by the total number of vehicles. The delay per vehicle is calculated as actual travel time minus the free flow travel time. To calculate the congested network miles, we use the congestion definition as volume over capacity greater than or equal to 1 for a link. For trip level metrics, the average travel distance and the average time are calculated from Mobiliti trip data. For the environment theme, total system fuel consumption and average trip fuel consumption are calculated from Mobiliti link and trip level outputs.

Evaluation Results

Fifteen indicators from the SAEF framework for each city are calculated and compiled using a color chart for visual comparison across the routing optimization scenarios. Since indicators are on different scales, we have used a min-max normalization method to rescale them between [0,1] for effective comparison. Figure 3.9 presents the results for San Jose. The summary table and charts for the other three cities are provided in Appendix 3.5. For added insights, we compare optimization scenarios for each of the indicators. We also compare our four focus cities to identify similarities and differences. For the rest of this section, we will discuss the results for San Jose. For comparison of optimizations, we take UET-optimized routes as our baseline.

City Level Indicator Comparisons

Theme: Neighborhood

a. VMT load increases on neighborhood residential streets with SOT and SOF-derived routes. While the total system VMT reduces with SOT and SOF, the residential VMT load increases for both cases. With SOF-derived routes, the load has doubled on these streets. However, it must be noted that the load value is less than 1 for all three strategies, as neighborhood streets account for the majority of the total network.

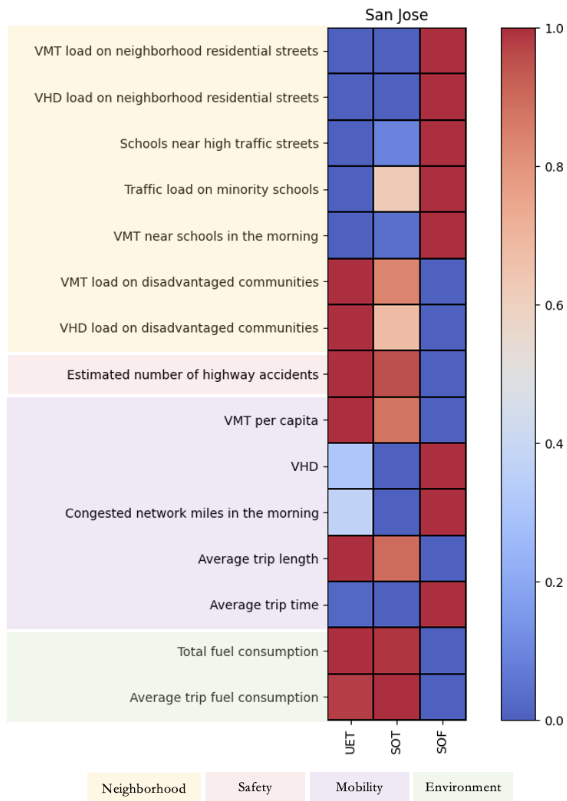


Figure 3.9: SAEF indicators for San Jose. Each metric is normalized to a scale between 0 and 1. Red and blue represent high and low, respectively. For instance, the VHD in the mobility theme is high for SOF and low for SOT.

b. VHD load on neighborhood residential streets decreases with SOT and increases with SOF. However, the share of delay carried by these streets out of the total system delay increases in both SOT and SOF compared to baseline showing both optimizations have attained its goal by routing more vehicles through previously less used streets. In baseline, these streets carry 62 hours of delay as opposed to 41 in SOT and 900 in SOF. Looking at the percentage share of these delays with respect to total, in baseline, it is 0.58% of the total city VHD, which slightly increases with SOT (0.73%) and more than doubles with SOF (4.5%). This increase in system delay with SOF reflects highway delay being decreased significantly.

c. The number of schools exposed to high and medium traffic increases significantly with SOF due to traffic shift to local roads. Exposure to high and medium traffic occurs for 9% of schools in the baseline. This percentage slightly increases with SOT; and doubles with SOF. VMT in the 250m buffer zone of the school also increases with SOT and SOF compared to baseline.

d. Minority schools bear disproportionate impacts of traffic exposure. The traffic load on minority schools is disproportionate (more than one) in San Jose for all routing strategies. The impact is lowest for the baseline UET and highest with SOF routing. While impacting all types of schools, it is estimated to be more prevalent in minority schools. 22% of the schools are categorized as minority schools in San Jose. The proportion of schools affected by this predicted exposure is 41% in the baseline. This percentage increases by at least five percentage points with SOT and SOF.

e. VMT and VHD load on disadvantaged communities is higher than 1 for all routing strategies signifying a disproportionate share of traffic on these streets. Street network in disadvantaged communities in San Jose contributes to 23% of total network miles but carries 36% VMT and 46% VHD with UET. This reflects the tendency of these communities to be located near highways with high flow rates.

f. The trends across the three routing strategies show that the VMT and VHD load in disadvantaged communities reduces with SOT and SOF routing.

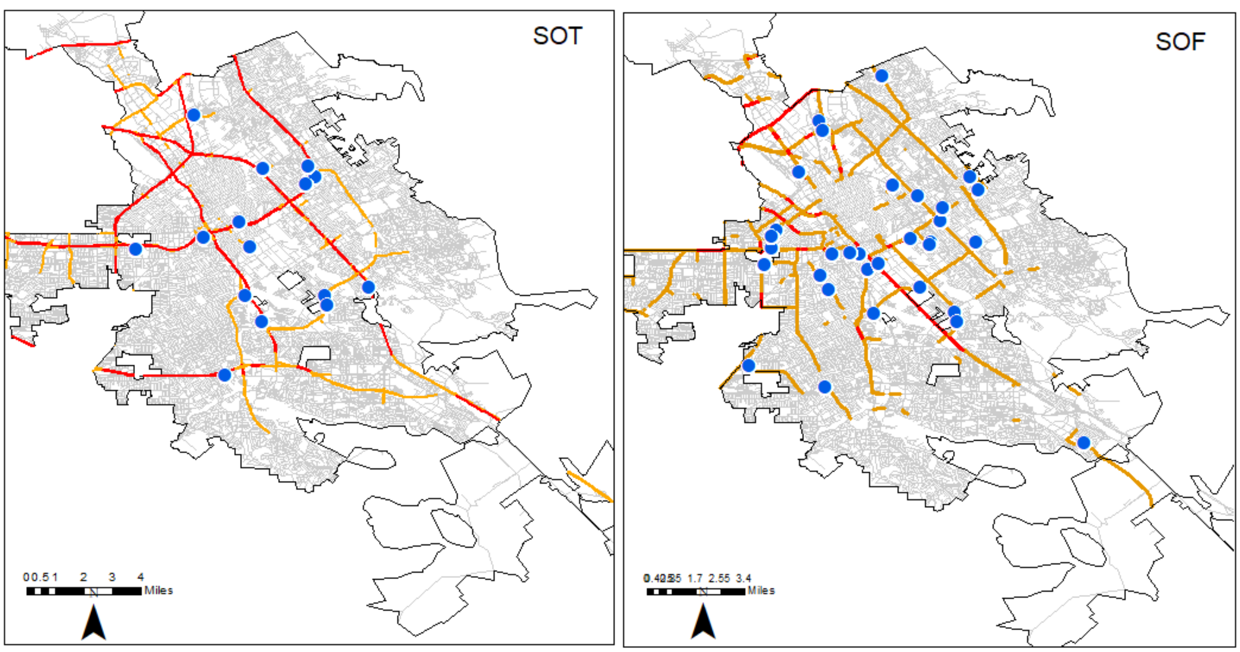


Figure 3.10: Theme Neighborhood: The figure illustrates the schools affected by high and medium traffic volume. Red links have an ADT greater than 50,000 and yellow links have ADT between 25,000 and 50,000.

Theme: Safety

a. Estimated number of highway accidents significantly reduces with SOF, while it remains similar for SOT and baseline. The obvious reason for the large reduction is the shift of highway traffic to local roads with SOF optimization. It will be important to include an estimate of urban accidents, which we aim to add for future analysis.

Theme: Mobility

a. Overall, system VMT per capita decreases with SOT and SOF compared to baseline UET.

b. VHD decreases with SOT and increases with SOF. SOF shifts traffic from highways to local roads in an attempt to save fuel, as seen in Figure 3.11. In SOT, the total system delay reduction happens by rearranging flows from highways to throughways instead of neighborhood streets.

c. Congested network miles in the morning peak decreases with SOT and increases with SOF consistent with delay increase.

d. Average trip length remains similar for all three cases. However, trip time increases with SOF.

Theme: Environment

a. As expected, SOF produced the lowest total system fuel consumption. SOT and baseline values are similar. Average trip fuel also shows similar trends with total system fuel consumption. These indicators are very sensitive to the fuel model used in the Mobiliti simulation, which currently considers only an average speed per link. We plan to improve this model in the future to account for speed variability, which will be necessary for local link modeling.

Comparison Across Cities

Size, structure, land use, and density vary widely across cities. By comparing routing optimizations across cities, similarities and differences can be seen with respect to our framework indicators which are listed below. Figure 3.12 presents the results for all cities and routing strategies using a radar chart.

Key Similarities:

a. For all four cities, the VMT load carried by neighborhood residential streets increases SOF compared to the baseline. The highest increase is for Oakland, followed by San Jose. The same trend can be observed for SOT for all cities, with the exception of Concord.

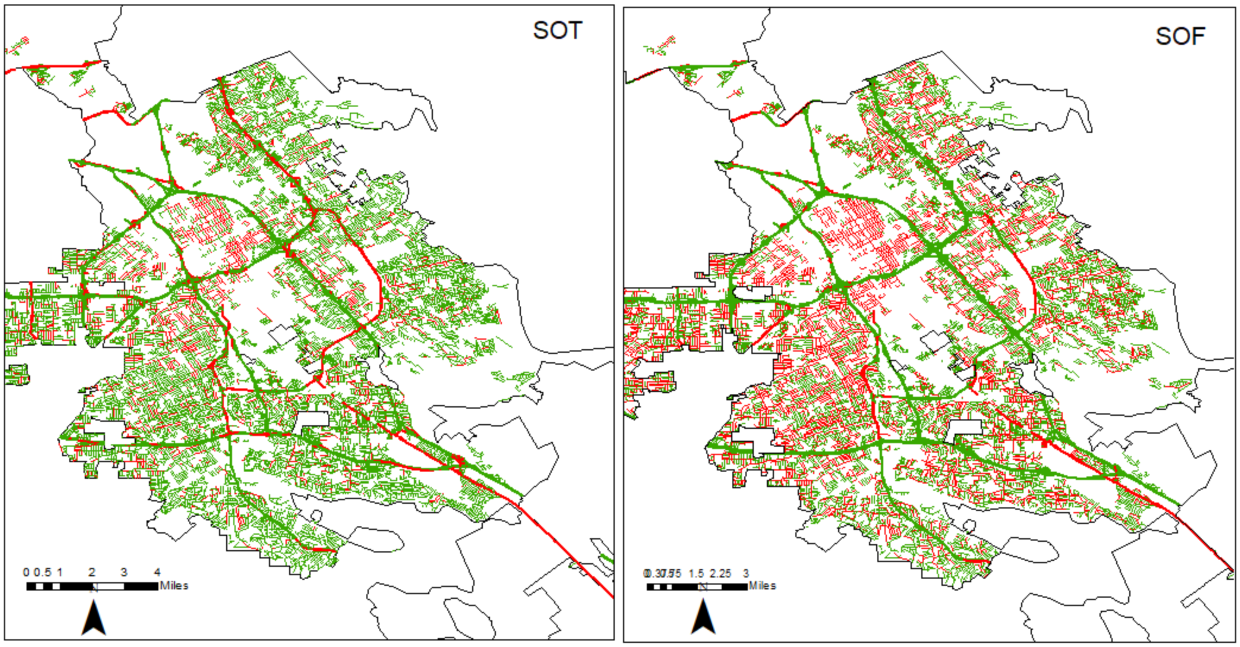


Figure 3.11: Theme Mobility: The figure shows the difference in VMT for SOT (left) and SOF (right) compared to baseline UET for San Jose. The red and green represent the increase and decrease in VMT for each link, respectively. The thickness of the links represents the magnitude of the difference. Only highways and neighborhood residential streets are shown. It can be observed from the map that SOF has shifted traffic from highways to residential streets, as indicated by red.

b. For all cities but San Francisco, VHD load on neighborhood streets remains the same with SOT and increases with SOF. However, the percentage share out of the total system delay increases in both cases for all cities. With SOT, the percentage increase is slight, and with SOF, the delay significantly increases for all cities, with Oakland facing the worst impacts. Neighborhood streets in Oakland are predicted to experience 30 times more delay than baseline. Oakland has higher highway miles within the city limits. With SOF routing traffic to local roads, it does not have as much capacity on its local roads to absorb the traffic and thus would experience high neighborhood residential delays. For Concord, the percentage delay increase is not as high as the other two cities.

c. San Jose and Oakland are predicted to have a higher number of schools exposed to high and medium traffic with SOF compared to baseline.

d. Disadvantaged communities bear a disproportionate share of VMT load in all cities for all routing strategies.

e. In terms of delay load, disadvantaged communities bear a disproportionate share for all cities except Concord.

f. The VMT per capita decreases with SOT and SOF compared to the baseline for all cities.

g. System level VHD is the minimum for SOT for all cities, as expected. Except for San Francisco, VHD increases with SOF for all cities.

Key Differences:

a. For Concord, the VMT load on neighborhood residential streets remains the same for SOT and baseline, while it increases for all other cities. Congestion was very low in the baseline UET case for Concord as such system-level optimization had little effect. This is likely due to the city's spatial spread and low-density character.

b. Concord also differed in the number of schools exposed to high traffic - with no impacted schools in baseline and SOT and one with SOF. The number of affected schools for San Francisco remains similar for all the routing cases. Note that only 24% schools in San Francisco are categorized as a minority, but they account for 47% of the schools exposed to high and medium traffic.

c. For San Francisco, the VHD load on neighborhood streets is low for SOT and high for UET. It is interesting to note that for San Francisco, neighborhood streets get the highest delay load with UET and not SOF, as is the case for other cities. A plausible explanation is that San Francisco has the lowest percentage of neighborhood residential streets in the network, and its gridiron structure may account for the different flow dissipation compared to other cities.

d. San Francisco also differed in the total system VHD. VHD in San Francisco is highest for UET compared to the other two routing strategies.

e. Overall, UET performs worse for San Francisco, while SOF performs worse for all other cities. This difference is likely due to the network characteristics such as street layout, street types, and density.

Our intent with this work is to provide an evaluation framework to enable reflection on the consequence of policies, traffic management strategies, and network changes. With an ability to model out proposed traffic management strategies, the planner can consider the trade-offs and potential unintended consequences. Realizing that there will always be undesirable consequences of a specific strategy due to the complexity and interconnectedness of transportation systems, the planner can develop mediation strategies for the predicted results.

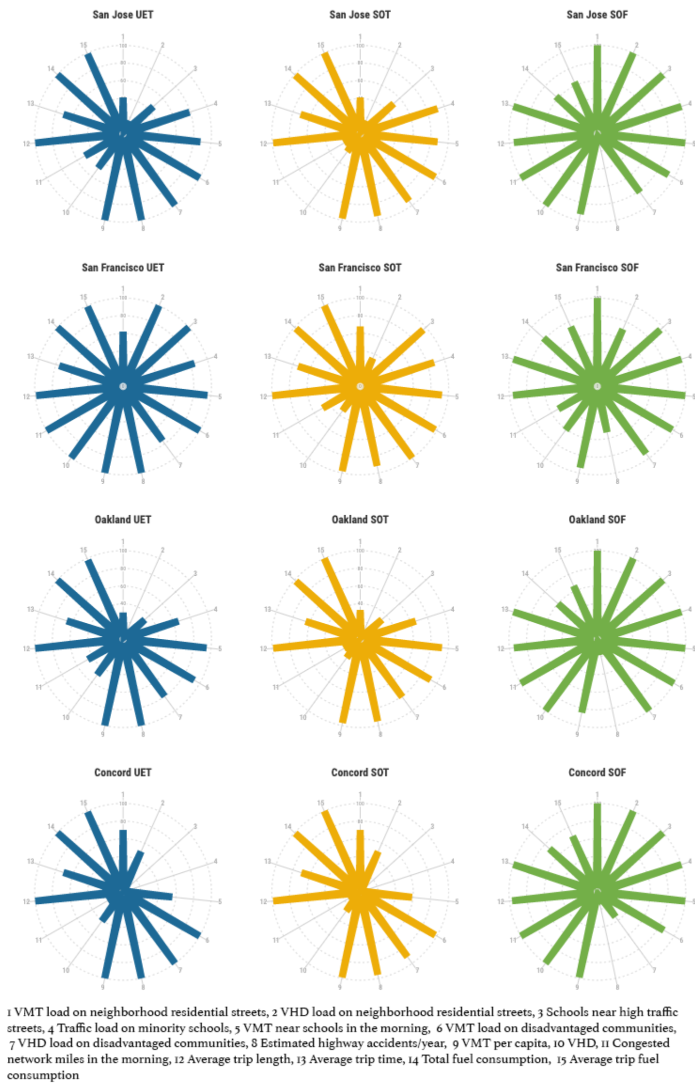


Figure 3.12: The figure compares SAEF metrics across cities for different route optimizations. The metrics are numbered from 1 to 15 on the chart. They are normalized with respect to the maximum values for a city so that the relative differences can be identified. For example, in San Jose, out of the three strategies, SOF has the highest values for metrics 1, 2, 3, 4, 5, 10, 11, and 13. In San Francisco, UET has the highest values for metrics 2, 3, 6, 8, 9, 10, 11, 14, and 15. Overall, the comparison reveals that UET performs worse for San Francisco whereas SOF performs worse for all other cities.

3.5 Conclusion and Future work

We have presented a multi-themed framework to holistically evaluate the impacts of traffic management policies. We specifically focus on routing strategies using our key themes of neighborhood, safety, mobility, and environment. A road network typology classification scheme that allows for the development of improved indicators is presented. Three traffic optimization strategies are evaluated to offer insights into how the resulting routes and consequent traffic dynamics will impact the constituents of a city. Four chosen cities in the Bay Area were assessed for comparison purposes. The results show that while many mobility theme indicators improved with system-optimal time and fuel-based routing strategies, most neighborhood theme indicators degraded. For instance, neighborhood residential streets in cities received higher traffic loads with system-optimal routing strategies. Strategies also differed in their traffic exposure impacts to schools, with minority schools bearing disproportionate impacts in the two cities. The results also highlight that disadvantaged communities bear disproportionate traffic exposure in all routing strategies. On the whole, it can be seen that SOF performs worse for all other cities, whereas UET performs worse for San Francisco.

We showed that the SAEF framework creates an assessment system that will enable cities to evaluate the effects of traffic routing and management strategies. It provides a tool for cities to assess their decisions in a comprehensive manner while recognizing the trade-offs resulting from the traffic dynamics. In future work, we plan to extend our analysis to include more cities and classify them based on their network characteristics to determine if patterns of traffic distribution/dissipation based on network characteristics exist. More importantly, we intend to use the framework to develop aggregate measures of safety and neighborhood that will drive novel socially-aware routing strategies and road network adjustments.

Appendix

SAEF Indicator Description

QDTA Formulations

$$UET : \sum_{a \in A} \int_0^{f_a} c_a(s)\, ds \tag{3.2}$$

$$SOT : \sum_{a \in A} f_a c_a(f_a) \tag{3.3}$$

$$SOF : \sum_{a \in A} f_a m_a(v_a) \tag{3.4}$$

where:

$c_a(f_a) = c_{0,a}(1 + \alpha(f_a C_a)^\beta)$

$c_a(f_a)$ is the travel time on link a; f_a is the traffic flow assigned to link a; $c_{0,a}$ and C_a are

Table 3.3: SAEF Indicator Description

Theme	Indicator	Description	Unit	Spatial level	Temporal level
Neighborhood	VMT load on neighborhood residential streets	It is calculated as the proportion of vehicle miles traveled on neighborhood residential streets to the proportion of the network miles in neighborhood residential streets. City streets need to be classified based on complete streets guidelines to identify neighborhood residential streets based on land use and transport functionalities. A load greater than 1 signifies a disproportionate impact.	Ratio	Community	Entire day/Peak hours
Neighborhood	VHD load on neighborhood residential streets	It is calculated as the proportion of vehicle hours of delay on neighborhood residential streets to the proportion of the network miles in neighborhood residential streets. City streets need to be classified based on complete streets guidelines to identify neighborhood residential streets based on land use and transport functionalities. A load greater than 1 signifies a disproportionate impact.	Ratio	Community	Entire day/Peak hours
Neighborhood	Schools near high-traffic streets	Streets with average daily traffic (ADT) greater than 50,000 and 25,000 are considered high-traffic streets and medium-traffic streets, respectively. All roads within 250 m of the school vicinity is considered for this analysis.	Number	City	Entire day
Neighborhood	Traffic load on minority schools	The traffic load on minority schools is calculated as the proportion of minority schools impacted by traffic to the proportion of minority schools in the city. Minority schools are identified based on the demographic characteristics of the children in the school.	Ratio	City	Entire day
Neighborhood	VMT near schools in the morning	Vehicle miles traveled in the 250-meter vicinity of schools. VMT is calculated for 7-8 am. This indicator helps in understanding the difference in traffic flow around schools for various routing strategies.	Miles	City	Peak hours
Neighborhood	VMT load on disadvantaged communities	It is calculated as the proportion of vehicle miles traveled on the streets in the disadvantaged communities to the proportion of the network miles in disadvantaged communities. Disadvantaged communities can be identified based on city's definition.	Ratio	Community	Entire day
Neighborhood	VHD load on disadvantaged communities	It is calculated as the proportion of vehicle hours of delay on the streets in the disadvantaged communities to the proportion of the network miles in disadvantaged communities. Disadvantaged communities can be identified based on city's definition.	Ratio	Community	Entire day
Neighborhood	Average travel speed on neighborhood residential streets	Average travel speed on neighborhood residential streets can be calculated for morning or evening peaks. This will give an estimate of how the traffic moves in neighborhoods.	Miles per hour	Community	Entire day/Peak hours

Theme	Indicator	Description	Unit	Spatial level	Temporal level
Neighborhood	Percentage of vehicles traveling above the speed limit in neighborhood streets	Percentage of vehicles traveling above the posted speed limit at different times of the day indicates how traffic flow affects the quality of life in neighborhoods.	Percentage	Community	Peak hours
Safety	Estimated highway accidents/year	Highway accidents estimated based on traffic volume and road geometry. Safety performance functions for highways can be used.	Number	City	Entire day
Safety	Estimated urban accidents/year	Urban accidents estimated from traffic volume, road geometry and other factors. Standard methods from the literature can be adopted.	Number	City	Entire day
Safety	VMT on high pedestrian and ATM streets	Vehicle miles traveled on streets with high active transport mode users and pedestrians. It measures the multi modal safety of roads. Routing strategies that increases VMT on these roads hinders others active users of the road.	Miles	City	Entire day/Peak hours
Safety	VMT on high risk streets	High risk roads are roads with hot spots and steep slopes and turns which can be dangerous when unknown drivers are routed through them.	Miles	City	Entire day/Peak hours
Mobility	Bicycle level of traffic (LTS)	Bicycle LTS rating can be given to road segments based on the type of facility, traffic volume and speed. Standard methods from literature can be adopted.		City/ Community	Peak hours
Mobility	Pedestrian level of traffic (LTS)	Pedestrian LTS rating can be given to road segments based on the type of facility, traffic volume and speed. Standard methods from the literature can be adopted.		City/ Community	Peak hours
Mobility	VMT per capita	Total miles traveled by all vehicles in the system divided by the city's population.	Miles per capita	City	Entire day
Mobility	VHD	Total hours of delay incurred by all vehicles in the system. It is computed by subtracting the estimated vehicle hours traveled if all travel demand was at free-flow speed.	Hours	City	Entire day
Mobility	Congested network miles in the morning	Congested miles are roads with volume over capacity greater than or equal to 1 during morning hours. This measures the congested network for each routing strategy. The spatial spread of congestion might be good to visualize as well.	Miles	City	Peak hours
Mobility	Average trip length	Average trip length for a city. It can be segregated into work and nonwork trips.	Miles	Individual/ City	Entire day
Mobility	Average trip time	Average trip time for a city. It can be segregated into work and nonwork trips .	Minutes	Individual/ City	Entire day
Environment	Total fuel consumption	Total fuel consumption by all vehicles in the system.	Litres	City	Entire day
Environment	Average trip fuel consumption	Average fuel consumption per trip.	Litres	Individual/ City	Entire day

Theme	**Indicator**	**Description**	**Unit**	**Spatial level**	**Temporal level**
Environment	Per capita GHG emissions	GHG emissions per person in a city. Methods to calculate emissions from vehicular traffic can be adopted from the literature.	CO2e	City	Entire day
Environment	Per capita air pollutant emissions	Air pollutant emissions per person in a city. Methods to calculate emissions from vehicular traffic can be adopted from the literature.	Micrograms per cubic metre	City	Entire day

the free-flow travel time and capacity associated with the link; α and β selected are BPR parameters 0.15 and 4 respectively.

$m_a(v_a) = l_a(A + \frac{B}{v_a} + Cv_a^2)$

$m_a(v_a)$ is the fuel consumption on link a; l_a is the length of link a; v_a is the link traversal speed calculated from BPR (Bureau of Public Roads); A, B, C are parameters estimated from Argonne National Laboratory drive cycle data $A = -0.00654170, B = 1.902150, C = 0.00001588$.

Bay Area Network

Bay Area network functional classification is provided in Table 3.4 and the network typologies are provided in Table 3.5

Table 3.4: Functional Road Classes

Functional Class	Definition
1	Allowing for high volume, maximum speed traffic movement
2	Allowing for high volume, high speed traffic movement
3	Providing a high volume of traffic movement
4	Providing for a high volume of traffic movement at moderate speeds between neighbourhoods
5	Roads whose volume and traffic movement are below the level of any other functional class

SPF Parameters Used for California Highways

The safety performance function parameters estimated using Caltrans Performance Measurement System (PeMS) data for the state of California is provided in Table 3.6 [89].

Table 3.5: Network Typologies for Bay Area

Sl No	Street Type	Length (thousand miles)	Remarks
1	Neighborhood Residential Street	26	Neighborhood streets with adjoining residential land use
2	Residential Throughway	2.9	Throughway streets with adjoining residential land use
3	Neighborhood Commercial Street	1.8	Neighborhood streets with adjoining commercial land use
4	Commercial Throughway	1.1	Throughway streets with adjoining commercial land use
5	Industrial Street	1.7	Neighbourhood or Throughway streets with adjoining industrial land use
6	PSP Street	2.5	Neighbourhood or Throughway streets with adjoining public and semi public land use
7	Highway	3.4	Highways including ramps
8	Others	9.9	Includes streets with adjoining land use as green spaces, undeveloped land,parking lots, water bodies etc.

Table 3.6: SPF Parameters for California Highways

Number of lanes	alpha	beta
1	-7.09	0.98
2	-7.09	0.98
3	-7.09	0.98
4	-5.78	0.82
5	-6.49	0.89
6	-6.49	0.89
7	-6.49	0.89
8	-10.75	1.24

Summary of Results

Summary of results is provided in Table 3.7 for the case study cities. Figure3.13 shows the SAEF charts for the three cities.

Table 3.7: Summary of Results: SAEF for case study cities

1*Indicator	San Jose			San Francisco			Oakland			Concord		
	UET	SOT	SOF	UET	SOT	SOF	UET	SOT	SOF	UET	SOT	SOF
VMT load on neighborhood residential streets	0.07	0.08	0.17	0.22	0.24	0.35	0.09	0.1	0.3	0.07	0.07	0.1
VHD load on neighborhood residential streets	0.01	0.01	0.06	0.14	0.05	0.1	0.01	0.01	0.09	0.01	0.01	0.02
Schools near high traffic streets	19	21	41	32	31	31	17	17	51	0	0	1
Traffic load on minority schools	1.66	1.93	2.09	1.96	2.03	2.3	0.86	0.86	1.3	0	0	2.55
VMT near schools in morning hours	109,467	111,090	130,674	112,712	113,790	127,388	3,263	3,430	6,557	110,035	110,617	125,779
VMT load on disadvantaged communities	1.55	1.53	1.45	1.31	1.30	1.29	1.18	1.18	1.27	1.62	1.60	1.41
VHD load on disadvantaged communities	2.00	1.89	1.66	1.21	1.59	1.50	1.13	1.14	1.40	1.28	1.175	0.45
Estimated number of highway accidents/year	4,793	4,582	170	3,002	2,869	608	537	516	36	1,519	1,453	887
VMT per capita	18.57	18.35	16.78	11.22	11.08	10.63 23.57	22.94	20.2517.74	17.65	17.71		
VHD	10,770	5,639	19,651	7,617	4,714	14,616	565	384	1,167	17,355	7,584	12,917
Congested network miles in the morning	43	17	85	20	10	33	1	1	5	21	10	14
Average trip length (miles)	8	7	8	9	9	9	9	9	9	7	7	7
Average trip time (minutes)	10	11	17	12	11	17	11	11	16	11	11	14
Total fuel consumption (litres)	3,520,859	3,519,303	2,267,914	1,700,216	1,683,629	1,049,879	405,936	404,637	294,039	1,295,692	1,294,413	1,081,003
Average trip fuel consumption (litres)	2	1	1	2	2	1	2	2	1	1	1	1

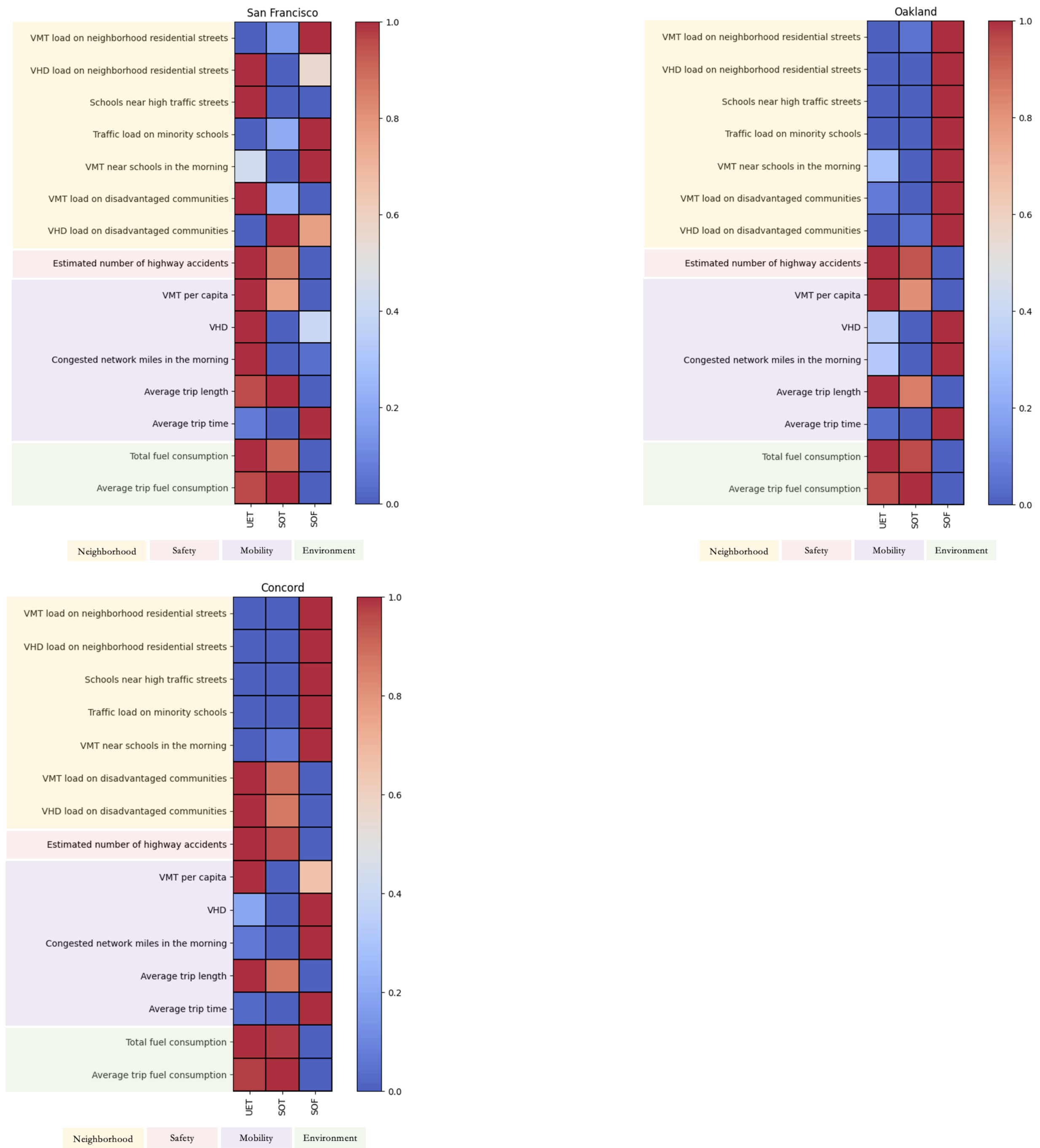


Figure 3.13: SAEF results for San Francisco, Oakland, and Concord

Chapter 4

Evaluating the Impact of Major Transportation Disruptions - San Francisco Bay Area Case Study

Abstract

The constraints of transportation networks are fundamental to disaster planning. Having the capability to evaluate the emergent dynamics of such networks in the context of large traffic incidents can inform the design of traffic management strategies. On February 7, 2019, the Richmond-San Rafael Bridge in the San Francisco Bay Area, connecting multiple cities and carrying over 100,000 vehicles daily, had to be suddenly closed for over 9 hours due to a structural failure of its upper deck. This incident caused major disruptions in the region as the typical traffic was interrupted and detoured as travelers found alternate routes.

In this study, we demonstrate the capability of large-scale traffic impact assessments of major network disruptions using the Richmond-San Rafael Bridge closure as a case study. Using a high-performance, parallel-discrete event traffic simulation, we evaluate the traffic impacts from the bridge closure at the regional system level and the city level. Our model estimates the region incurred an additional 14,000 vehicle hours of delay and 600,000 vehicle miles in the distance due to the bridge closure. The incident impacted over 55,000 trips; some trips saw an increase of 46 minutes in delay and 26 miles in trip distance. The median traffic volume on neighborhood streets in San Francisco, Vallejo, and San Rafael increased by 30%, 22%, and 13%, respectively. The results suggest that the cities' local roads provided the additional adaptive capacity to disperse the traffic. With large-scale modeling of a critical network disruption using dynamic rerouting capability, complete road network, and full demand, we provide valuable insights into the response dynamics of this specific event. In doing so, demonstrate the value of such regional analyses to incident and disaster planning.

4.1 Introduction

With the increasing occurrence of natural and man-made disasters in urban environments, understanding the impacts of major disruptive events is extremely important for evaluating a city's resilience. Transportation networks in cities are fundamental to disaster planning as they may either be part or the entirety of the event (e.g., bridge collapse); they may reflect the dramatic reactions to the event (e.g., major congestion in a hurricane evacuation); or it may play a part in the management of the event (e.g., using both directions of a highway to increase traffic flow out of the path of a hurricane). As such, evaluating the dynamics of transportation networks in the context of events can inform disaster plans and aid in traffic management strategies in preparation for or during an event.

Existing research on road network disruptions typically employs short-term, small-scale network models. Large-scale urban simulation models have been primarily absent in disaster management literature and practice due to their computational challenges. Instead, small-scale micro-simulation models are commonly used to design a deployable response plan, such as modifying signal timings and ramp metering plans, for a few highways and major arterials in the vicinity of the incident [72].

An example of a major event is the closure of the Richmond-San Rafael Bridge, a prominent East-West roadway link across the San Francisco Bay Area. On February 7, 2019, the Richmond-San Rafael Bridge had to be suddenly closed for over 9 hours due to a structural failure of the upper bridge deck. This double-deck bridge, officially named the John F. McCarthy Memorial Bridge, typically carries over 100,000 vehicles daily. The unplanned closure from 10:30 am to 8:00 pm caused significant disruptions to traffic flows across the region as commuters and other travelers had to find alternate routes [97]. Evaluating the traffic impacts of this significant network disruption requires large-scale regional analysis as the bridge is a critical part of the cross-bay transportation network connecting multiple cities (Figure 4.1), and serves as a significant commuter and truck route.

In this paper, we demonstrate the capability of large-scale traffic impact assessments of major network disruptions using the Richmond-San Rafael Bridge closure as a case study. We use a large-scale parallel-discrete event simulation platform, Mobiliti [25, 27]. The Mobiliti platform, which runs on high-performance computing at Lawrence Berkeley National Laboratory, provides the computational capability to simulate traffic conditions in large metropolitan areas in a matter of minutes. It is a mesoscopic simulation model that also includes micro-level simulation dynamics needed to replicate actual traffic conditions, e.g., queuing and queue spillback at intersections. In contrast to previous work that uses equilibrium-based solutions, we model the dynamic routing of individual vehicles, similar to routing adjustments provided by in-vehicle or mobile navigation applications. Instead of modeling a few links surrounding the bridge closure, we model a complete road network (including arterials and local roads) in the San Francisco Bay Area region. We validated the simulated results using real-world fixed sensor data and global positioning system device data from the closure day. We assessed the traffic impacts resulting from the bridge closure at both the regional system and city levels. While the system-level impact evaluation provides a way to quantify the traffic impact on the entire region using aggregate metrics, the city-level assessment enables us to understand which cities and local streets were most affected by the detoured traffic. Because the bridge closure was unplanned and short-term, we used a fixed origin-destination-time (ODT) trip matrix in the study. However, we conducted a sensitivity analysis to assess the potential impact of trip cancellations and departure time shifts, recognizing that even a short-term closure can lead to behavioral changes.

The associated analytics at the regional and city levels reveals how the transportation system could perform when a significant network disruption occurs. Through the large-scale modeling of a significant network disruption using dynamic rerouting capability and a complete road network, we provide valuable insights into the response dynamics of this specific event. The ability to model and evaluate traffic impacts at a regional scale will help cities and transportation organizations analyze different scenarios and predict the potential impacts of future incidents. As climate change continues to exacerbate wildfires in California, and aging infrastructure makes network disruptions more likely, this information could prove critically important to evacuation and network design strategies.

The subsequent sections of this paper are structured as follows. Section 2 presents a comprehensive overview of previous studies on network disruption. In Section 3, we detail the experimental design and simulation components. Section 4 discusses the findings from the network impact analysis and demand sensitivity analysis. Finally, the conclusions are discussed in Section 5.

4.2 Literature Review

Road network disruptions can be categorized into four types based on anticipation and time duration, as shown in Table 4.1. Planned short-term incidents, such as road lane closures for construction, have lesser impacts than unplanned long-term incidents like a bridge collapse,which have long-lasting effects on traffic dynamics and driver behavior (Zhu et al., 2010) The incident in our study falls into the short term unplanned disruption.

Table 4.1: Types of road network disruptions

Anticipation	**Time horizon**	**Example**
Unplanned	Short term	Bridge closure for a day
Unplanned	Long term	Bridge collapse
Planned	Short term	Road closure for construction
Planned	Long term	Decommissioning of a highway

Road network traffic flow patterns are modeled using a variety of mathematical and simulation-based methods. The traffic assignment models formulated by [90] are classical mathematical models with many extended versions considering different problem assumptions and settings. With regards to network disruption modeling, several studies have used the user equilibrium principle [105] for traffic assignment. These models assume travelers

Table 4.2: Traffic impact studies on bridge closure

Impacted Bridge		Richmond Bridge, California, USA	Macdonald Bridge, Halifax, Canada	I-35 Mississippi Bridge, Minnesota, USA	Stony Plain Road Bridge, Alberta, Canada
Authors (Year)		This paper	[6]	[109]	[111]
Event Type		Short term 9 hour closure, Unplanned	Short term 4 hour closure, Planned	Long term full collapse, Unplanned	Long term 4 month closure, Planned
Modeling Approach		HPC agent-based parallel discrete event mesoscopic simulation, Mobiliti	Micro simulation, VISSIM	Minneapolis-Minnesota Twin Cities travel demand model, SONG 2.0	Micro simulation, Dynameq
Demand Response	**Route Choice**	Dynamic routing with 60% penetration rate	Dynamic User Equilibrium	Stochastic User Equilibrium	Dynamic User Equilibrium
	Departure Time Change	• 60 min shift • 120 min shift	-	-	-
	Trip Volume	• Fixed ODT demand of 5 million trips • 5% reduction • 15% reduction	• Fixed ODT demand of 1275 trips	• Fixed ODT auto trips (number not specified) • Trip destinations are allowed to vary	• Fixed ODT trips of auto, truck, and transit (number not specified)
Scale of Road Network		135,690 links	613 links	20,380 links	4,085 links
Temporal Coverage		One full day	4 hours morning peak	2 hours morning peak	2 hours evening peak
Evaluation Metrics	**System Level**	Vehicle miles traveled, Vehicle hours delayed, Fuel consumption	Vehicle hours delayed	Vehicle kilometers of travel, Vehicle hours of travel, USD loss per day	Vehicle kilometers traveled, Vehicle delay hours, Average speed, Queue length
	City Level	Miles with increased traffic volumes, Median traffic volume increase, and Congested miles metrics segmented by road types	-	-	-
	Trip Level	Average trip time and trip distance	Average trip delay, Average speed reduction	Average trip length and trip time	-

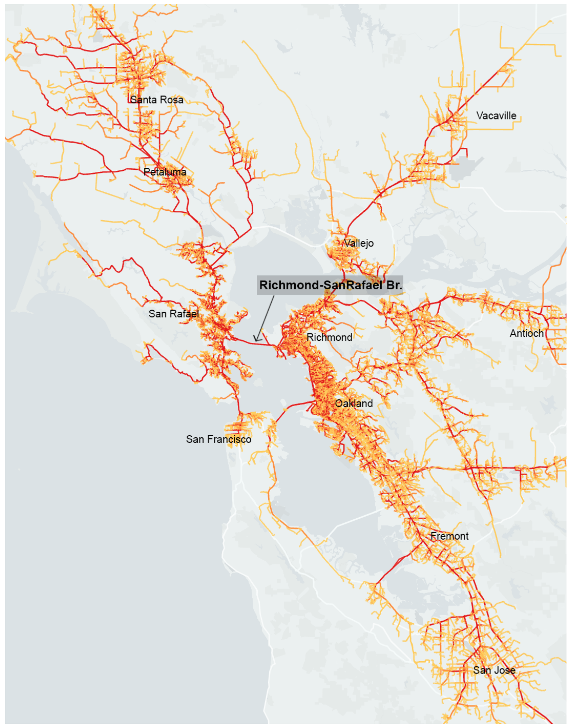


Figure 4.1: Simulated network use by the Richmond-San Rafael bridge users in both directions on a normal day. The links are colored by the number of trips, with red or yellow representing high or low.

have complete information about road conditions after an incident occurs. Other studies have employed a partial user equilibrium model where user behavior is semi-adaptive due to limited information on network conditions [50]. [45] proposed a prediction-correction traffic assignment model that captures day-to-day travel behavior after a disaster, incorporating gradually improving the information on network conditions over time.

Many simulation models also use user equilibrium assumption to model travelers route choice post-disaster (Alam et al., 2017; Xie & Levinson, 2011; Xin et al., 2013). Table 4.2 summarises the recent traffic impact studies of bridge closures using simulation models. These studies' route choice principles include dynamic and stochastic user equilibrium. While equilibrium models have been very popular in the past due to mathematical clarity, their main drawback is the inability to capture the congestion-dependent evolution of a driver's route. Dynamic traffic assignment (DTA) addresses this by capturing the dynamic diffusion of traffic flow under time-varying demands in a stochastic network (Alam et al., 2017; Auld, Verbas, & Stinson, 2019; Shekar et al., 2017). However, DTA approaches typically model converged dynamics adapted to daily congestion patterns, rather than more reactive dynamic rerouting scenarios that explore how traffic can respond to unexpected events. The assumption that people have perfect knowledge of the environment in which they operate is not reasonable in the event of sudden disruptions [40]. This limitation is overcome in simulation models with dynamic routing mechanisms that allow for modeling route guidance dynamics and unexpected events such as incidents or evacuation strategies (Ashfaq et al., 2021; Behrisch, Krajzewicz, & Wang, 2008; Cascetta & Cantarella, 1991; FHWA, 2021; Kim, Oh, & Jayakrishnan, 2009; Rojo, 2020; Xie, Bao, & Chen, 2023). Specific transportation operations applications like major network disruptions and evacuations require non-equilibrium models (Cascetta & Cantarella, 1991; Zhu et al., 2010)

Further, large-scale traffic simulations can often lead to impractical computational requirements, as they involve loading a big travel demand model in the order of millions of trips onto a road network of millions of links and nodes. The most common strategy to overcome this is to a) reduce the analysis region to a small area around the incident and b) reduce the size of the road network to include only highways and major arterials [111, 6]. However, for a major network disruption impacting multiple cities and people, limiting the analysis region will not help capture the full traffic impact of the incident (Ansari Esfeh et al., 2022) Also, reducing the road network can overestimate highway congestion patterns and miss capturing the impacts on throughways and local streets. For our study, by using a large-scale urban simulator that runs on high-performance computing, we model a large region around the closure with a complete road network representation to understand the full impact of the bridge closure.

Due to a lack of behavioral data and models associated with disruptions, most simulation studies in the literature consider the ODT trip demand as fixed for the bridge open and closed simulations (refer to Table 4.2), not accounting for travel behavior changes except for route choice. Studies that look into the behavioral impacts of network disruptions have used surveys and statistical models to evaluate them (Dahlgren, 2001; Hunt, Brownlee, & Stefan, 2002; Marsden et al., 2016; Wesemann et al., 1996; Zhu et al., 2010). These studies are conducted for disruptions with long-time horizons, and impacts are assessed days or months after the incident rather than on the day of closure. Zhu et al., (2010) looked into the behavioral impacts of the sudden collapse of the I-35 bridge in Minneapolis one month after the incident. They reported 8% trip cancellations and 41% change in trip departure times. The study also reported that 27% departed early with an average advance of 16 minutes, and 4% departed late with an average delay of 61 minutes. They concluded that changing routes and journey departure time shifts are the most common behavioral responses to bridge collapse. Another study on the impact assessment of I-880 reconstruction in Oakland reported 3% trip cancellations, and 94% departed early for the morning trips if the bridge had not been reconstructed [33]. [49] evaluated travelers' responses to a 14-month-long closure of the Center Street Bridge in Calgary, Canada, based on traffic counts and telephone surveys three months after the closure. The study reported a 4.4% drop in daily trips, a shifting of the morning peak 15 minutes ahead, and 3.4% of respondents leaving home early. From the above, it can be seen that route choice is the prominent behavioral response to incidents, followed by changes in departure time shifts and trip cancellations. In light of this, we conduct a sensitivity analysis later in the study.

In addition to assessing traffic impacts resulting from a predetermined link closure, a significant body of literature exists on vulnerability analysis to identify critical links and nodes in a network. These studies identify critical links in the network through various methods, such as iteratively removing links and using mathematical formulations, among others. The consequences of link closures are then measured in terms of reduced network performance to identify the most critical link in a region. As this topic is not the primary focus of this paper, interested readers can refer to the works of (Ansari Esfeh et al., 2022; Bell, 2000; Chen et al., 2007; Chen et al., 2012; Lopez et al., 2017) if interested.

To summarise, previous studies assessing the traffic impacts from network disruptions have three main limitations. First, they employ user-equilibrium assumptions to model route choice, which cannot realistically capture the reactive driver behavior during incidents. Second, due to computational limitations, most previous studies use reduced road network representation and limit the study region to a small area around closure. Third, all the previous analyses were conducted for a few hours in the morning or evening peak period and then extrapolated to the whole day to get the daily impacts. This could lead to overestimating the congestion as the dynamics in peak and non-peak periods are very different. Thus, to evaluate a highly congested regional network disruption consisting of many links and intersections, an advanced network model with high computational efficiency is required to capture relevant traffic dynamics. Therefore, our study employs a large-scale, mesoscopic simulation model with dynamic routing capability and can simulate a full-scale urban network with an entire day's demand to assess the regional traffic impact of the incident.

4.3 Experimental Design

Simulation Scenario Design

We use Mobiliti (Chan, Kuncheria, & Macfarlane, 2023; Chan et al., 2018), an agent-based scalable parallel discrete event simulation platform that runs on Lawrence Berkeley National Laboratory's NESRC computer. It instantiates millions of network nodes, links, and vehicle agents to simulate the movement of the population through the road network and provide estimates of the associated congestion, energy use, and productivity loss. Fleet compositions of both statically and dynamically routed agents provide a mechanism for simulating the dynamic response of vehicles under congestion, thus providing insights into the emergent dynamics associated with driver rerouting. Our results show excellent computational performance scalability on multiple compute nodes for a scenario involving 60% dynamically-routed agents, simulating $\tilde{1}$9 million trip legs over a road network with $\tilde{0}$.5 million nodes and $\tilde{1}$ million links, representing 7 million drivers and 4 million truck trips, processing 4.5 billion events in less than three minutes.

Network and Travel Demand Representation

For this study, we use a San Francisco Bay Area map derived from a HERE Technologies [47] map consisting of 450,000 nodes and 1 million links. For vehicle trip demand, we initialize the network with 19 million trip legs based on disaggregate, synthetic trips from the San Francisco County Transportation Authority (SFCTA) CHAMP6 model [87]. Each trip leg is specified with an origin (e.g., home) and destination (e.g., work), traffic analysis zone (TAZ), and a start time. Because our simulator models vehicles traversing specific links at discrete times, we assign a specific origin and destination node to each vehicle within the given TAZ weighted by population density [39]. Figure 4.2 (left) shows the trip demand by their origin, and the bar graph on the right shows the temporal distribution of the trip legs during the simulated model day. For demand modeling, we assume the ODT trips are the same for the baseline and scenario except for route choice. This assumption is reasonable given that the bridge closure was sudden, unplanned, and short-term. Literature on behavioral impacts suggests that route choice changes are the predominant behavioral response for such incidents (Dahlgren, 2001; Zhu et al., 2010).

Modeling the Bridge Closure in Simulation

We use the dynamic routing capability in Mobiliti to model the bridge closure traffic dynamics, thus capturing the emergent behaviors of the agents as they react to the event. In Mobiliti, roadway links are modeled as actors, and vehicles are represented as events passed between links as they travel through the road network. The routes in the simulation are determined based on the shortest travel time, with a percentage of randomly selected trips given the option to reroute based on the current congestion patterns, modeling the traveler's navigation app usage. The initial shortest path is calculated using the contraction hierarchy algorithm, and in the dynamic rerouting, the link weights are constantly changing based on congestion varying over the course of the simulated day. For more details on the simulator's implementation, please refer to our previous article (Chan, Kuncheria, & Macfarlane, 2023; Chan et al., 2018).

To model the bridge closure, we blocked the main freeway links approaching the bridge (after the last exit) from either side and the last on-ramp onto the freeway. Vehicles that would have crossed the bridge under baseline conditions are then forced to reroute (i.e., exit the freeway at the last exit before the bridge) and choose an alternate path around the bridge to get to their intended destinations. Vehicles that had already begun to traverse the bridge at the time of the closure are allowed to complete the bridge transit. This diversion mechanism reroutes vehicles near the bridge itself, modeling the behavior of drivers without advance knowledge of the bridge closure. Those who depart later in the day and may already be aware of the incident news through various sources can avoid going to the bridge. To model this, we enable dynamic rerouting for those vehicles starting at the origin so that they may plan alternate routes.

With our link actor and discrete event formalism, we introduce a new set of events that the

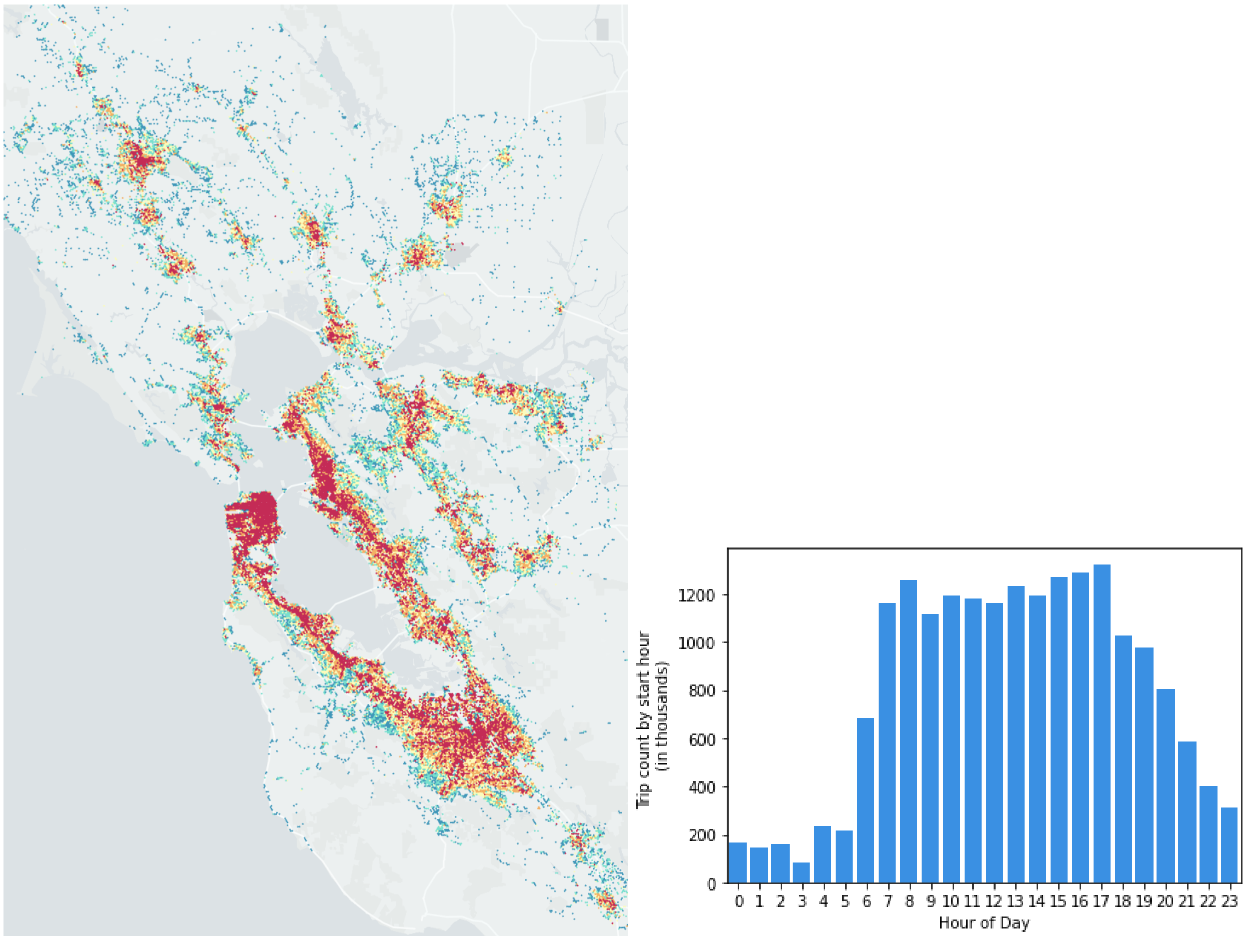


Figure 4.2: (Left) Heat map of 19 million trip origins during the simulated day. Red shows the areas with the highest demand, and blue shows low-demand areas. (Right) Temporal profile of the ODT trips during the simulated day.

actors responsible for the blocked links execute at the time of the scenario. The blocked link actors schedule a special scenario event to be executed at the time of the bridge closure. At the specified scenario time, the blocked links notify the vehicle controllers and their respective upstream links that they are blocked. After a link becomes blocked, any upstream vehicle wishing to enter the link must contact the local vehicle controller to request a new route. The vehicle controller then computes an alternate route based on the new network state and sends the new route back to the upstream link actor, which updates the vehicle's route and sends it along its new alternate path.

Modelling Disruption Information Dissipation

To simulate the impact of information spread, we have divided travelers into two categories for the purpose of this research. In view of the unexpected and substantial disruption, a one-hour threshold has been deemed suitable for determining when the news is considered to have spread.

- Vehicles departing before noon: These vehicles will only reroute if the bridge is closed when they reach it. This simulates commuters following their usual route without active navigation and only learn about the closure upon reaching the bridge.
- Vehicles departing in the afternoon: These vehicles will be rerouted dynamically at the beginning of their trip. This is meant to simulate drivers who have heard about the closure and proactively choose alternate routes.

For the analysis in the next section, we have two simulation runs 1) a baseline simulation with no bridge closure and 2) a scenario simulation with bridge closure. The bridge links were closed in the scenario simulation from 11:00 a.m. to 8:00 p.m. For both simulations, the overall population dynamic rerouting penetration was set at 60% using a uniform random selection, based on previous experiments that best reflected reality (Chan, Kuncheria, & Macfarlane, 2023). The simulation generated flow, speed, and fuel consumption data for each network link every 15 minutes throughout the day, as well as individual trip details such as time, distance, fuel consumption, and routes (Chan et al., 2018). Our analysis of the incident's impact focused on a 15-mile radius around the bridge, which encompassed 135,690 links and 60,421 nodes (Figure 4.3). We examined these links and nodes to evaluate the effects of the incident.

Validation

We have previously validated our simulation results using multiple data sources in our earlier work for the baseline run, which the interested reader can refer to (Chan, Kuncheria, & Macfarlane, 2023). In this section, we specifically focus on the validation conducted for the simulation of the bridge closure scenario.

Data Preparation

In order to validate the simulation outputs, we employed two distinct sources of data. Firstly, we used the Freeway Performance Measurement System (PeMS) data, which is a well-established network of fixed sensor loop detectors deployed on highways throughout California to collect traffic data [29]. Specifically, we utilized PeMS flow data collected from 432 highway locations in the region on the day of the bridge closure.

In addition, we also incorporated Global Positioning System (GPS) probe data from vehicles present on the day of the bridge closure. Although this data represented only a

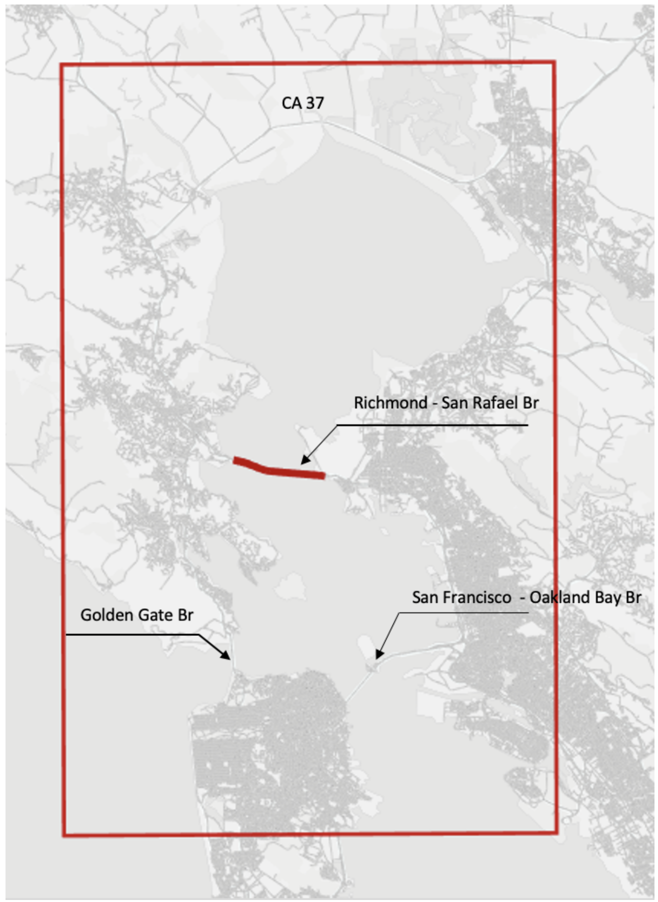


Figure 4.3: The red rectangular box highlights the impact region from the bridge closure.

small subset of the total number of vehicles in the region, it provided valuable insights into the average vehicle speeds across various roadway links, including highways, arterials, and local roads. To process this data, we employed a pipeline that filtered and map-matched the vehicle trajectories, resulting in accurate and high-quality data. The processed data provided us with the average speed of vehicles traversing different links.

Validation Results

The study evaluated traffic counts using two metrics, Median Absolute Percentage Error (MdAPE) and R-squared (R^2), for 432 PeMS stations. MdAPE measures the absolute error between the traffic counts and field data for the entire day using Eq.(4.1). The second metric, R-squared is a time series metric that compares the traffic count for each link against the field data in 15-minute increments for the entire day calculated as shown in Eq.(4.2). It is a goodness-of-fit metric that indicates the degree of similarity between the simulated data and actual data for a day. For this study, a MdAPE of 25% and R^2 value of 0.7 was used as satisfactory criteria for link count checks. For speed comparison, in addition to the above two metrics, we also employed the Median Absolute Error (MdAE) as shown in Eq.(4.3) as it calculates error in the same units as speed, making it easier to interpret.

$$MdAPE = median\left(\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right) \times 100\% \tag{4.1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4.2}$$

$$MdAE = median\left(|y_i - \hat{y}_i|\right) \tag{4.3}$$

where: $y_i : Actualvalueoftheobservations$
$\hat{y}_i : Simulatedvalueoftheobservations$
$\bar{y} : Meanoftheobservedvalues$
$n : Numberofobservations$

The results indicate that the MdAPE for traffic counts is 23%, which is lower than our threshold. In terms of R-squared, 50% of links have R^2 values greater than 0.7, indicating a good fit between the traffic count and field data. Meanwhile, 46% of links have R^2 values between 0.4 and 0.7, indicating a moderate fit. The remaining 4% have R^2 values lower than 0.4, indicating a poor fit. Additionally, the overall R^2 for all links for the entire day is 0.73 indicating a good fit.

To compare speeds, we analyzed 3,000 GPS map-matched links. These links were divided into different speed categories based on their free speeds. The comparison was conducted at 4-5 pm, and the results are presented in Figure 4.4. The simulation generally overestimated speeds for most categories, indicated by the positive bias sign, except for the 50 mph category, which showed a negative bias. The MdAE magnitude ranged from 6 - 13 mph, which corresponded to a MdAPE error of less than 25% for all categories except for 25 and 40 mph. The higher percentage error for these two categories can be attributed to the signal dynamics of the roads, which were not taken into account in the simulation. Out of the total links analyzed, 6% had an error greater than 25%. Additionally, the R^2 value obtained for all links was 0.52, indicating a moderate fit between the simulated and actual data. To improve simulation accuracy for speeds, future work will involve enhancing link modeling and incorporating traffic signals into the simulator.

Overall, the simulation counts demonstrated a reasonable level of agreement with the real-world data. The differences between the two data sets could be attributed to three possible factors. Firstly, it is expected that the dynamics of the real-world, such as the partial opening of the bridge throughout the day, introduce variations that cannot be captured in a simulation due to a lack of accurate information. Secondly, differences in ODT demand due to varying behavioral responses, such as trip cancellations, could not be accounted for due to a lack of data to support a model for this behavior. Finally, it should be noted that PeMS data is susceptible to measurement errors, while GPS probe data has high variance

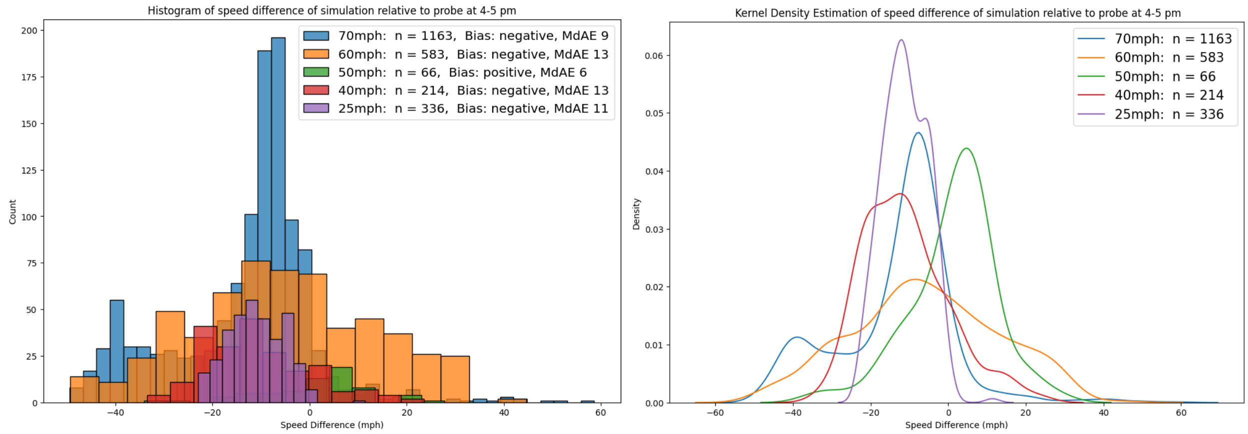


Figure 4.4: (Left) Histogram of the speed difference of the simulation relative to the probe for different speed categories. (Right) Kernel density estimate of the speed difference.

based on sampling frequency. Typically, data from multiple days are averaged before making comparisons. However, in this study, we were comparing data from a single specific day of the bridge closure, so it was not possible to average the data over multiple days.

4.4 Network Impact Analysis

We analyze the traffic impacts caused by the closure at a regional system level and local city level. While the system-level impact assessment helps us measure the impact on the whole region using aggregate metrics, the city-level assessment helps quantify which cities and their local streets were the most impacted by the detoured traffic. At the system level, we use vehicle miles traveled (VMT), vehicle hours of delay (VHD), and fuel consumption to quantify the impacts of the bridge closure. We also look at the resulting increases in trip travel time and distance. At the city level, we investigate changes in flow and congestion by link types. Three-link classifications are considered based on our previous work [60]. This classification is based on the links' functional class and speeds. Highways group higher functional class links of 1, 2, and 3 with speeds greater than 50 mph, throughways group the rest of class 3 and 4 links that carry greater volumes and higher speeds of vehicle traffic, and neighborhood streets group class 5 links with lower speeds and volumes. Table 4.3 shows the resulting distribution of the region's link types.

System-wide Impacts

In the baseline simulation of one day, 103,682 trips use the Richmond-San Rafael bridge. Figure 4.5 (left) shows the distribution of these trip legs by start hour. 63% of these trips are

Table 4.3: Link types in the region of study

Type	**Length (miles)**
Highway	460
Throughway	1380
Neighborhood street	6300

work-home commutes, 11% are truck trips, and the rest are personal business, recreational or social trips. When the bridge was closed from 11:30 a.m. to 8:00 p.m., 55,000 trips were rerouted, most of which were evening commute trips returning home (Figure 4.5 (right)). In addition to the trips that normally cross the bridge, many nearby regional trips were also impacted by additional delays arising from the closure.

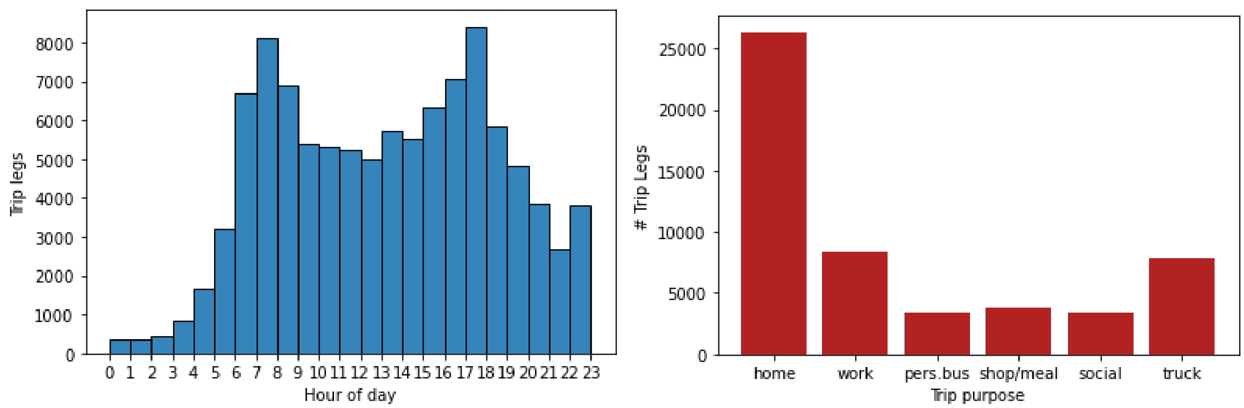


Figure 4.5: (Left) Start time of trips that use Richmond-San Rafael bridge on a normal day. (Right) The trip purpose of the affected trips during the bridge closure.

Table 4.4 summarizes the system-wide traffic impact metrics. The bridge's closure increased the system delay by 14,000 vehicle hours and the total vehicle miles by 600,000. The rerouted trips consumed 17,000 additional gallons of fuel. At the trip level, 2600 trips experienced over 46 minutes of additional delay and 26 miles of extra distance from the detour. In the evening rush hours, a small number of trips experienced high delays of over 120 minutes. Overall, the bridge closure impacted 55 thousand trips with a mean increase of 24 minutes in travel time and 13 miles in trip distance.

It was observed that 150 highway miles in the region received more than 5% of their normal traffic volumes, with a median increase of 5,500 additional vehicles in the day. Figure 4.6 (left) shows the roadways that experienced high increases in VHD in the evening hours. As the figure shows, highways 101, CA 37, and I-80 carried the most traffic and delays from the rerouted trips.

Table 4.4: System metrics

System Metrics	Baseline	Scenario	% Change relative to baseline
VMT (in thousand miles)	32,652	33,330	+2.0
VHD (in hours)	109,513	124,178	+13.4
Fuel consumption (in thousand gallons)	1,230	1,247	+1.4

Local Traffic Impacts

Analyzing the impact by link types, we see an additional VMT of 1-2% for all street types (Table 4.5). However, the percentage of delay increase is highest for neighborhood streets followed by highways. The increased VMT on neighborhood streets from the detoured vehicles significantly increased delays in the previously free-flowing or empty streets. It is estimated that 100 miles of throughways and 125 miles of neighborhood streets in the region received over 5% more traffic volumes than the baseline, with a median increase of 770 and 100 additional vehicles in the day, respectively.

Table 4.5: VMT and VHD increase on the scenario day relative to the baseline

Street Type	VMT Increase (%)	VHD Increase (%)
Highways	2.3	20
Throughways	2	9
Neighborhood streets	1.5	34

Further, breaking down the impact by cities, five cities in the region received the highest increases in traffic flow, as shown in Table 4.6. The local streets in San Francisco, Vallejo, and San Rafael had a median traffic volume increase of 30%, 22%, and 13%, respectively. Figure 4.6 (right) shows the link level traffic volume increases in San Francisco and Richmond in the evening peak period. As Golden Gate Bridge and the Bay Bridge are alternate routes for detoured traffic from the Richmond - San Rafael Bridge, the connecting city of San Francisco received higher traffic volumes.

In San Francisco, traffic volume increased significantly on the local roads near the bridges (Figure 4.7). Most of the traffic rerouted through two paths. The eastbound traffic from the Golden Gate Bridge to the Bay Bridge bridge used Baker St. - Scott St. - Post St. - Geary Blvd. - McAllister St, whereas the westbound traffic mainly existed from 2B, then went through Fremont St. - Pine - St.Kearny St - Columbus Av - Bay St - Marin Blvd. Figure 4.8 shows the cumulative traffic counts on three streets that received high traffic volumes. The results reveal little variation in traffic flow on many parallel/alternative city streets in San Francisco, signifying these roads could have been used to dissipate the rerouted traffic.

Upon analyzing the traffic flows and congestion levels on the links, it appears that additional routes could have been utilized to enhance traffic management. Our findings reveal that alternate eastbound routes and alternate westbound routes, as depicted in Figure 4.9, could have been employed to alleviate the existing congestion. It is important to note that while these alternative routes may entail longer travel distances compared to the primary routes, they possess the capacity to significantly dissipate traffic congestion. By leveraging simulation analysis, we are able to effectively identify and evaluate alternative routes that can be implemented to facilitate traffic dispersion. This study highlights the practical significance of employing such strategies to enhance traffic management and reduce congestion levels.

Similarly, the highway CA 37 in the north, another alternate route used by many, increased flows for local streets in the neighboring city of Vallejo. The results suggest that the local roads in the neighboring cities provided the additional adaptive capacity to disperse the traffic. However, this also caused increased congestion in certain roadways, which could have been better dispersed with an effective traffic diversion plan guiding the affected road users.

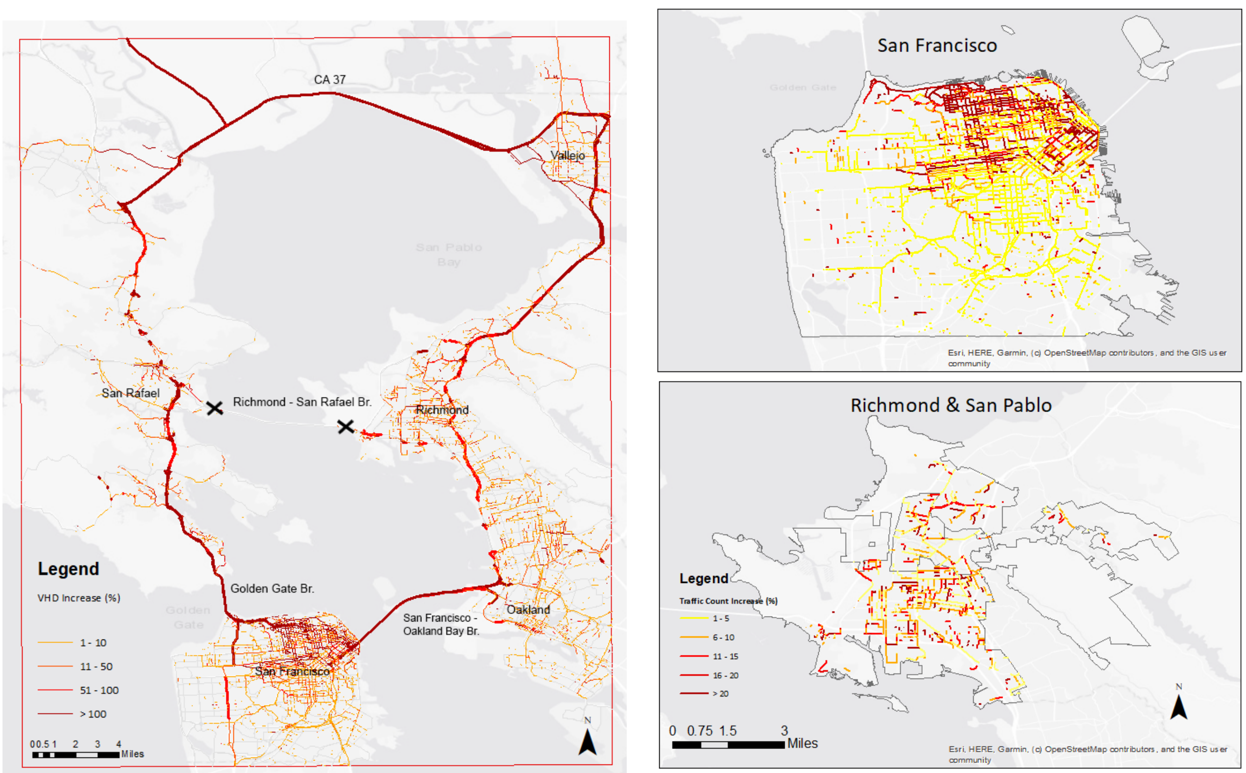


Figure 4.6: (Left) Increase in VHD on the scenario day compared to the baseline in the evening (3-7 pm). Only links that experienced an increase in vehicle counts are shown. (Right) Traffic volume increase in the city streets of San Francisco and Richmond in the evening (3-7 pm).

Table 4.6: Impacted cities in the region

2***City** 2*	Miles with increased traffic volume on the scenario day relative to baseline		Median traffic volume increase (%) on the scenario day relative to baseline		Miles congested at 5pm on the scenario day	
	Throughways	Neighborhood streets	Throughways	Neighborhood streets	Throughways	Neighborhood streets
San Francisco	43	57	16	30	8	5
Vallejo	15	5	35	22	1	1
San Rafael	8	4	9	13	1	2
Richmond	5	15	8	7	1	1
Oakland	4	6	11	9	1	1

Note: Only links with more than 5% increase in traffic is included in the analysis.

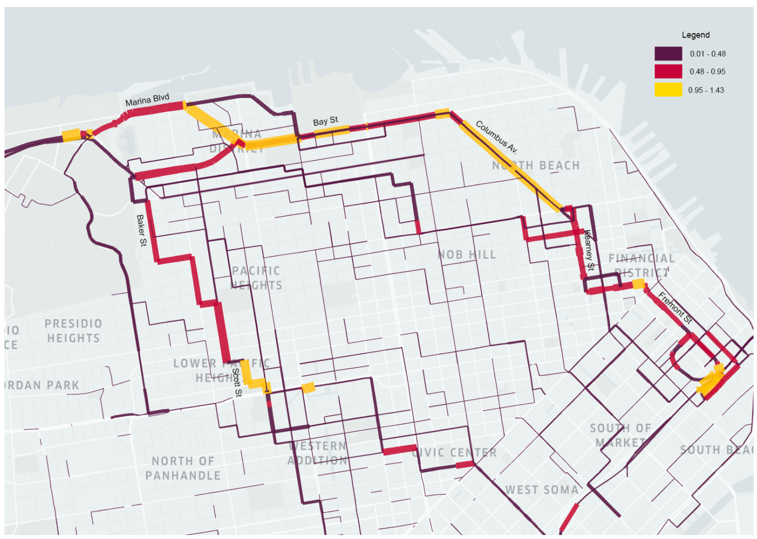


Figure 4.7: Volume over capacity (v/c) increase on the streets at 5 pm on the scenario day relative to the baseline for San Francisco.

Demand Sensitivities

In the above analysis, we consider the ODT demand for the scenario day the same as the baseline except for route choice. However, we recognize that even a short-term closure can cause travel pattern changes due to the travelers' varying behavioral responses to the incident. The literature on behavioral responses to incidents shows that route choice changes are the most common. We already account for this in the simulation using the dynamic routing mechanism. Trip cancellations and departure time changes are the subsequent two frequent incident responses, for which we conducted a sensitivity analysis.

To conduct the analysis, we varied the trip cancellation and departure time parameters based on the literature and ran eight additional simulations. All trips that start or end in the study region or that uses the bridge are candidates for change. Trip purpose and start times were also considerations for making changes. For cancellations, we chose five and fifteen percent non-mandatory trips (nonwork and schools) with a random selection that started

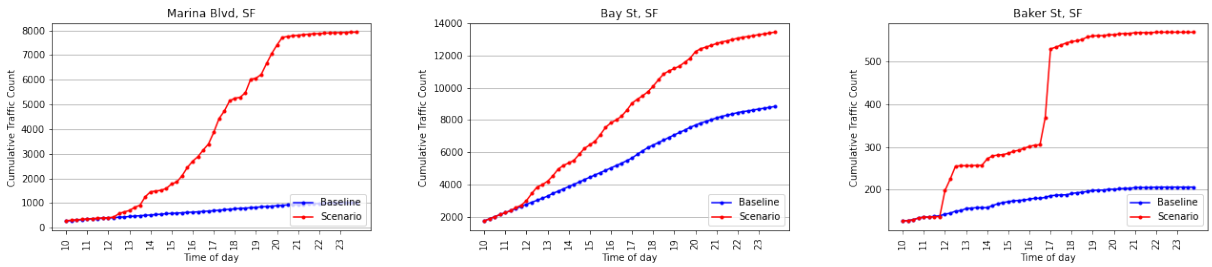


Figure 4.8: The figures show the cumulative traffic counts on local roads in San Francisco.

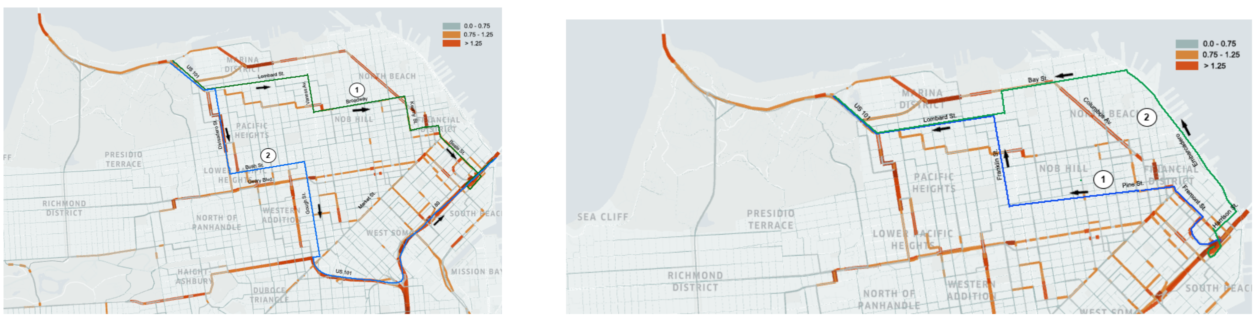


Figure 4.9: The alternate eastbound (left) and westbound (right) routes in San Francisco city. The colors on the map correspond to congestion levels on the scenario day at 5 pm, represented by the ratio of volume over capacity.

one hour after the bridge was closed. For departure time shifts, half trips with a random selection were allowed to change time by 60 minutes or 120 minutes. Mandatory trips (work and school) were allowed to start early, whereas all other trips could start late. The start time was also changed to avoid rush hours. This gave us eight combinations of parameters - four with only one parameter changed and four with a combination of both parameters. High values of 15% cancellation and 120-minute departure time shift were investigated to account for the extreme impacts of behavioral change.

The results from the sensitivity analysis are presented in Table 4.7. In scenarios where trips were canceled, both VMT and VHD decreased. However, when only the departure time was changed, only VHD was affected because the trips still had to traverse their path. In cases where both parameters were changed, the percentage changes in VHD ranged from +13.4 to -2, while VMT ranged from +2 to -0.1. In the final scenario, where there is an extreme threshold of 15% trip cancellation and a 120-minute shift in departure time, VMT and VHD has reduced below the baseline. This demonstrates the potential to mitigate the effects of an incident if enough announcements are given and there is a significant behavioral shift. However, this is not likely possible in our specific case since the disruption occurred suddenly and after the morning commute hours, and hence the commuters needed to return home in the evening. Therefore, the possibility of trip cancellations was low. The more significant behavioral effect of this incident is the departure time shifts of the commuter trips.

Table 4.7: Demand sensitivity analysis

Simulation	VMT (in thousand miles)	% Change relative to the baseline	VHD (in hours)	% Change relative to the baseline
Baseline	32,652	-	109,513	-
Scenario 0 (fixed ODT matrix)	33,330	+2	124,178	+13.4
Scenario 1 (trip cancel 5%)	33,106	+1.4	122,182	+11.5
Scenario 2 (trip cancel 15%)	32,630	-0.7	116,343	+4.2
Scenario 3 (departure time shift 60 min)	33,323	+2	119,381	+9
Scenario 4 (departure time shift 120 min)	33,302	+1.9	114,087	+6.2
Scenario 5 (trip cancel 5%, departure time shift 60 min)	33,085	+1.3	114,969	+5.0
Scenario 6 (trip cancel 5%, departure time shift 120 min)	33,066	+1.2	111,063	+2
Scenario 7 (trip cancel 15%, departure time shift 60 min)	32,617	-0.1	110,730	+1
Scenario 8 (trip cancel 15%, departure time shift 120 min)	32,615	-0.1	107,409	-2

4.5 Conclusion

Simulation is an essential tool in understanding how disasters can paralyze traffic operations in a region. Smartphone navigation apps with up-to-date road congestion, roadway condition information, and incident notification can help reduce traffic congestion during disasters by dynamically providing drivers with alternate travel routes. Thus, simulation tools capable of modeling the dynamic routing of vehicles based on updated traffic conditions are more realistic in capturing traffic dynamics during disasters or large incidents.

This study presented a traffic impact assessment of the sudden closure of a critical bridge in the San Francisco Bay Area using a dynamic routing-based simulation model with complete road network representation. The simulation results revealed that the bridge closure significantly affected the system and city-level transportation network. Specifically, the closure lead to an estimated increase of 14,000 vehicle hours of delay and 600,000 vehicle miles in the system. In terms of individual trips, 55,000 journeys were affected, with an average increase of 24 minutes in travel time and 13 miles in trip distance. Furthermore, highly impacted trips experienced a mean increase of 46 minutes in delay and 26 miles in distance. The model results show that 125 miles of neighborhood streets in the region received additional traffic volumes, with a median increase of 100 vehicles per day. Traffic on neighborhood streets in San Francisco, Vallejo, and San Rafael experienced median traffic volume increases of 30%, 22%, and 13%, respectively. These findings suggested that local roads in the cities provided the additional adaptive capacity to disperse traffic during the incident. However, certain city streets experienced higher traffic, indicating the need for better traffic management plans to effectively disperse traffic and minimize congestion.

The data and analytics of this incident offer a unique opportunity to understand how the transportation system performed in the context of a significant network disruption. The ability to analyze in-depth traffic flow changes in response to disasters can enhance evacuation planning efforts and facilitate the design of better coordinated traffic management strategies by improving our understanding of the resulting dynamics at scale. Road users could be alerted to alternative routes using variable message signs, and vehicles could be diverted to prevent clogging on streets. Additionally, cities could establish traffic management plans at the worst affected links, such as prioritizing traffic flows in critical directions and extending cycle lengths to shorten wait times at intersections.

The study has some limitations. First, it assumes that the travel demand remains constant, except the route choice, when estimating the traffic impact of the incident. This assumption may result in an overestimation of congestion, as it fails to account for the changes in behavior induced by the incident. While we conducted sensitivity analyses on two demand parameters, a comprehensive understanding of the behavioral changes that occurred during the incident would require well-designed surveys, which were beyond the scope of this study. Second, the simulator does not have a mechanism to provide travelers with multiple alternate routes to choose from. It provides the first shortest path and reroutes based on current traffic conditions assuming full compliance of agents. The choice of multiple route options is a focus of future work.

Nevertheless, with large-scale modeling of a critical network disruption using dynamic rerouting capability, complete road network, and full demand, we provide valuable insights into the response dynamics of this specific event. In doing so, we demonstrate the value of such regional analyses to incident and disaster planning. Particularly, large-scale traffic impact assessment becomes critical when knowledge of the regional impacts of this kind of incident is almost non-existent.

Chapter 5

Beyond Centrality: Understanding Urban Street Network Typologies Through Intersection Patterns

Abstract

The structure of road networks plays a pivotal role in shaping transportation dynamics. It provides insights into how drivers experience city streets and helps uncover the unique characteristics and challenges of each urban environment. Consequently, characterizing cities based on their road network patterns can facilitate the identification of similarities and differences, informing collaborative traffic management strategies, particularly at a regional scale. While previous studies have investigated global network patterns for cities, they have often overlooked detailed characterizations within a single large urban region. Additionally, most existing research uses metrics like degree, centrality, orientation, etc., and misses the nuances of street networks at the intersection level, specifically the geometric angles formed by links at intersections, which could offer a more refined feature for characterization. To address these gaps, this study examines 94 cities in the San Francisco Bay Area, taking into account diverse road network features. We introduce a novel metric for classifying intersections, distinguishing between various types of 3-way, and 4-way intersections based on the angles formed at the intersections. Through the application of clustering techniques in machine learning, we have identified three distinct typologies—grid, orthogonal, and organic cities—within the San Francisco Bay Area. We demonstrate the effectiveness of the new metric in capturing the differences between cities based on street and intersection patterns. This approach not only distinguishes them according to their road structures but also encapsulates aspects of how drivers experience intersections upon arrival. The typologies generated in this study could offer valuable support for city planners and policymakers in crafting a range of practical strategies tailored to the complexities of each city's road network, covering aspects such as evacuation plans, traffic signage placements and traffic signal control.

5.1 Introduction

The road network serves as the backbone of any city, providing essential connections between different parts of the urban landscape. The structure and connectivity of these roads influence how drivers experience the city as they navigate streets and intersections, thereby affecting traffic flow, behavior, and the overall dynamics of the city. These road networks are carefully planned in some cities, while they have evolved organically in others.

Analyzing cities based on their street layouts offers valuable insights for formulating effective traffic management strategies, particularly in large urban areas. This understanding can foster collaboration among cities within a broader urban region. By characterizing each city, it becomes feasible to devise strategies that are not only efficient but also attuned to the distinctive features of each layout, thereby optimizing the overall functionality of the urban landscape.

Over the last two decades, there has been a substantial body of research in network science, with a focus on developing metrics to delineate and understand networks. In the realm of transportation networks, there has been an emphasis on classifying cities based on both network topology and geometric features [94, 17, 32, 13]. Despite the extensive exploration of topological metrics, there is still a gap in investigating geometric metrics. Specifically, no studies have examined the identification of intersection patterns based on the geometric angles formed. These intersection patterns, especially at 3-way and 4-way intersections, exhibit variations contributing to distinct intersection configurations, thereby resulting in different road network structures. Explicitly considering these intersection patterns holds the promise of generating better, more accurate, and representative typologies. These patterns also directly impact driving behavior, as intersection angles directly affect driving dynamics, thereby influencing the traffic characteristics of a city.

Furthermore, the majority of existing literature is dedicated to characterizing cities worldwide, enabling the recognition of overarching trends and patterns. However, to derive practical insights and effectively apply them to planning and design, performing clustering at a metropolitan level or contiguous regional level is crucial.

To address these research gaps, our study concentrates on characterizing cities in the expansive urban region of the San Francisco Bay Area, encompassing over 90 cities. Through the application of various topological and geometric measures, we establish distinct typologies for cities based on their network structure. Additionally, we introduce a novel metric to identify node patterns linked to three-way and four-way intersection types. Subsequently, we develop two clustering models: a baseline employing existing metrics and an enhanced model integrating additional measures. Our analysis entails a thorough comparison and contrast of cities within these two models, emphasizing the effectiveness of the new metric in delineating city structures. Lastly, we engage in a discussion on how these classifications can inform effective transportation management strategies.

The subsequent sections of this paper are structured as follows. Section 2 presents a comprehensive overview of previous studies on city characterization. In Section 3, we detail the data and methods of the study. Section 4 discusses the results, and Section 5 provides a discussion. Finally, the conclusions are presented in Section 6.

5.2 Literature Review

Several studies have explored urban street network layouts, utilizing both topological and geometrical metrics to comprehensively characterize the overall structure. Topological metrics unveil connectivity patterns, while geometrical metrics elucidate spatial features within the network.

Past research has characterized cities worldwide using a combination of topological and geometric network properties, with the aim of discerning similarities and differences among them. For instance, [17] classified 100 cities worldwide into three primary and eight secondary levels based on four features average node degree, orientation order, median street length, and average street circuit. They introduced a novel metric called "orientation order" to gauge the overall alignment of streets within a city. Their metrics were designed to assess whether a city's street layout resembled a grid, and they observed that cities in the United States exhibited a stronger grid-like pattern compared to those in other parts of the world. [32] utilized four node centrality metrics: closeness centrality, betweenness centrality, straightness centrality, and information centrality, to classify 18 cities into three types: planned, self-organized, and model. They demonstrated that employing various centralities enables the capture of valuable structural properties within networks. [94] examined the geometric properties such as average street length, the distribution of angles between streets, and the proportion of dead ends. Additionally, it explored four centrality measures, categorizing cities into two groups based on the presence or absence of significant geographical constraints. In their study, [13] classified 80 cities into five distinct categories—Gridiron, Long Link, Organic, Hybrid, and Mixed cities—by examining both topological and geometric characteristics of road networks. This classification was based on various metrics, including node degree distribution, intersection angle distribution, and link length distribution.

In addition to city clustering, a significant body of literature is dedicated to understanding network structure properties using various metrics [65, 88, 113, 23, 70, 104]. [110] presented three new metrics aimed at capturing network heterogeneity, including entropy, connection patterns, and continuity. Their study demonstrated the utility of these measures in quantifying and comparing structural attributes of road networks. [18] investigated topological metrics, network efficiency, and network robustness as means to characterize the properties of street networks. [28] analyzed the distributions of various geometric metrics of street links, including link length, link angle, and double-angle, across 20 German cities. [51] examined the topological metrics such as degree, path length, and clustering coefficient across 40 cities, illustrating their small-world properties with scale-free characteristics. Their findings showed that roughly 80% of streets have lengths below the average, while 20% have lengths that exceed the average.

While both topological and geometric features have been extensively investigated, a notable gap exists in capturing the nuanced geometric angles of the network. Two studies have captured the overall street angles [94, 13]; however, its approach treats all angles independently, neglecting the intricate patterns formed at intersections as a collective entity. This level of detail is essential for determining whether a city can be classified as having a grid-like structure or not. The precise capture of intersection patterns based on the angles formed is paramount for the development of accurate network typologies. Furthermore, the majority of existing literature focuses on cities globally, allowing for the identification of broad trends. However, to transform findings into practical strategies and align them with planning and design processes, it's crucial to conduct clustering analysis at a regional level. This study addresses this need by concentrating on California's San Francisco Bay Area region.

5.3 Methods

Data

Our study focuses on the San Francisco Bay Area in California, encompassing nine counties and 101 municipalities. In California, municipalities have the flexibility to use either the term "city" or "town" in their official names, as there is no legal differentiation between the two [2]. To ensure a fair and balanced comparison, we have excluded very small cities with sparse road networks and only included municipalities with populations exceeding 5000, resulting in a total of 94 cities under consideration.

The road network used in this study is the Mobiliti Bay Area network [25], which serves as the foundation for an urban-scale, parallel discrete event simulator jointly developed by the Lawrence Berkeley National Laboratory (LBNL) and the Smart Cities Research Center at the Institute for Transportation Studies at UC Berkeley. This road network graph is derived from a professional HERE Technologies map [47]. The Mobiliti map is designed as a directional map, with links having a start and end node, representing the direction of traffic flow. The map was pre-processed to transform it into a primal graph representation, where nodes represent intersections or dead ends, and links denote streets connecting these nodes. The graph is then clipped to each city's boundaries using administrative boundary data from Metropolitan Transportation Commission (MTC).

Existing Metrics

As noted in the previous section, metrics used to quantify urban street networks encompass both topological and geometrical aspects. In quantifying the topological properties of road networks, the literature explores various measures, including degree, betweenness centrality, closeness centrality, and clustering coefficient [65, 57]. Each metric captures different aspects of road networks: degree measures connectivity at intersections, betweenness centrality assesses the network's ability to facilitate paths between regions, and closeness centrality indicates proximity within the network. For our study, we specifically focus on node degree and betweenness centrality as topological metrics, as they provide comprehensive insights into the overall properties of road networks.

The degree of a node reflects the number of connections it possesses with other nodes, identifying the most interconnected nodes within a city (Equation 5.1). In a directed graph G with N nodes and E edges, two types of degrees exist: in-degree, indicating connections into a node, and out-degree, representing connections exiting the node. Generally, in-degrees and out-degrees are equal, except for intersections with one-way streets. For instance, if a one-way street leads into an intersection, the in-degree of that intersection would exceed its out-degree.

$$D(i) = \sum_{j \subseteq N} a_{ij} \tag{5.1}$$

where:
$D(i)$ is the degree of node i
a_{ij} is the element of the adjacency matrix, when a node i is connected to the node j, $a_{ij} = 1$, otherwise $a_{ij} = 0$.

For all 94 cities, both in-degree and out-degree range from 1 to 6. Most nodes exhibit equal in-degree and out-degree. The median percentage of nodes with divergent in and out degrees is 3%. For the clustering in the next step, we incorporate the proportion of nodes falling into 5 node degrees (1, 2, 3, 4, and more than 4) as a feature. Figure 5.1a illustrates the distribution of node degree proportions in the top twenty cities in the Bay Area.

Betweenness centrality (BC) evaluates the degree to which a node lies on the shortest paths connecting pairs of other nodes, measuring the node's intermediate importance in facilitating interactions among other nodes [57, 65]. Nodes with high betweenness centrality are pivotal for network resilience, as they serve as critical connectors between multiple areas within a region. It is calculated as shown in Equation 5.2. To ensure equitable comparisons across cities of varying sizes, the BC is normalized by the number of nodes in a city. The study employs the median values of the normalized BC for analysis.

$$BC(i) = \frac{1}{c} \sum_{a \neq b \subseteq N} \frac{\sigma_{ab(i)}}{\sigma_{ab}} \tag{5.2}$$

where:
$BC(i)$ is the BC of node i
σ_{ab} is the number of shortest paths going from nodes a to b
$\sigma_{ab(i)}$ is these number of the shortest paths going from a to b through node i
c is a normalisation constant

For geometric metrics, we computed the mean link length, network density, and link-node ratio for all cities. The distributions for the cities are shown in Figure 5.1b. Additionally, link bearings for each link in a city were calculated [76] and discretized into 20-degree bins.

The proportion of links in each bin is considered a feature for the subsequent analysis. An adjustment was made to the order of the bins, ensuring that the first bin with a large proportion is considered bin 1. This adjustment is implemented so that the clustering is not influenced by specific cardinal directions (e.g., east-west or north-south). The primary focus of this metric is on identifying the number of predominant orientation directions rather than the specific orientation itself. We also calculated a metric to determine the number of dominant bins. A dominant bin is defined as a bin where more than 10 % of a link's orientation falls. If a city's streets are oriented predominantly in a few directions, the number of dominant bins will be higher, as more bins will satisfy the 10% threshold. Conversely, if a city's streets are oriented in many directions, there won't be any bins that pass the 10% threshold. In addition to the link bearing proportion, this metric summarizes the overall orientation of streets in a city.

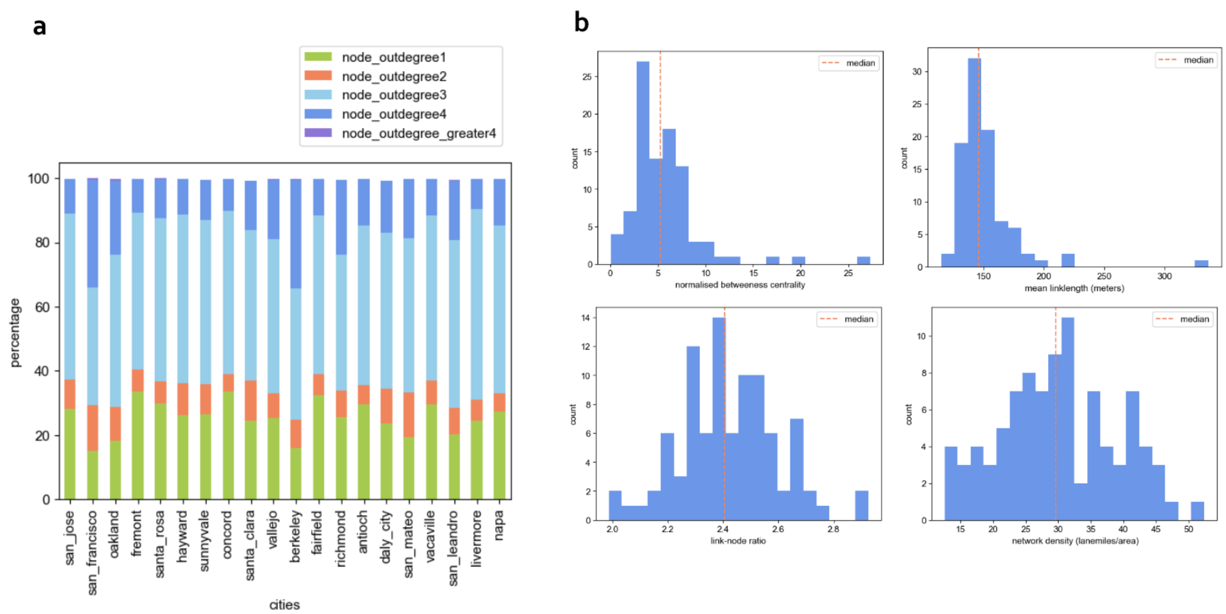


Figure 5.1: a. The out-degree distribution of the top twenty cities in the Bay Area. b. Distribution of various geometric metrics across cities.

Proposed Metric

To capture the nuances of the geometry of the road network, we propose a novel metric for identifying intersection patterns within the network. These patterns are discerned by analyzing the angles created by outgoing links at every intersection for nodes with degrees 3 and 4. The reason for choosing out-degree instead of in-degree for node patterns is that we want to capture the angles the vehicles have to take when they arrive at intersections. By capturing the angles of outgoing links, the metric aims to provide a more nuanced understanding of how vehicles navigate intersections. The angles formed by links at intersections are then categorized as acute, obtuse, right, or reflex angles, which are then used in conjunction with node degrees to facilitate pattern recognition.

Since in our graph, nodes correspond to intersections, and links represent edges connecting these nodes, the curvature of the link is not captured in the graph. To address this, we incorporate the shape points provided in the links file. The shape points of a link represents the curvature or sharp bend in the link, reflecting real-world features. Thus, by calculating the angle formed by the start node and the first shape point of a link, we will be able to capture the true geometry of the links meeting at the intersection. The angles between links are calculated based on coordinate geometry (Equation 5.3). Given three points, denoted as a, o, and b, formed by two lines, we can calculate the arctangent to determine the angles formed by the line segments connecting o to a and o to b. Subsequently, we compute the difference between these angles and convert the result from radians to degrees. This process is repeated for all angles formed at the intersection.

$$angle(a,o,b) = \{ \ degrees(atan2(b_y - o_y, b_x - o_x) - atan2(a_y - o_y, a_x - o_x)) if angle(a,o,b) > 0$$

$$\text{degrees(atan2(b}_y - o_y, b_x - o_x) - atan2(a_y - o_y, a_x - o_x)) + 360 if angle(a,o,b) < 0$$

(5.3)

where:

a_x, a_y are the coordinates of point a,

o_x, o_y are the coordinates of point o,

b_x, b_y are the coordinates of point b

$degrees$ represents the conversion of an angle from radians to degrees

Once the angles are calculated, patterns are identified for each node degree. For nodes with a degree of 3 (three-way intersections), seven distinct patterns emerge from various angle configurations. For instance, in degree 3 Type 1, a traditional T intersection is represented with two right angles and one 180-degree angle. When the angles comprise acute, obtuse, and 180-degree angles, it falls under Type 2. Additional types demonstrate alternative three-way intersection configurations 5.2.

Similarly, for nodes with a degree of 4 (four-way intersections), seven distinct patterns emerge based on the angles formed by the four links. Type 1 signifies a scenario where all four angles are perfect right angles, commonly found in planned grid layouts. The other types are as shown in Figure 5.2.

Examining node patterns across the entire Bay Area, for degree 3 intersections, the most common type is Type 1 (74%), followed by Type 2 (13%), and then Type 6 (6%). In the

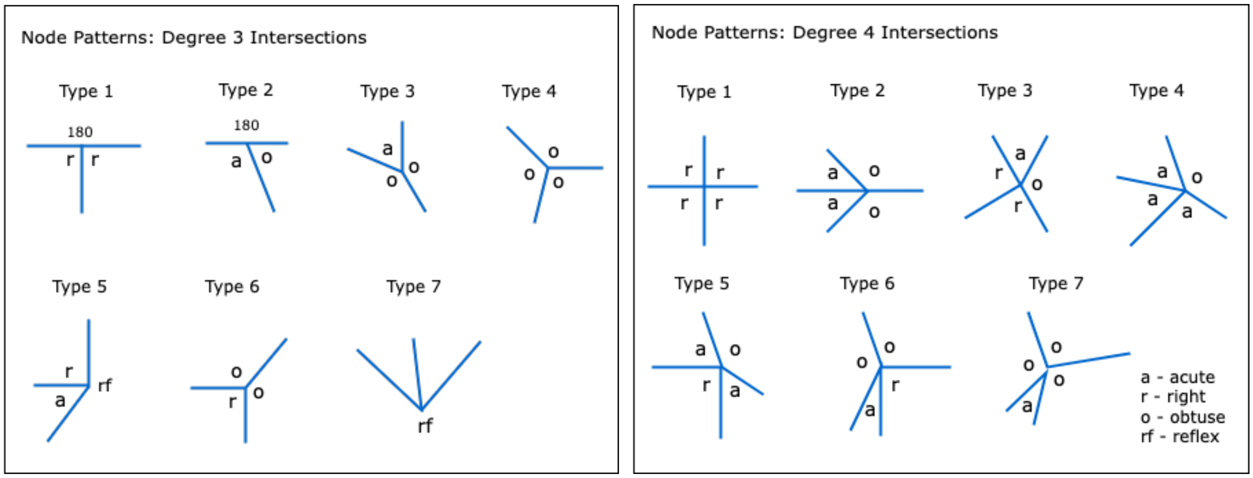


Figure 5.2: 3-way (left) and 4-way intersection patterns (right) for nodes.

case of 4-way intersections, the predominant pattern is Type 1 (69%), with Types 3 (18%) and 2 (6%) following in frequency.

To illustrate distinctive node patterns, we examine three cities with notable differences in their road networks (Figure 5.3). Berkeley, known for its planned grid network, displays a substantial concentration of both degree 4 and 3 intersections. Within degree 4 intersections, Berkeley stands out with the highest proportion of Type 1 intersections, emphasizing the city's grid network layout. Within degree 3 intersections, the majority are Type 1 T intersections.

In Cupertino, degree 3 intersections dominate, closely followed by degree 1 intersections. Notably, Cupertino's degree 3 intersections are predominantly characterized by Type 1 intersections, classic T intersections. In contrast to Berkeley, Cupertino showcases a mix of Type 1 and Type 3 intersections among its degree 4 intersections, presenting a mix of perpendicular and angled links. This is evident in the city's orthogonal structure and the presence of dead ends within the blocks.

On the other hand, Los Altos Hills features a substantial proportion of degree 1 intersections, followed by degree 3 intersections. The degree 3 intersections in Los Altos Hills are primarily Type 2 and 6, featuring angled three-way intersections. For degree 4 intersections, Los Altos Hills is distinguished by a higher proportion of Type 3 intersections, again featuring angled configurations. This is evident when examining the full network of the city, where most streets wind and lack a specific order or orientation.

It is evident that the diversity in intersection types provides valuable insights into the distinct geometric patterns and urban layouts of these cities. Analyzing node patterns alongside degrees proves to be a clear and effective method for distinguishing street layouts and can be an important feature for city clustering.

Figure 5.3: The figure displays a zoomed-in portion of the road networks for selected cities.

Feature Correlations

Before clustering, we performed a correlation analysis using the Pearson correlation coefficient, which captures linear relationships between variables, to identify notable trends in our dataset. In alignment with established literature, we observed a substantial positive correlation between node in-degree and out-degree, exceeding values of 0.99 and thus providing redundant statistical information about the networks. Therefore, we use node out-degree as the degree metric for the subsequent analyses. For the remainder of this paper, when we mention "degree," it specifically refers to out-degree.

Degree 1 shows an inverse correlation with degree 4, betweenness centrality, and the link-node ratio, aligning with findings from previous studies [28, 19, 35]. Furthermore, it exhibits an inverse correlation with the node pattern for degree 4 Type 1. This observation aligns with the logic that cities characterized by a higher proportion of dead ends tend to have fewer 4-way intersections.

Degree 4 demonstrates a positive correlation to betweenness centrality and link-node ratio as expected. Furthermore, it displays a positive correlation with node pattern Degree 4 Type 1, indicating that cities characterized by a high proportion of 4-way intersections are more inclined to feature 90-degree angled four-ways. Moreover, the degree 4 Type 1 intersection pattern is positively correlated with the link-node ratio, expected from a gridded network structure.

Degrees 3 and 1 do not show any correlations. However, Degree 3 Type 1 is inversely correlated with Degree 1, indicating a lower proportion of T intersections associated with a city with a high proportion of dead ends. Degree 3 Type 1 also exhibits inverse correlations with Types 2, 3, and 6, which are non right angled 3-way intersections.

Clustering

To categorize cities into distinct groups, we use unsupervised machine learning clustering techniques. We conduct two separate clustering processes: one is a baseline clustering using metrics commonly found in existing literature, and the other is an enhanced clustering where we supplement the baseline with additional metrics. The purpose of this is to highlight the distinctions between the two clustering approaches and demonstrate how the inclusion of new metrics adds value to characterizations.

In the baseline clustering, we use five metrics: node degree, betweenness centrality, mean link length, network density, and link-node ratio. For enhanced clustering, we expand this set by incorporating two additional metrics. The first addition is node patterns, the new metric introduced and explained in the previous section, represented by 13 features. The second addition is link bearings, which comprise 19 features. While [17] employed orientation entropy, a derived metric from link bearings, in his study, we believe that directly including link bearings as a feature adds intrinsic value to clustering.

We normalized all metrics to account for the different features and city sizes. Then, we conducted a factor analysis to reduce the feature size by extracting all their commonalities into a smaller set of factors. Ten factors were chosen, giving an eigenvalue greater than 1, a common standard used in the field. For clustering, we use the K-means method [53] with varying numbers of clusters and choose the number of clusters based on the elbow method and explainability. For the evaluation of clusters, we use the Silhouette score and the Davies-Buldin Index. The Silhouette Score quantifies how well a data point fits into its assigned cluster and how distinct it is from other clusters. Davies-Buldin Index is another metric that looks at within-cluster and between-cluster distances. It is improved (lowered) by increased separation between clusters and decreased variation within clusters.

5.4 Results

In this section, we present the results for baseline clustering, followed by enhanced clustering. Subsequently, in the next section, we offer a comparison between the two methodologies to provide insights into their differences.

In the baseline clustering, we identify three clusters, with the most crucial features being node degrees, link-node ratio, and network density (Figure 5.4). Cluster 1 is characterized by high-degree 4 nodes and low-degree 1 nodes. Cluster 2 is distinguished by high-degree 3 nodes, and Cluster 3 by high-degree 1 nodes. It is commonly assumed that cities with high degree 4 are indicative of gridded urban layouts. However, upon scrutinizing city networks, it becomes apparent that several cities are misclassified. For instance, Richmond and Palo Alto, despite featuring a visible grid network, are incorrectly assigned to Clusters 3 and 2, respectively. Similarly, Clusters 2 and 3, marked by a high proportion of degree 3, display numerous instances of mixed classifications.

In the enhanced clustering with added features, we obtain 3 clusters. The key features

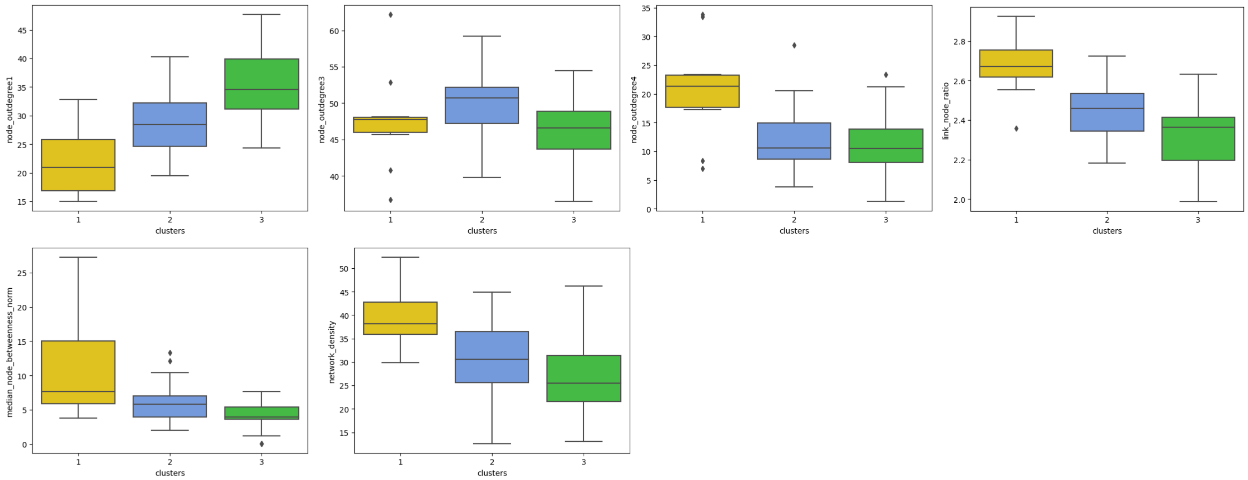


Figure 5.4: The figures show the distribution of metrics for baseline clusters.

driving this classification include node degrees, node patterns, link-node ratio, and link bearings. Figure 5.5 shows the example cities in each cluster and Table 5.1 provides a summary for each cluster. The polar plots are generated as specified in [16], utilizing our road network.

Cluster 1, distinguished by a high proportion of node degree 4, a significant prevalence of Type 1 node patterns, and a high number of dominant bearing bins, can be referred to as **Gridded cities**. These cities predominantly exhibit a grid layout with right-angled four-way intersections and three-way T intersections.

Cluster 2, featuring a high proportion of degree 3, elevated Type 1 degree 3 node patterns, a moderate link-node ratio, and a high number of dominant bearing bins is referred to as **Orthogonal cities**. These cities are characterized by numerous perpendicular streets, marked by T intersections, and fewer street orientations. These cities also have a hierarchical road system with major arterials that can handle high volumes of traffic, while local streets serve residential and commercial areas.

Cluster 3 is characterized by a high proportion of degree 1 nodes, a significant prevalence of non-Type 1 intersections, and a low number of dominant bins. These cities display winding circuitous roads with few T and right-angled intersections. Furthermore, the low number of dominant bearing bins suggests that the street orientations are dispersed across various directions and not concentrated in any specific few. They are referred to as **Organic cities**.

The differentiation of node patterns for degrees 3 and 4 by clusters is illustrated using box plots in Figure 5.6. As observed in the figure, the node types vary significantly for Orthogonal and Organic cities. Orthogonal cities exhibit a high proportion of T intersections, denoted by Type 1, whereas Organic cities have a high proportion of non-T intersections. For degree 4, the distinction is only prominent for Gridded cities denoted by a high proportion of Type

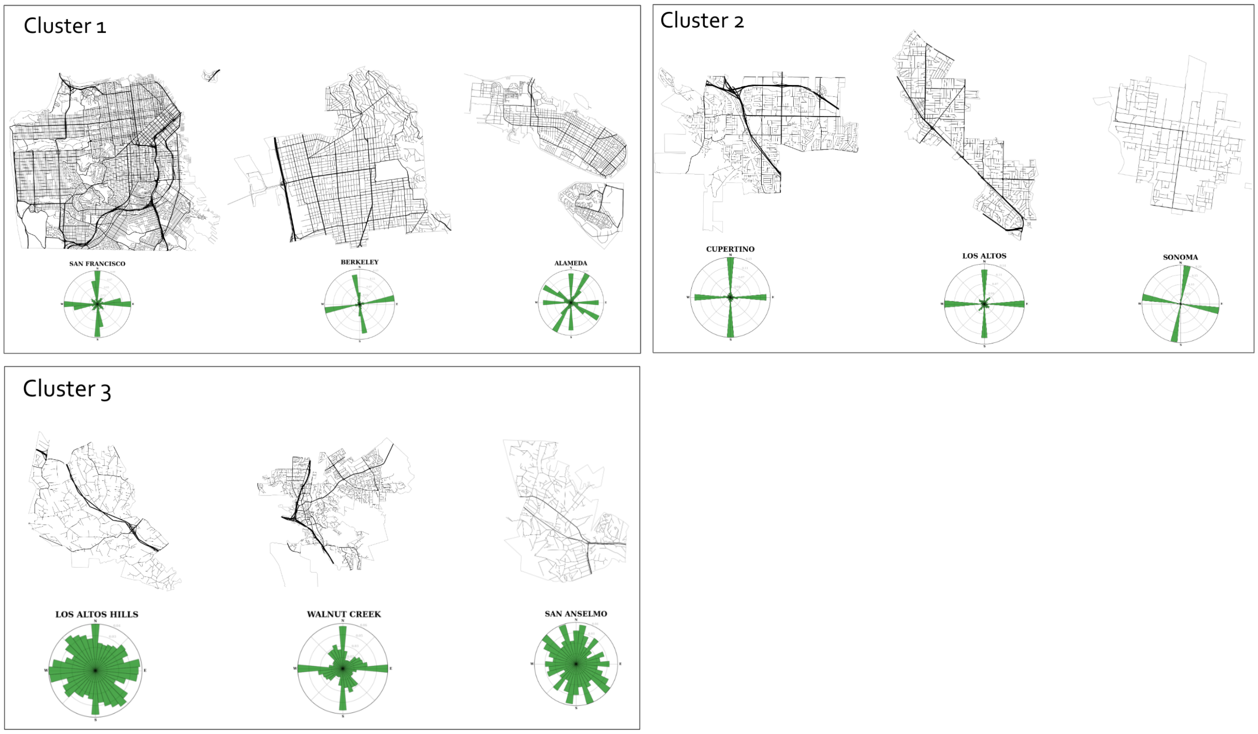


Figure 5.5: The figures display example cities from enhanced clustering. The green polar plots illustrate the street bearings of all links in the city.

1 intersections. The distribution of other important metrics for enhanced clustering results is shown in Figure 5.7.

5.5 Discussion

In this section, we compare the cities clustered in the two approaches and identify the differences and improvements made in the enhanced method compared to the baseline. Figure 5.9 shows the typologies for all cities in the San Francisco Bay Area.

In the baseline clustering, Cluster 1 exhibits a high concentration of nodes with a degree of 4, making it particularly comparable to Gridded cities identified in the enhanced clustering approach. In the baseline, only 10 cities are allocated to Cluster 1. In contrast, the enhanced clustering method identifies 15 cities within the Gridded cluster. Noteworthy is the inclusion of additional cities like Albany, Emeryville, Richmond, San Mateo, etc., characterized by distinct perpendicular grid street layouts. The baseline clustering algorithm falls short of accurately capturing these cities. Additionally, in the baseline clustering, there are also two outlier cities - San Anselmo and Piedmont - that do not exhibit a gridded layout. These

Table 5.1: Summary of Enhanced Network Clusters

Feature	**Cluster 1**	**Cluster 2**	**Cluster 3**
Node degree	Highest prop of degree 4 nodes (4 way intersections)	Highest prop of degree 3 nodes (3 way intersections)	Highest prop of degree 1 nodes (dead ends)
Node pattern: Degree 3	High proportion of Type 1 intersections	High proportion of Type 1 intersections (T intersections)	High proportion of non Type 1 intersections
Node pattern: Degree 4	High proportion of Type 1 intersections	High proportion of Type 1 and 3 intersections	No significant patterns
Link bearings	High percentage of links are concentrated in a few specific bearing directions	High percentage of links are concentrated in a few specific bearing directions	Links distributed in all bearing directions
Number of dominant bearing bins	High number of dominant bearings bins (median 4)	High number of dominant bearings bins (median 4)	Few dominant bearing directions (median 0)
Mean link length	132	140	150
Mean Link node ratio	High	Medium	Low
Number of Cities	15	38	40
Example Cities	San Francisco, Berkeley	Cupertino, Los Altos	Los Altos Hills, Walnut Creek

cities are correctly classified in the enhanced clustering (Figure 5.8e).

Cluster 2 from the baseline is subdivided into two categories in the enhanced clustering. This division is determined by the geometry of the intersections: if there is a significant prevalence of right-angled T intersections, the city is placed in the Orthogonal cluster; otherwise, it is assigned to the Organic cluster. We observe that 21 from cluster 2 remained in the Orthogonal cluster, while 20 cities moved to the Organic cluster and 6 moved to the Gridded cluster (Figure 5.8a,b).

Based on high node degree 1, Cluster 3 in the baseline can be compared to the Organic cluster in the enhanced clustering approach. High-degree 1 cities also exhibit a substantial proportion of degree 3 nodes, forming 3-way intersections. The baseline clustering model struggles to distinguish the nuances of degree 3 intersection geometries, leading to the inclusion of cities with perpendicular 3-way intersections, such as Newark, Fremont, Los Altos, etc. This gets moved to Orthogonal in the enhanced clustering. We observe that 16 cities

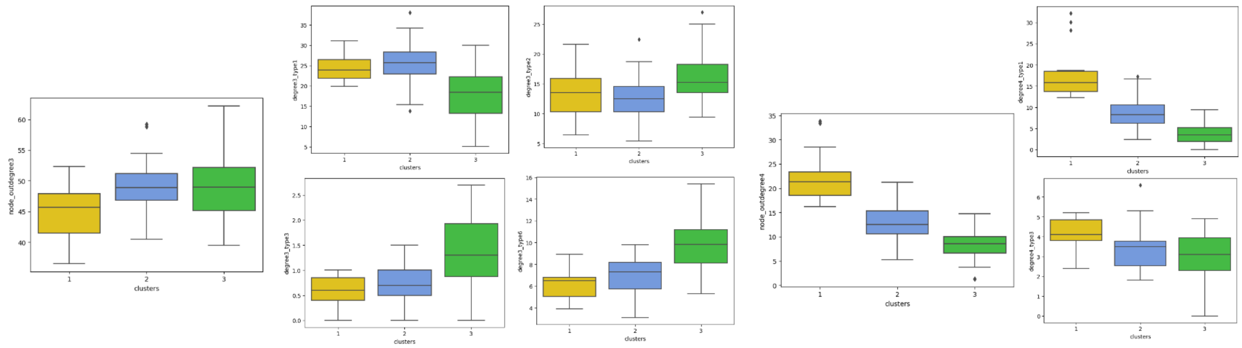


Figure 5.6: The figure shows the distribution of degree 3 and 4 intersection types for enhanced clusters.

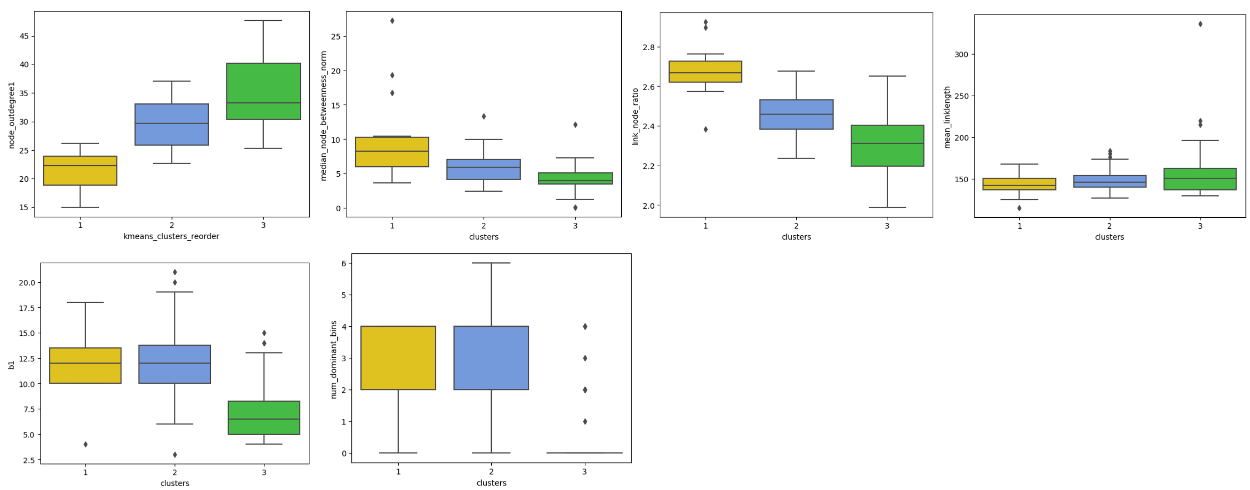


Figure 5.7: The figures show the distribution of relevant metrics for enhanced clusters.

moved to the Orthogonal cluster, and 2 moved to the Gridded cluster(Figure 5.8c,d).

Overall, for gridded cities, the primary distinction introduced by enhanced clustering lies in refining the identification of grids by explicitly considering the angles at intersections and the street bearings. Together with node degrees, the node patterns and bearings provide a more nuanced approach.

The most improvement in enhanced clustering arises in non-gridded cities where there is a significant prevalence of nodes with degree 3. While many cities have a predominance of degree 3 nodes, the specific nature of their 3-way intersections can vary significantly based on the angles involved. This variability results in either a curved or rectangular layout, depending on the geometric characteristics of the intersections. The enhanced clustering with

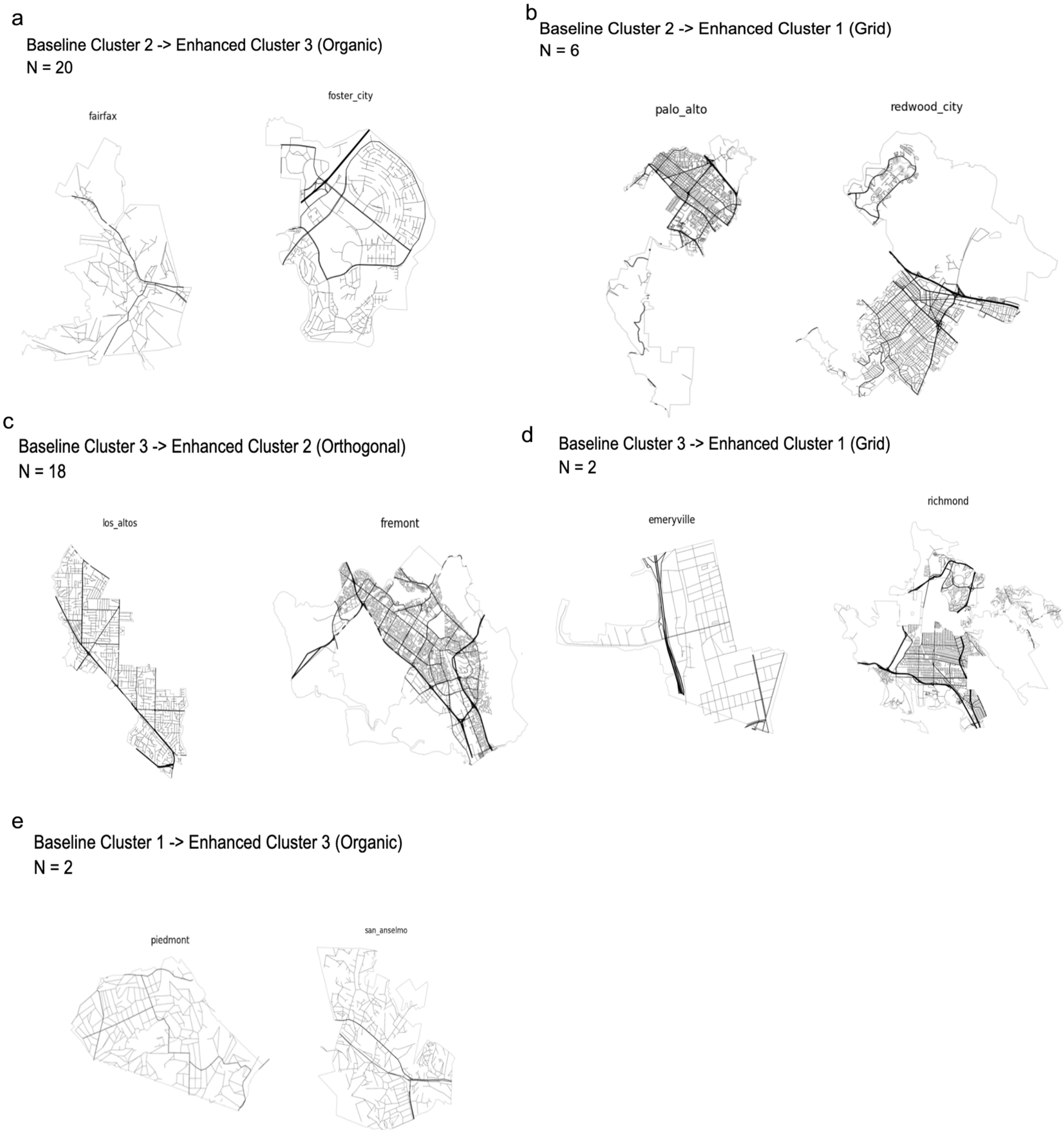


Figure 5.8: The figure displays the road network of some example cities that shifted between baseline and enhanced clustering. 'N' represents the total number of cities that moved.

specific node patterns is adept at capturing these distinctions among cities. For example, consider Lafayette and Los Altos, both with an equal proportion of nodes with degree 3

(47%). Despite this numerical similarity, the street and intersection geometries in these cities differ markedly. In the baseline clustering, both cities are grouped into cluster 3, overlooking their geometric nuances. However, the enhanced clustering accurately assigns Lafayette to cluster 3 and Los Altos to cluster 2. This showcases the algorithm's capability to discern and differentiate cities based on subtle variations in street and intersection patterns.

Finally, the evaluation metrics also show that enhanced clustering outperforms the baseline (Table 5.2). A higher Silhouette score and a lower Davies-Bouldin Index suggest better performance for the enhanced clustering model.

Table 5.2: Evaluation Metrics

Metric	**Baseline**	**Enhanced**
Silhouette Score	0.22	0.24
Davies-Buldin Index	1.32	1.16

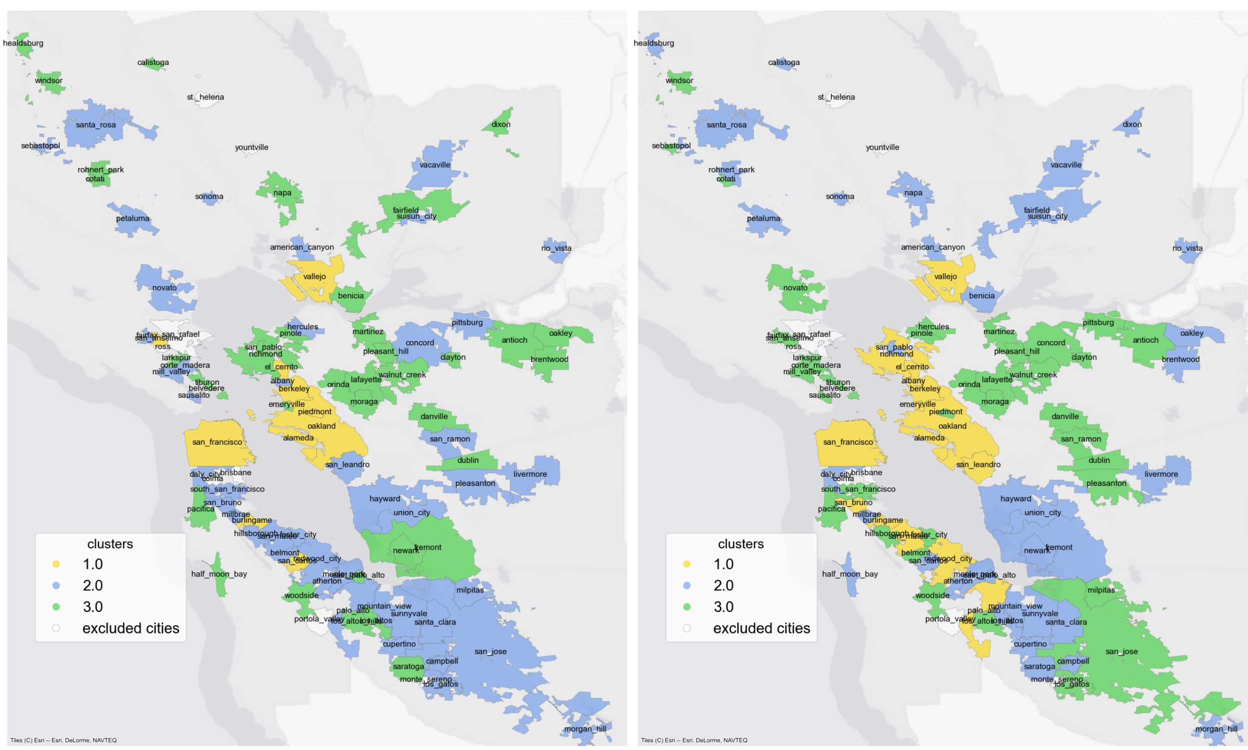


Figure 5.9: The figure shows the results from the baseline clustering (left) and enhanced clustering (right) for all cities in the San Francisco Bay Area.

Classifying cities within a large urban region provides many practical insights, facilitating the development of tailored transportation policies and strategies. For instance, customizing traffic management systems can address the distinct challenges presented by gridded, organic, and orthogonal cities. One example is designing evacuation management plans tailored to accommodate three distinct types of road networks for San Francisco Bay Area. Gridded cities, characterized by well-connected, perpendicular street patterns, offer multiple entry and exit points during emergencies. This connectivity facilitates efficient movement of people and vehicles, aiding in evacuation efforts. In contrast, evacuating Organic cities, with their winding roads and dead ends, poses more challenges. The limited alternative routes underscore the need for carefully planned evacuation strategies in these cities. Orthogonal cities, known for their perpendicular street layout, require a unique approach to evacuation planning. The perpendicular nature of the streets can impede traffic flow, necessitating the prioritization of certain routes and consideration of contraflow measures. Understanding the unique characteristics of each city type allows transportation planners to devise effective evacuation strategies that minimize congestion and enhance safety.

Another potential traffic management strategy is the implementation of coordinated signal control, which can prove effective in both gridded and orthogonal cities. Conversely, organic cities, characterized by longer street lengths and winding roads, necessitate a focus on clear signage to address potential issues with dead ends and irregular intersections, thereby enhancing safety measures.

Additionally, the formulation of new transportation policies, such as the testing of autonomous vehicles, can be tailored to specific city layouts. In the early stages, autonomous vehicles may perform better in a connected city layout like a grid with low speeds and multiple stop signs. Similarly, emerging modes of non-motorized transportation might be more suitable for a specific layout than others. Therefore, based on the network classification, a variety of policies and strategies can be designed to address the unique characteristics of each type.

Beyond its application in city clustering, the metric of intersection patterns introduced in this study can prove valuable for various purposes. Intersection angles play a crucial role in influencing traffic flow, enhancing safety measures, and contributing to overall urban design. For example, intersections characterized by acute angles may present challenges for larger vehicles, whereas those with obtuse angles may necessitate more extensive pedestrian crossings. Furthermore, optimizing the placement of traffic signals and signage can be achieved by considering the geometric characteristics of each intersection. This metric offers a versatile tool for addressing diverse aspects of urban planning and traffic management.

5.6 Conclusion

Road network plays a crucial role in shaping a city's character and influencing the quality of life for its citizens. While previous studies characterizing cities have typically focused on specific cities worldwide, there has been a lack of research concentrating on cities within large urban regions, where the street network structures can impact each other's dynamics and exhibit intricate interplay. This study addresses this gap by categorizing cities within the expansive urban region of the San Francisco Bay Area. Additionally, a new metric was developed to capture the nuances of geometry at intersections, which can better aid in classifying city networks. We conducted two clustering approaches – baseline clustering with existing metrics from the literature and enhanced clustering with additional features such as link bearings and intersection patterns.

Our findings reveal that enhanced clustering surpasses the baseline in effectively characterizing cities, identifying three distinct typologies: Gridded cities, Orthogonal cities, and Organic Cities. Gridded cities exhibit a high proportion of degree 4 nodes, right angled 4 way intersections, 3 way T intersections, and a significant number of dominant bearing bins. Orthogonal cities are distinguished by high proportion of perpendicular streets, marked by T intersections, and fewer street orientations. Organic cities feature a high proportion of nodes with degree 1, a notable prevalence of non-Type 1 intersections, and street orientations spanning multiple directions.

Compared to the baseline, the enhanced clustering improves the differentiation of gridded cities by explicitly considering intersection angles and street bearings, offering a more nuanced approach alongside node degrees. The most notable enhancement is observed in non-gridded cities, particularly those with a significant prevalence of nodes with degree 3. While many cities exhibit a high proportion of degree 3 nodes, the variability in intersection angles contributes to distinct layouts, whether curved or rectangular. The enhanced clustering method excels in capturing the diverse nature of their 3-way intersections, leading to more accurate classifications based on geometric characteristics.

Our study has a few limitations. The directed nature of our graph and the reliance on out-degree for node pattern identification may not fully capture the representation of intersections for one-way streets. Additionally, to enhance the analysis's accuracy in future iterations, integrating the ordering of angles into node patterns could be advantageous.

Nevertheless, this study demonstrates that incorporating nuanced geometric features enables a more realistic classification of street networks within a large urban region. When combined with network topology metrics, geometric metrics prove to be valuable tools in accurately categorizing city networks. While our current study is focused on characterizing cities based on their network structure, representing one dimension of urban environments, our future work aims to incorporate additional dimensions of transportation for a more comprehensive city characterization.

Chapter 6

Exploring Urban Typologies using Comprehensive Analysis of Transportation Dynamics

Abstract

As urban areas continue to expand and develop, the categorization of cities into typologies proves to be a valuable tool for comprehending the intricate dynamics of urban areas and fostering meaningful cooperation among cities. However, current typologies related to urban mobility exhibit limitations, failing to consider cities within a single large urban region and often overlooking crucial dimensions such as trip demand and traffic flow. In this paper, we introduce a transportation-focused characterization for cities within a large urban region, specifically the San Francisco Bay Area, California. We incorporate over 40 metrics across five transportation dimensions: trip demand, road network, multi-modal network, traffic flow, and land use. Specifically, regarding the trip demand dimension, we incorporate metrics that capture residents' trip characteristics, such as mode share, intra-city trips, and inter-city trip share. Additionally, we analyze the characteristics of trips entering the city by purpose to better understand the incoming trips to a city. Regarding the traffic flow dimension, our analysis includes metrics such as vehicle miles traveled, delay, and, congestion to capture the traffic conditions on the street network. Together with other dimensions, the metrics from these two dimensions are important to capture the full state of traffic dynamics in the city. Using unsupervised machine learning clustering methods, we identified eight distinct typologies for the Bay Area: Live Work; Job and Activity Magnets; Anchor Cities; Multi-modal; Hyper-connected; Low-density residential; Medium-density Residential; and Mixed-use residential. The results revealed that many clusters were characterized by predominant features captured from travel demand and traffic flow metrics. Finally, we provide a discussion exploring the implications of this typology and its potential utility in developing collaborative transportation management strategies. The typologies can serve as

a basis to create discourse among Bay Area cities that focuses on evaluating the typologies generated by our work and determining if, through success/failure experiences, common strategies can be formed.

6.1 Introduction

City typologies have captured the interest of urban planners since the late 20th century. Cities embody a complex blend of features, encompassing street networks, land use patterns, demographics, and various economic and environmental factors. This intricate mix shapes and confines a city's transportation dynamics, resulting in a unique spatial logic for each urban setting. As a result, traffic policies and strategies effective in one city may not translate universally or prove successful elsewhere. Establishing city typologies, founded on a deep comprehension of traffic features, becomes essential for facilitating the exchange of policies and resources among cities. As cities evolve and confront shared challenges, the dissemination of knowledge rooted in underlying transportation features becomes increasingly crucial for sustainable development and efficient resource utilization.

Traditionally, research on city characterization has predominantly focused on analyzing network structures to identify distinct street layout patterns, leading to classifications such as gridded, organic, and radial cities [17, 32, 94, 13]. In addition to network topology, a limited number of studies have broadened their scope to incorporate indicators such as economics, demography, and employment for classifying cities based on factors like congestion, mode choice, and urban density. This broader approach has facilitated more holistic city classifications, resulting in typologies such as auto cities, transit cities, and congested cities [73, 79]. However, an observation worth noting is that none of these studies have integrated comprehensive features related to two key dimensions - traffic flow and trip demand - into their characterizations. These dimensions are crucial for capturing essential dynamics in urban transportation.

This study addresses these gaps by developing a comprehensive transportation-oriented city typology based on five key dimensions of transportation: trip demand, road network, multi-modal network, traffic flow, and land use. A distinctive aspect of our research is the specific focus on cities within a contiguous urban area. Unlike previous studies that look at cities around the globe, our research concentrates on cities in the large metropolitan region of the San Francisco Bay Area, encompassing 101 cities. Within this regional context, we derive two sets of typologies. In our earlier work, we exclusively considered typologies based on network metrics, providing insights into the structural characteristics of road networks in cities. In this study, in addition to the network dimension, we incorporate other transportation dimensions like demand, traffic flow, etc, providing a more comprehensive perspective on cities.

Our typologies reveal distinct representations of each city within the metropolitan region, obtained through the application of dimensionality reduction and clustering algorithms to the input metrics. We evaluate these typologies for error and explainability, contributing to a better understanding of the unique position of each city within the broader urban context. This classification allows cities to identify others facing similar challenges and opportunities, offering valuable insights for urban planning and transportation management. To the best of our knowledge, this study represents the first comprehensive characterization of cities within a large urban region.

The subsequent sections of this paper are structured as follows. Section 2 presents a comprehensive overview of previous studies on city characterization. In Section 3, we detail the data and methods of the study. Section 4 discusses the results, and Section 5 provides a discussion. Finally, the conclusions are presented in Section 6.

6.2 Literature Review

Cities can be depicted in various ways, offering different representations based on the researcher's objectives [63, 95]. Examining the network structure can reveal information about the connectivity of streets and how drivers experience the city. Analyzing activities and land use can indicate the city's vibrancy and how land use has shaped its urban form. Considering all factors related to transportation demand and supply provides yet another perspective. The latter is our topic of interest.

In the field of transportation research, numerous studies focus on understanding the network structure of cities, while only a limited few delve into exploring the multifaceted dimensions that influence transportation within urban areas. A considerable body of literature categorizes cities based on their street networks, utilizing metrics derived from geometry and topology [17, 51, 18, 32, 94, 13]. [17] used network features to classify 100 cities globally into three primary and eight subsidiary categories and found that American cities had a more pronounced grid-like layout compared to other cities in the world. [13] employed topological and geometric properties to classify 80 cities into categories such as gridiron, long link, organic, hybrid, and mixed cities. By analyzing the geometric and centrality metrics, [94] divided cities into two groups according to whether or not there were major geographical restrictions.

Moreover, many investigations have delved into urban forms and their impact on travel demand, particularly regarding mode choice behavior [102, 71, 48, 9, 41, 86, 20]. Additional studies have taken a focused approach to categorizing cities, considering factors such as energy consumption[93], global status, and political and economic considerations [67]. [85] classified Latin American cities based on indicators of the socioeconomic urban environment, utilizing factor analysis and finite mixture modeling to establish typologies, resulting in five distinct classifications primarily distinguished by education, employment, and gender-specific labor participation.

In addition to typologies based solely on network structure and urban form, a few studies have developed classifications considering multiple dimensions of transportation. For instance, [73] categorized 331 cities into 12 typologies based on economic, demographic, urban form, mobility, and environmental indicators, grouping them into six categories: Auto, BusTransit, Congested, Hybrid, MetroBike, and MassTransit. They used factor analysis and hierarchical clustering in their analysis. The investigation addressed the dimension of trip demand by incorporating mode share as a feature, while for analyzing traffic flow, congestion served as a metric. In their study, [79] classified 73,057 census tracts in the US, first creating microtypes and then establishing geotypes at the county level. They used factor analysis and CLARA clustering algorithm. For the trip demand dimension, the study approximated travel demand determinants using population density, job type, job density, and proportion of trips by distance. In examining the traffic flow dimension, the study utilized truck volume as a metric; however, it did not encompass flow or speed data for automobiles or other modes of transport. In a recent study, [82] utilized a classification model to determine a city's typology by extracting data from Wikipedia pages via natural language processing. They developed a logistic regression model trained on a sparse set of five features acquired through text matching from Wikipedia. Their classification categorized 2000 cities into four classes: congestion, auto-heavy, transit-heavy, and bike-friendly cities.

While some research has extended beyond network topology to include indicators such as economics, demography, and employment in city classification, a limitation exists in explicitly integrating metrics on trip demand and traffic flow characteristics to formulate transportation-oriented typologies for cities. Researchers have frequently restricted their analyses to a small number of metrics because of limited data availability. A comprehensive set of metrics pertaining to traffic flow and trip demand dimensions is notably absent from current city characterizations. This integration is pivotal for capturing the complete spectrum of travel behavior and traffic dynamics within cities, facilitating the development of meaningful and comprehensive typologies. Furthermore, no studies have undertaken a comprehensive examination of cities within a large metropolitan region, as data availability may be limited to only the top cities in the world. This article aims to bridge this gap by proposing a new transportation-based typology that incorporates detailed trip demand and traffic flow data to enrich city typologies, specifically focusing on contiguous cities within a metropolitan region. By integrating trip demand characteristics such as trip purpose and mode share, along with traffic flow metrics like VMT (Vehicle Miles Traveled) and VHD (Vehicle Hours Delay), with traditional demand drivers like land use, a more comprehensive understanding of urban transportation systems can be achieved. Moreover, examining cities within a large urban region allows for the development of typologies conducive to meaningful collaborations. These integrated typologies facilitate optimized transportation planning and policy-making, ultimately leading to improved mobility outcomes and sustainable urban development.

6.3 Methodology

Our study region is the San Francisco Bay area in California comprising nine counties and 101 municipalities. In California, local governments have the freedom to designate themselves as either a "city" or a "town" in their official titles, as there exists no legal distinction between the two terms [2]. Consequently, this study encompasses all 101 municipalities for characterization, albeit with specific limitations. To ensure equitable comparisons, only cities with populations exceeding 5000 are included (totaling 87 cities). Additionally, because the travel demand model cannot accurately represent cross-city traffic outside the region, cities in the boundary of the metropolitan region have been omitted, resulting in a final count of 83 cities.

We collected urban data from various sources covering five primary urban transportation dimensions: trip demand, road network, multi-modal network, traffic flow, and land use. The road network and multi-modal network represent the supply side, whereas trip demand constitutes the demand side. Moreover, trip demand is closely associated with land use. Together, these factors contribute to observable traffic flow and impact the dynamics of cities, influencing both spatial and temporal traffic variations.

After collecting the data, we extracted pertinent metrics from the five dimensions, forming the foundation for city characterization. Subsequently, we conducted exploratory factor analyses to reduce the feature size dimensions and capture the most meaningful relations among variables. Finally, we conducted a clustering analysis to establish typologies. By closely examining typology traits across important variables, we verified our conclusions.

Dimensions & Metrics

Trip Demand

The San Francisco Bay Area includes multiple cities, and people regularly travel between them for work, recreation, and other purposes. Having a comprehensive understanding of all trips originating and concluding within the urban area, as well as inter-city trips, will help to analyze intercity dynamics and the resulting traffic patterns on streets. For example, regions with significant job centers experience a considerable influx of trips, resulting in increased traffic volume and congestion on city streets. Conversely, predominantly residential cities have a lower influx of traffic. Understanding trips and their patterns is key to gaining insights into the travel behavior of the population.

Cities and Metropolitan Planning Organizations (MPOs) employ activity-based travel demand models to predict future traffic patterns and assess the impact of alternative policies on individuals' travel behavior, offering a high level of temporal and spatial resolution [30]. These models forecast when, where, for how long, with whom, and using what mode individuals will conduct various activities and the travel choices they will make to complete them. They are developed through multi-step processes involving the observation of residents' travel patterns (through surveys), transportation systems, population and employment data, and various other data sources, with validation against multiple data sets. For our study, we rely on the output of the San Francisco County Transportation Authority (SFCTA) Champ 6 model [87]. The dataset covers the entire San Francisco Bay area and comprises twenty-four million trips, each assigned with a specific origin and destination traffic analysis zone, transportation modes (including walking, biking, transit, single-occupancy vehicles, high-occupancy vehicles), and trip purposes (such as home, work, school, shopping, meals).

Multiple variables are generated from the trips file, which were utilized in the subsequent city classification. The trips for a city are divided based on their direction of flow into outbound and inbound trip demand. Outbound trip demand encompasses all trips originating in the city by residents, categorized based on modes such as car, transit, bike, and walk. Additionally, the proportion of commute trips concluding within the city versus those heading to inter-city destinations was also computed.

For inbound trips, we assess trips by purpose, categorizing the purpose of all trips entering the city, such as work, home, and recreation. We also use a metric to capture additional commute trips entering the city, contrasting them with commute trips leaving the city. This metric helps capture the increase in the floating population during the daytime. A full list of variables is provided in Table 6.2.

Road Network

The Mobiliti Bay Area network [25] is the road network used in this study. Mobiliti is a large-scale, high-performance traffic simulator built jointly by Lawrence Berkeley National Laboratory (LBNL) and the Institute for Transportation Studies at UC Berkeley's Smart Cities Research Center. The Mobiliti map, which is composed of over a million links and 0.5 million nodes, is organized as a directional map with each link representing the flow of traffic from a start node to an end node. The network was preprocessed into a primal graph representation before analysis, with nodes denoting intersections or dead ends and links representing the streets that connect these nodes. Furthermore, administrative boundary data from the Metropolitan Transportation Commission [**mtc**] was used to trim the graph to each city's boundaries.

We use both topological and geometric features to describe road networks. The literature quantifies the topological features using a number of metrics, including degree, betweenness centrality, closeness centrality, eigenvector centrality and clustering coefficient [65, 57, 88, 23, 28]. We concentrate on node degree and betweenness centrality as topological metrics in our work since they provide a thorough understanding of the general characteristics of road networks. Additionally, we compute the average link length, network density, and link-node ratio for geometric variables across all cities. The variables and their summaries are presented in Table 6.2.

Multi-modal Network

The San Francisco Bay Area offers a diverse array of transportation modes, encompassing transit, biking, and ferry services to serve its sizable population. In our characterization, we go beyond the automobile road network, integrating metrics related to other transportation modes. The data for this analysis was sourced from the Metropolitan Transportation Commission (MTC) Open dataset portal. Transit metrics, such as total network miles and persons per stop, were calculated. In the case of biking, the total network miles of bike paths within each city were computed as part of the analysis.

Traffic Flow

The interaction between demand and supply influences traffic flows on the network, contributing to various dynamics. Traffic flow assessment encompasses factors such as vehicle count, speed, congestion, pass-through traffic, Vehicle Miles Traveled (VMT), Vehicle Hours of Delay (VHD), among others. However, collecting real-world traffic dynamics data for multiple cities poses practical and financial challenges. In such instances, simulations emerge as a valuable alternative to replicate real-world data.

Simulations offer a cost-effective method to analyze transportation dynamics, providing insights into city characterization and enriching our understanding of urban mobility. They serve as a practical solution when obtaining extensive real-world data is challenging, enabling researchers to explore and evaluate the complexities of traffic interactions across different urban environments.

For our research, we rely on simulation output produced by Mobiliti. Running on the NERSC computer at Lawrence Berkeley National Laboratory, Mobiliti [25] is an agent-based scalable parallel discrete event simulation platform. Mobiliti generates data on traffic flow, speed, and energy consumption at fifteen-minute intervals throughout an entire day for the entirety of the San Francisco Bay Area. This large-scale traffic simulator covers one million links and half a million nodes, with an input automobile trip demand of nineteen million.

We compute a range of metrics, including Vehicle Miles Traveled (VMT), Vehicle Hours of Delay (VHD), trip distances, and travel times. Building upon our previous work in reclassifying streets based on land use [60], we employ these street classifications to evaluate the traffic load on different street types. A comprehensive list of metrics is detailed in Table 6.2.

Land use

Land use plays a crucial role in shaping travel demand, either enhancing or reducing it depending on the types of land use and their spatial arrangements. Therefore, a key aspect of city characterization involves focusing on land use mix of a city to gain a comprehensive understanding of the urban landscape. The land use data is obtained from MTC and population data from Wikipedia [66]. We utilize the land use share of the city as a feature, encompassing percentages of residential, commercial, industrial, Public Semi-Public (PSP), and Open/Green Space.

Clustering

From the five dimensions, we have a total of 44 features, which were normalized to scale the data to a standard range. This normalization helps prevent specific features from exerting a disproportionately strong influence on the model's output based on their value sizes. Next, we performed exploratory factor analysis (EFA) to unveil the latent structure of the dataset and to reduce dimensionality for the subsequent clustering. Starting with 44 features, we identified 14 factors that capture 80% of the variation in the data.

To categorize cities, we employed unsupervised machine learning clustering techniques, specifically using the K-means method. The factors obtained from the EFA were used as input for clustering. The determination of the optimal number of clusters was performed using the elbow method, resulting in the selection of 8 clusters. The resulting silhouette score for this clustering is 0.45.

6.4 Results

Eight typologies were identified through clustering. Figure 6.1 provides key features for each typology, where shades of blue represent the values of each feature for the particular type—light blue indicating low values and dark blue indicating high values. The stars highlight the most distinct features of each cluster. Table 6.1 offers a concise overview of each typology, emphasizing key features and representative cities. Additionally, Figure 6.2 presents the Bay Area cities and their corresponding typologies.

Live Work

Live Work cities are urban areas where residents both reside and work within the same locality. These cities are characterized by a significant volume of commuting trips taking place within the city limits, a minimal proportion of commutes to and from other cities, and short distances traveled by residents to their workplaces. Furthermore, these cities feature a high percentage of commercial land use and a moderate percentage of residential land use. The predominant mode share is cars, but the VMT per capita is low, mainly because of shorter travel distances. Additionally, they also exhibit a high share of walking as a mode of transportation. Examples include the wine-producing cities in the northern Bay Area, such as Napa and Sonoma, as well as business park cities in the eastern Bay Area, like Livermore and San Ramon.

Job and Activity Magnets

These cities have a significant share of job opportunities and attract commuters from neighboring cities, making them key job destinations. Among all the trips concluding within the city, they exhibit the highest proportion of work-related journeys. For residents, the distance to their workplaces is generally short. However, these cities also experience high congestion on their streets and have elevated VMT on their roads due to workers from outside the city. Their mode share is predominantly car, followed by transit. The walk mode share is low. They are characterized by low residential land use and high commercial land use. Examples of such cities include the tech centers in the South Bay Area, such as Mountain View and Cupertino.

Anchor

These are the major cities in the Bay Area (San Francisco, Oakland, and San Jose) that attract considerable traffic, featuring vibrant commercial, residential, and recreational activities. They also boast diverse transportation options, including transit, biking, and walking, and hence VMT per capita is low. The commuting distance for residents is relatively short. However, these cities are often congested, with high VHD per capita. The cities in this typology exhibit multiple overlapping characteristics of other typologies, such as high job and activity magnets and multi-modal cities.

Of the three cities, San Jose is the largest in the Bay Area in both population and land area. However, San Francisco boasts the highest population density. San Jose shares similarities with the other two cities regarding the percentage of intra-city commute trips, the proportion of work trips, and the share of commercial land use. Nevertheless, it differs from the other two cities in terms of mode share. San Jose has the highest car mode share and the lowest transit and walk mode share compared to the other two cities in this cluster. Its population density is closer to Oakland's. Despite these differences, San Jose is more closely aligned with cities in the Anchor cluster than with others.

Multi-modal

These cities feature a substantial portion of transit and walk trips. They possess extensive transit network coverage with a low person-to-bus stop ratio. Additionally, these cities exhibit high walk mode share while sustaining a lower car mode share. Examples include Berkeley with commendable transit, bike, and walk infrastructure, and Sausalito, known for its ferry service and robust bike infrastructure. Daly City, in close proximity to San Francisco, has a well-developed bus transit network compared to other cities.

The cities in this typology have an average transit mode share of 10% and a walk mode share of 11%. Among the four cities, Berkeley and Daly City high the highest population density. In terms of land use, Emeryville differs from the other cities with low residential land use and high commercial land use.

Hyper-connected

These cities are situated in close proximity to job centers, forming a strong connection with them. They are characterized by short to medium distances to work and frequent inter-city commute trips. In terms of land use, they exhibit a significant share of commercial and residential land uses. Additionally, they maintain a moderate population density. Most of them are near the Job and Activity Magnet or Anchor City typology.

Examples include Dublin, Redwood City, and Piedmont. Dublin is situated near cities with business parks, such as Livermore and San Ramon in the East Bay. Redwood City is in proximity to tech centers like Mountain View and Cupertino in the South Bay, and Piedmont is close to Oakland in the East Bay.

Low-density Residential

These cities are primarily dedicated to residential land use, marked by a significant proportion of neighborhood residential streets and dead ends. Commercial land use is notably low, contributing to minimal congestion. With a high car mode share and frequent inter-city commute trips, these cities exhibit low population density. Regarding network structure, these cities display a sparse network density, a significant prevalence of degree 1, and high link lengths. Examples include suburban wealthy cities such as Woodside, Los Altos in South Bay, and Larkspur in Marin County.

Medium-density Residential

These cities are characterized by a medium proportion of residential and low commercial land use. They exhibit a high distance to work and have high VMT on city streets. Additionally, they maintain a medium population density. In terms of network structure, these cities have low network density, a high proportion of degree 1, and link lengths similar to cities in the low-density residential typology. Examples include Los Gatos, San Carlos and Vallejo.

Compared to the low-density residential cluster with a mean population density of 2700, this cluster has a density of 3200. In contrast to the low-density residential cluster, which has a mean 72% residential land use share, this cluster has a 42% residential land use.

Mixed-use Residential

These cities are primarily residential but, in contrast to the other two residential types, they feature a high share of commercial activities. They exhibit a notable presence of neighborhood commercial streets (NCS) and commercial throughways (CT). With a moderate distance to work and intra-city commute trips, these cities are characterized by medium population density. Examples are Alameda, Walnut Creek, and San Leandro.

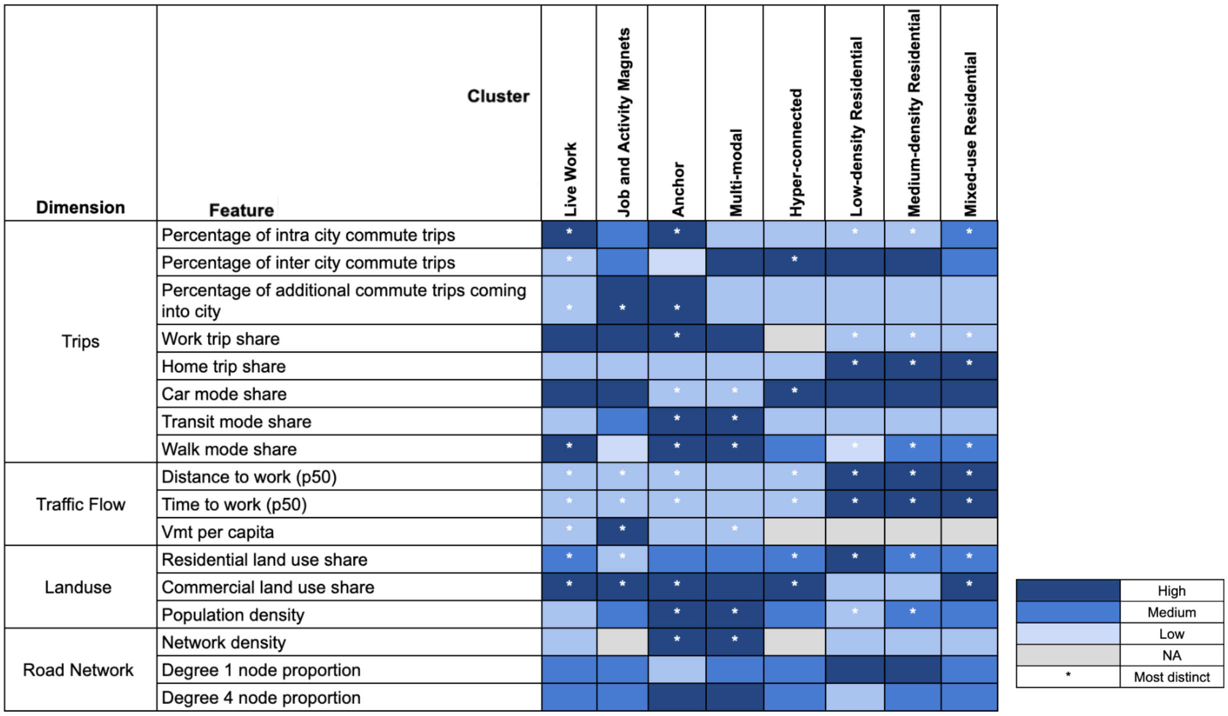


Figure 6.1: Key features for the city typologies

6.5 Discussion

The San Francisco Bay Area is a polycentric region with multiple urban centers and a complex network of connections among them. Our classification enables cities to comprehend their unique positions within the broader urban context, identifying shared challenges and opportunities. To the best of our knowledge, this study marks the first comprehensive characterization of cities within a large urban region, offering valuable insights for urban planning and transportation management.

The typologies developed through our research yield several valuable insights. Firstly, they empower city officials to delve into the strengths and weaknesses of their respective cities, facilitating the identification of areas requiring improvement. This knowledge informs decision-making and resource allocation for targeted enhancements. For example, job and activity magnets experiencing high outside city commute trips may need effective management of the daytime floating population. Moreover, they must strategize for potential shifts in the workforce landscape if remote working becomes a prevalent trend. Cities dependent on outside commuters, lacking a significant residential population, may encounter challenges if remote work continues. It becomes crucial for them to explore alternative strategies, transitioning towards a live-work city typology to attract residents and prevent potential economic and social depreciation. Moreover, typologies act as a local guide for city operations, informing resource allocation by highlighting the need for investment in bike lanes in cities with a significant number of short work trips and high car usage, such as hyper-connected cities. This localized approach to infrastructure development promotes mode share and encourages sustainable transportation choices.

Secondly, these typologies assist in understanding the differential impacts of regional policies on cities. For instance, when implementing fuel-saving routing strategies, the redirection of traffic from highways to local streets will affect cities differently. Cities with a high proportion of thru-traffic will experience greater impacts than others. This understanding guides policymakers in assessing potential consequences of various regional policies.

Thirdly, as highlighted by [73], typologies serve as a valuable tool in gaining deeper insights into travel behavior. By considering a mix of dimensions that affects how people choose to travel, these typologies aids in deciphering the distinct patterns of how individuals navigate and commute within diverse urban environments, allowing for more informed and tailored urban planning strategies.

Lastly, by comparing and contrasting cities across different typologies, cities can learn from one another, gaining a better understanding of their similarities and differences. This exchange of knowledge and experiences fosters collaborative efforts and inspires innovative approaches to addressing shared challenges.

Our study has certain limitations. One limitation of clustering techniques is the challenge of achieving a clear division between clusters; at times, outliers may be present within clusters. However, this issue has already been discussed in existing literature [96, 1], and our objective with this work is to explore meaningful and explainable typologies. Another limitation involves the use of simulated data for both travel demand and traffic flow metrics. We chose simulated data for a comprehensive representation of the Bay Area. In the future, real-world data sources such as GPS data could replace simulated data.

6.6 Conclusion

In conclusion, this study has delved into the intricate interplay of street network structure, land use mix, travel demand and various urban characteristics that shape and constrain a city's transportation dynamics. By incorporating these features, along with trip demand and traffic flow metrics, our research has identified eight distinct typologies for cities in the San Francisco Bay Area region. Notably, our approach stands in contrast to existing literature by encompassing all cities within this large urban metropolitan region and introducing metrics from two additional dimensions of transportation—trip demand and traffic flow.

The analysis of 100 cities in the San Francisco Bay Area involved the collection of data from diverse real-world sources and simulated data. Leveraging machine-learning methods, including feature extraction and cluster analysis, our study identified Live Work, Job and Activity Magnets, Anchor Cities, Multi-modal, Hyper-connected, Low-density Residential, Medium-density Residential, and Mixed-use Residential as the primary typologies characterizing the region.

Each typology reflects unique urban characteristics. Live Work is distinguished by a high proportion of residents living and working within the city. Job and Activity Magnets exhibit high commercial land use, a significant proportion of work trips, and a notable influx of commute trips. Anchor Cities are major urban centers in the Bay Area, feature high population density and commercial vibrancy. Multi-modal cities showcase high usage of transit and walk mode shares. Hyper-connected cities, located in close proximity to Anchor and Job and Activity Magnets, demonstrate medium commute distances and high inter-city trips. The last three typologies predominantly encompass residential cities with varying mixes of population density and residential land use proportions.

Ultimately, the derived typologies offer valuable insights for city officials, facilitating a nuanced understanding of policy impacts, guiding local operations, and fostering intercity learning and cooperation. This comprehensive analysis contributes to the discourse on urban transportation dynamics within a major metropolitan region, emphasizing the importance of considering a broad spectrum of factors for effective urban planning and policy development.

6.7 Appendix

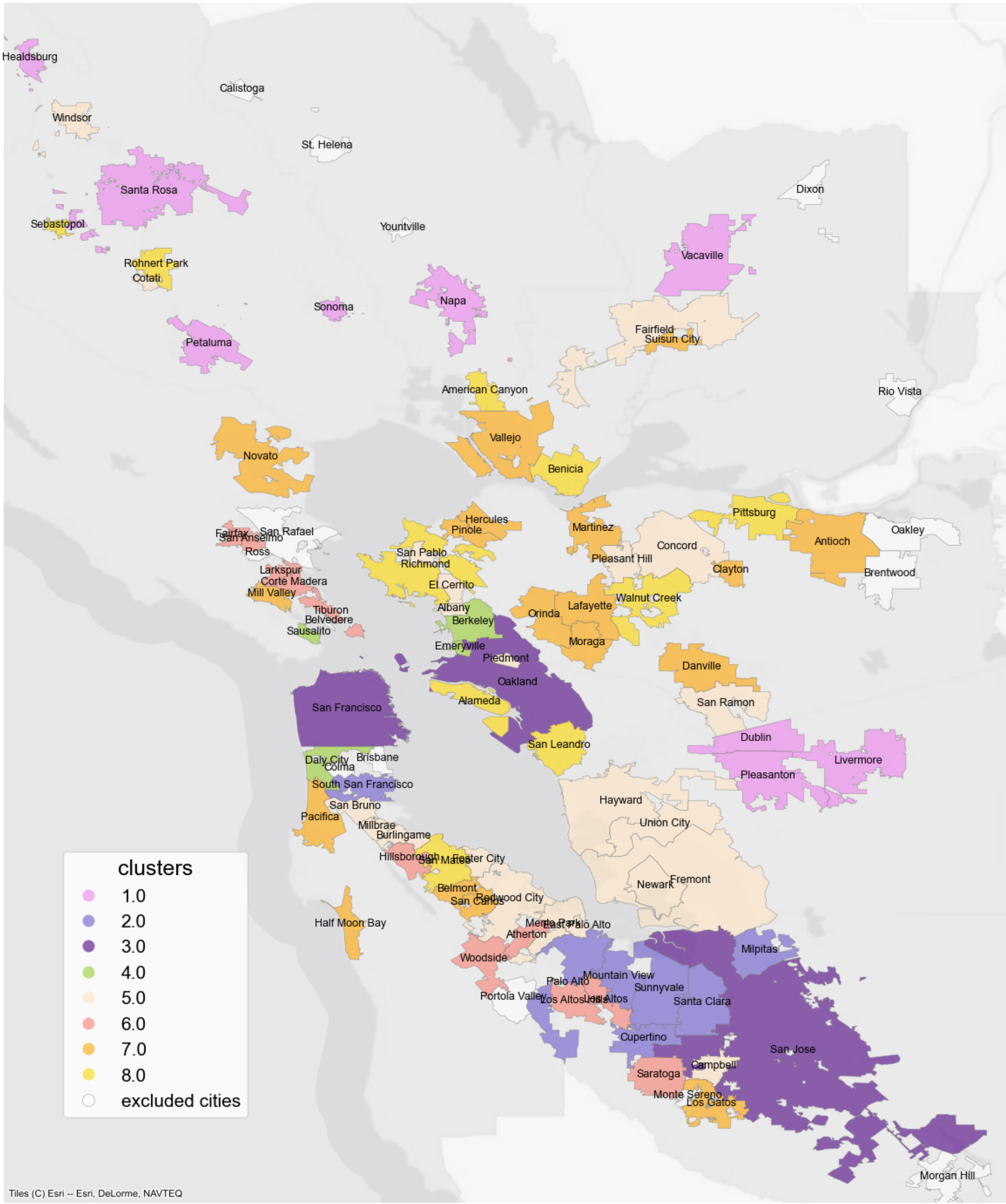


Figure 6.2: San Francisco Bay Area Map with cities in each typology

Table 6.1: City Typologies

Cluster	Typology	Features	No. cities	Example Cities
1	Live Work	High percentage of intra-city and low percentage of inter-city commute trips; low distance to work; low vmt per capita ; Moderate residential and high commercial land use	9	Napa, Sonoma, Livermore, Pleasanton
2	Job and Activity Magnets	High inflow of outside commute trips; low distance to work; high car mode share; high vmt per capita; low residential and high commercial land use	10	Milpitas, Palo Alto, Mountain View
3	Anchor	High proportion of commute trips inflow;high intra-city commute trips; high transit, walk, bike mode share; low vmt per capita; high vhd per capita; high network density; high population density	3	Oakland, San Francisco, San Jose
4	Multi-modal	High transit and walk mode share; low car mode share; low distance to work ; high commercial land use ; high network density; low vmt per capita; moderate distance to work	4	Daly City, Berkeley, Emeryville, Sausalito
5	Hyper-connected	Low distance to work;low intra-city and high inter-city commute trips; high proportion of thru-traffic; high proportion of commercial and residential landuse	19	Redwood City, Dublin, Piedmont, Newark
6	Low-density Residential	High proportion of residential land use; high prop of dead ends; low commercial landuse; low congestion; high proportion of home trips; high car mode share;low population density	11	Woodside, Los Altos Hills, Larkspur
7	Medium-density Residential	High proportion of residential land use; medium proportion of NCS and CT; high distance to work; high vmt per capita; medium population density	19	Los Gatos, Vallejo, Hercules
8	Mixed-use Residential	Medium proportion of residential and high commercial land use; moderate distance to work ; moderate intra-city commute trips; low population density	9	Alameda, San Leandro, Walnut Creek

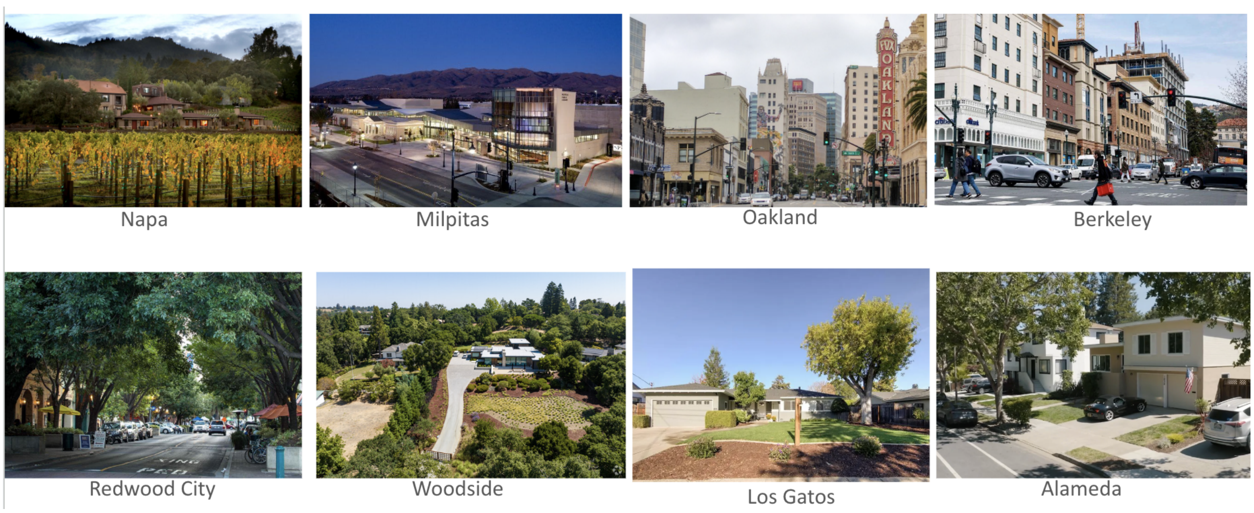
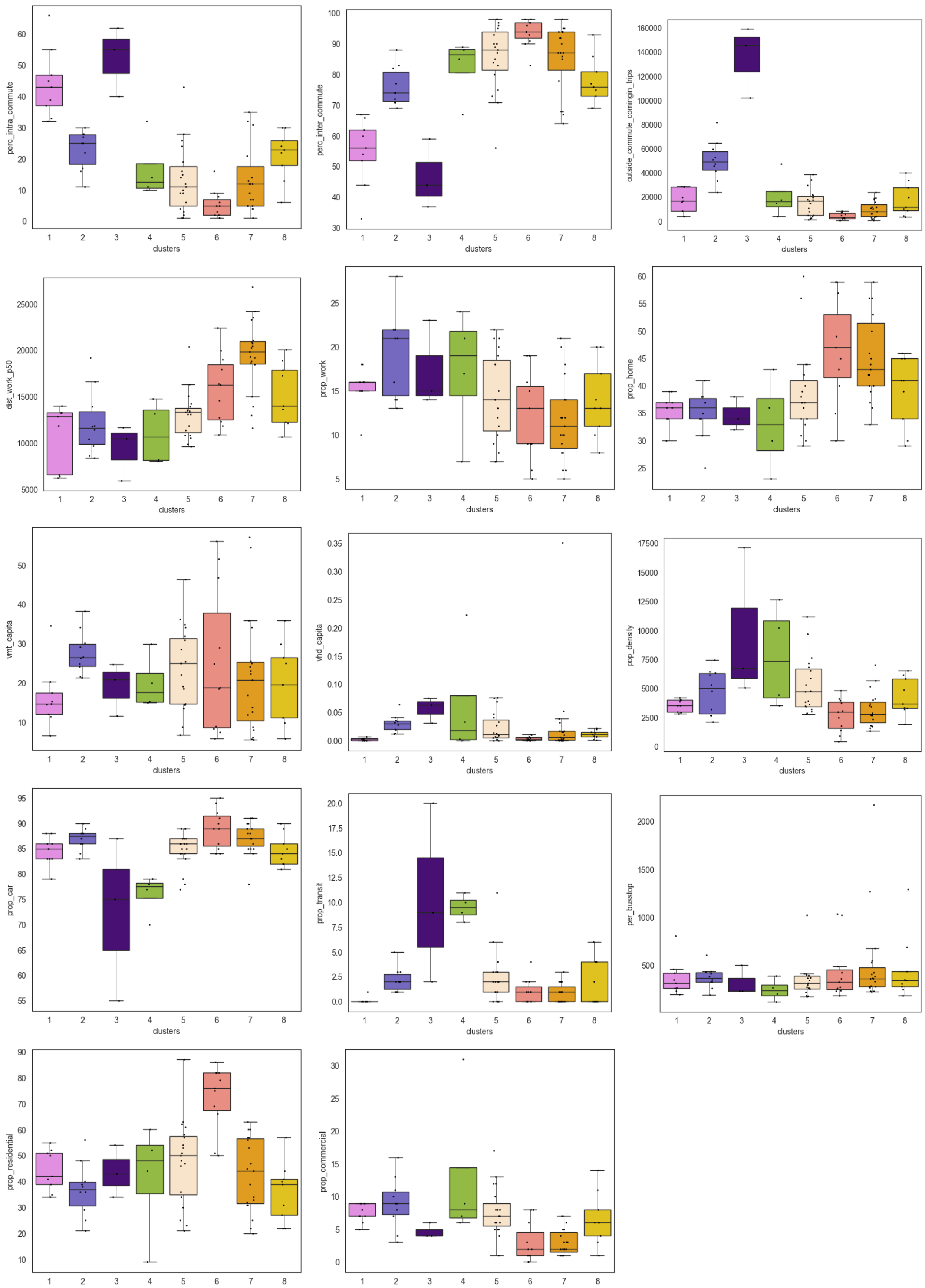


Figure 6.3: Representative cities from each typology

Table 6.2: Metrics

Dimension	**Metric**	**Min**	**Max**	**Median**
Trip Demand	*Outbound Trip Demand:*			
	Car mode share	55	95	86
	Transit mode share	0	20	1
	Walk mode share	2	21	8
	Bike mode share	0	3	1
	Percentage of intra city commute trips	1	66	14.5
	Percentage of inter-city commute trips	33	98	84.5
	Inbound Trip Demand:			
	Work trip share	5	28	14
	Home trip share	23	60	38.5
	Recreational trip share	15	29	22
	Percentage of additional commute trips coming into the city	-109	74	6.5
Road network	Network density	12.5	52.3	30.3
	Degree 1 node proportion (dead ends)	15	47.7	29.7
	Degree 2 node proportion	3.7	19.8	8.1
	Degree 3 node proportion	36.5	62.2	48.3
	Degree 4 node proportion (4-way intersections)	1.3	33.8	10.6
	Median betweenness centrality	0.05	27.27	5.29
	Link - Node ratio	1.9	2.9	2.4
	Percentage of neighborhood residential streets	8.8	79.6	50.2
	Percentage of residential throughways	0.4	26	7.2
	Percentage of neighborhood commercial streets	0.3	13.7	3.5
	Percentage of commercial throughways	0.2	11.5	4.7
	Percentage of highways	0	27.5	13.5
Multi-modal Network	Persons per bus stop	121	2172	340
	Percentage of bus route miles	0.3	39	15
	Percentage of other transit service miles	0	4	0.75
	Percentage of bike lane miles	0	21.3	6.8
Traffic flow	VMT per capita	5.5	57.1	21.1
	VHD per capita	0	0.35	0.008
	VMT: VHD ratio	153	148480	2237
	Percentage of congested miles	0	3	0
	Percentage of pass-through traffic	0	87	44
	Trip Time by purpose starting in a city (P50)	367	1413	668
	Trip Distance by purpose starting in a city(P50)	5945	26820	12512
Land use	Residential land use share	9	87	45
	Commercial land use share	0	31	6
	Industrial land use share	0	21	2.5
	PSP land use share	0	18	5
	Open/green land use share	0	16	1
	Population density	440	17132	3683


perc_intra_commute
perc_inter_commute
outside_commute_comingin_trips
dist_work_p50
prop_work
prop_home
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prop_residential
prop_commercial
clusters

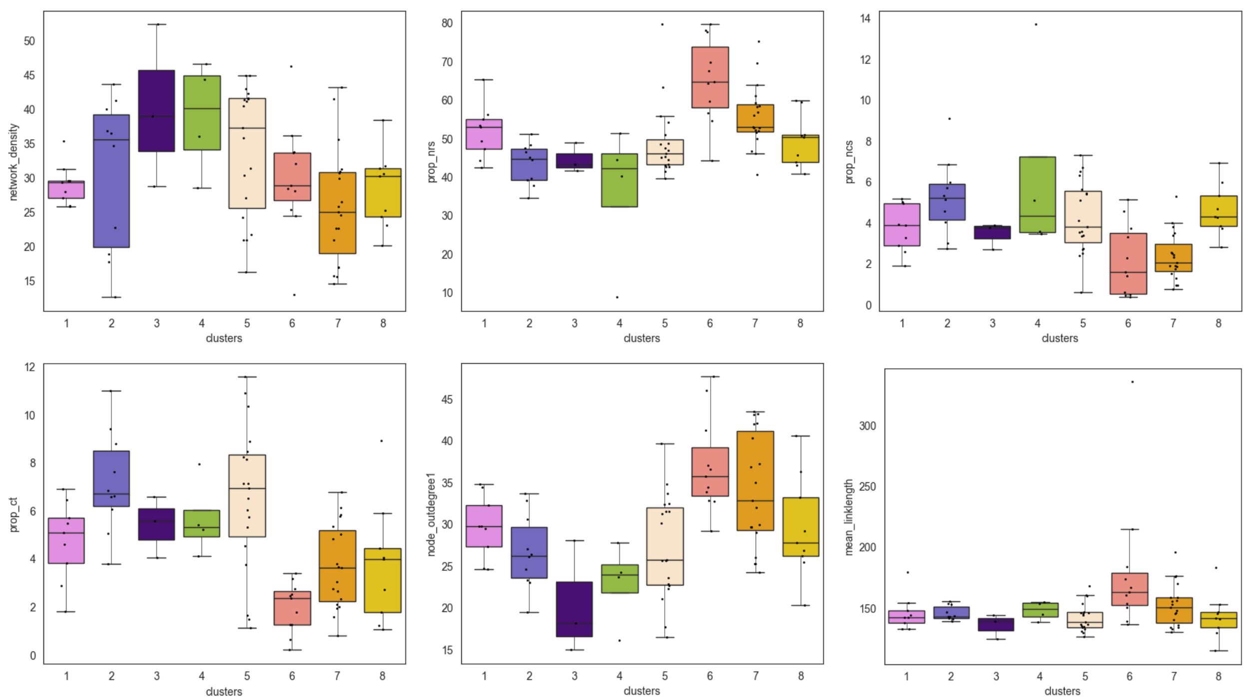

Figure 6.5: Box plots of selected variables by typology.

Chapter 7

Conclusion

7.1 Summary of Contributions

In this dissertation, we have advanced the characterization of regional traffic dynamics by developing innovative analytical frameworks and models specifically tailored to capture the nuanced and complex traffic dynamics found in large metropolitan regions. Leveraging the Mobiliti simulator alongside data analytics and machine learning, we studied diverse scenarios, including the influence of navigation apps, the impacts of different routing strategies, the evaluation of large incidents, and the development of city typologies.

In Chapter 2, our investigation of dynamic routing and its varying penetration rate represents the first large-scale regional study examining the impact of real-time traffic routing. Our findings indicate that beyond a 70% penetration rate of dynamic routing, the marginal benefits of rerouting begin to decline. Nonetheless, dynamic rerouting adeptly redistributes vehicle flows from heavily utilized highways and arterials to less congested neighborhood links, thereby mitigating overall system delay. Notably, despite the heightened traffic volume on local roads, congestion does not consistently ensue, as many links do not reach congested levels despite the increased flow.

The SAEF framework presented in Chapter 3 represents the first analytical framework that comprehensively captures the impact of various routing strategies, enabling the identification of trade-offs. Our framework's indicators are carefully chosen to detect system changes when routing strategies are altered, with a focus on neighborhood-related indicators, often overlooked in existing frameworks. The results demonstrate that many neighborhood impacts, such as traffic load on residential streets and around minority schools, degraded with routing strategies that optimize for the system rather than at the user level. The findings also show that all routing strategies subject the city's disadvantaged neighborhoods to disproportionate traffic exposure. With the widespread adoption of navigation apps, the evaluation framework enables reflection on the consequences of traffic routing, allowing city planners to recognize the trade-offs and potential unintended consequences.

We enhanced the analysis of large-scale disruption events in Chapter 4 by incorporating the entire region, modeling the full road network and demand, and capturing drivers' dynamic rerouting behavior. Our findings indicate that the region experienced an additional 14,000 vehicle hours of delay and 600,000 vehicle miles due to the closure of the Richmond-San Rafael Bridge in the San Francisco Bay Area. Additionally, the median traffic volume on neighborhood streets in San Francisco, Vallejo, and San Rafael increased by more than 10%, highlighting the role of local roads in accommodating the traffic overflow, a factor often overlooked in prior studies. These evaluations of transportation network dynamics in the context of events are extremely useful in informing disaster plans and aiding in traffic management strategies for preparation or during an incident, particularly for areas such as the San Francisco Bay Area, which are connected by many bridges and have limited alternate routes.

In Chapter 5, we developed city typologies based on street network structure. This classification can provide valuable insights into how drivers experience a city, which in turn can influence travel behavior and traffic dynamics. We examined 94 cities in the San Francisco Bay Area, considering diverse road network features. To aid in this classification, we introduced a new metric for categorizing intersections that distinguishes between various types of 3-way and 4-way intersections based on geometric angles. Through the application of clustering techniques in machine learning, we identified three distinct typologies within the San Francisco Bay Area: grid, orthogonal, and organic cities. Gridded cities are distinguished by their dense network of right-angled four-way and three-way intersections. These cities exhibit a compact layout with smaller link lengths and slower traffic speeds. On the other hand, orthogonal cities exhibit a different street network configuration, characterized by a predominance of right-angled three-way intersections and longer street lengths. Organic cities represent a third typology, characterized by their irregular and non-grid-like street network. These cities feature long links with numerous dead ends and winding, circuitous roads. Our findings indicate that the integration of the new metric has improved our ability to distinguish between different types of cities, complementing the existing metrics. In gridded cities, the introduction of the new metric enhances the recognition of grid patterns by explicitly considering 90-degree intersection angles. Conversely, for non-gridded cities, a notable advancement is the ability to differentiate between various types of degree 3 nodes (3-way intersections). While many cities have a significant number of degree 3 nodes, the arrangement of these intersections can vary greatly due to angle variations, resulting in either 90-degree T intersections or non-T intersections. Our study showcases the effectiveness of the new metric in capturing these distinctions, facilitating the classification of cities with a high proportion of T intersections into orthogonal cities and those with non-T intersections into organic cities.

Finally, in Chapter 6, we expanded upon our previous city characterization work, which focused on network structure, by incorporating multiple transportation dimensions. We developed transportation-focussed typologies for all cities in the metropolitan region of San Francisco Bay Area. As cities evolve and face shared challenges, the development of city typologies, rooted in a comprehensive understanding of traffic characteristics becomes crucial for facilitating the effective exchange of policies and resources among them. In addition to incorporating metrics from dimensions like road network, multi-modal network, and land use, commonly used in literature, we integrated metrics related to trip demand and traffic flow dimensions. Using factor analysis and unsupervised machine learning clustering methods, we identified eight distinct typologies for the Bay Area: Live Work; Job and Activity Magnets; Anchor Cities; Multi-modal; Hyper-connected; Low-density residential; Medium-density Residential; Mixed-use residential. The results revealed that many clusters were characterized by features from travel demand and traffic flow dimensions, thus signifying their importance in typology generation. These typologies can serve as a foundation for facilitating the effective exchange of policies and resources, relying on a thorough understanding of traffic characteristics.

7.2 Future Research Directions

Future research could leverage the SAEF framework to develop aggregate measures of safety and neighborhood that will drive novel socially-aware routing strategies and road network adjustments. These strategies would assign appropriate weights and values to different metrics based on the priorities of cities, with the aim of optimizing for their specific needs and objectives. This is increasingly crucial as traditional traffic routing agencies typically prioritize factors like travel time or fuel efficiency. However, with the evolving landscape of transportation, including the rise of autonomous vehicles and the increasing prevalence of electric vehicles, routing based on alternative metrics such as safety or neighborhood quality will become essential for cities and their residents.

Future research could also delve into network structure typologies and investigate whether a city's network configuration correlates with congestion levels. By comparing cities within typologies such as gridded, organic, or orthogonal, we can explore correlations with mobility metrics including traffic speed, congestion levels, and overall dynamics. This research holds promise, as these correlations can provide insights into current conditions and guide the design of future cities. By examining how street networks should be planned in future urban developments, we can anticipate and mitigate potential traffic issues, contributing to more efficient and sustainable transportation systems.

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