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Publication Date

DOI

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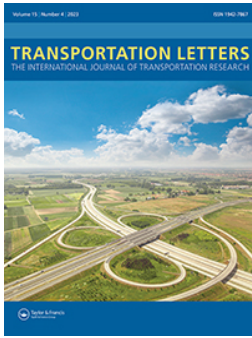
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Socially-aware evaluation framework for transportation

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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.

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) (Hendawi et al. 2017; Siuhi and Mwakalonge 2016), with up to 60% of drivers using them daily (2018a). 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 (Macfarlane 2019).

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 (Chan et al. 2018) that implements a Quasi Dynamic Traffic Assignment (QDTA) (Chan et al. 2021). 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.

Literature review

Traffic routing in cities

There has been much previous work in the area of transportation modeling, and traffic route choices (Chen and Ben-Akiva 1998; Groot, De Schutter, and Hellendoorn 2015; Ran, Boyce, and LeBlanc 1993; Zhu and Ukkusuri 2015). Understanding the

distribution of traffic on local road networks gained popularity in the past decade with route guidance systems rerouting traffic differently than before (Ackaah 2019; Paricio and Lopez-Carmona 2019). Most route guidance systems aim to provide a user with the least travel time route (2015; Mahmassani and Peeta 1993). This might mean taking people off the highway to local streets to save a few minutes of travel time (Jou et al. 2005). 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 (Alfaseeh and Farooq 2020; Ahn and Rakha 2013). Studies evaluating the impacts of navigation systems model app-based and non-app-based users differently to understand the resulting congestion patterns (Lazarus et al. 2018; Cabannes et al. 2018). 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 Los Angeles and measured the outcome in terms of fuel consumption and congestion levels (Elbery and Rakha 2019). 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 (Ahvenniemi et al. 2017). 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 dimensions and six sustainability indicator groups for Swedish cities (Koglin, Toth-Szabo, and Angjelevska 2011). 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 British Standards Institution (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 (Orlowski and Romanowska 2019). Benevolo et al. (2016) investigated the role of Information and Communications Technology (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 (Benevolo, Dameri, and D'Auria 2016). 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, 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 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.

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 the neighborhood, safety, mobility, and environment that encompass the multitudes of traffic impacts on cities (Figure 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 (Koglin, Toth-Szabo, and Angjelevska 2011; Onatere, Nwagboso, and Georgakis 2014; Toth-Szabo and Várhelyi 2012). 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 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
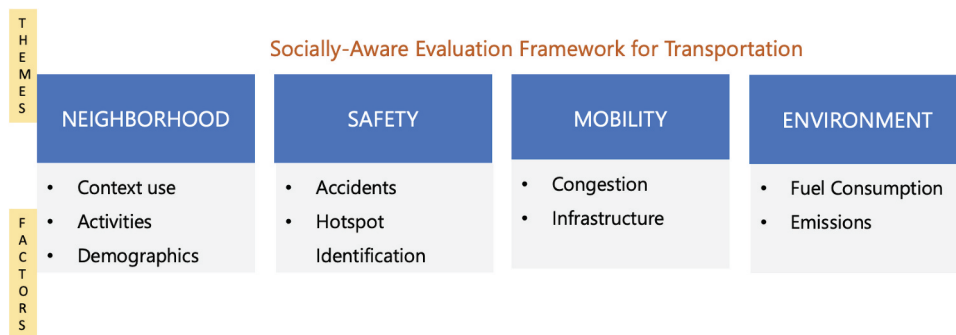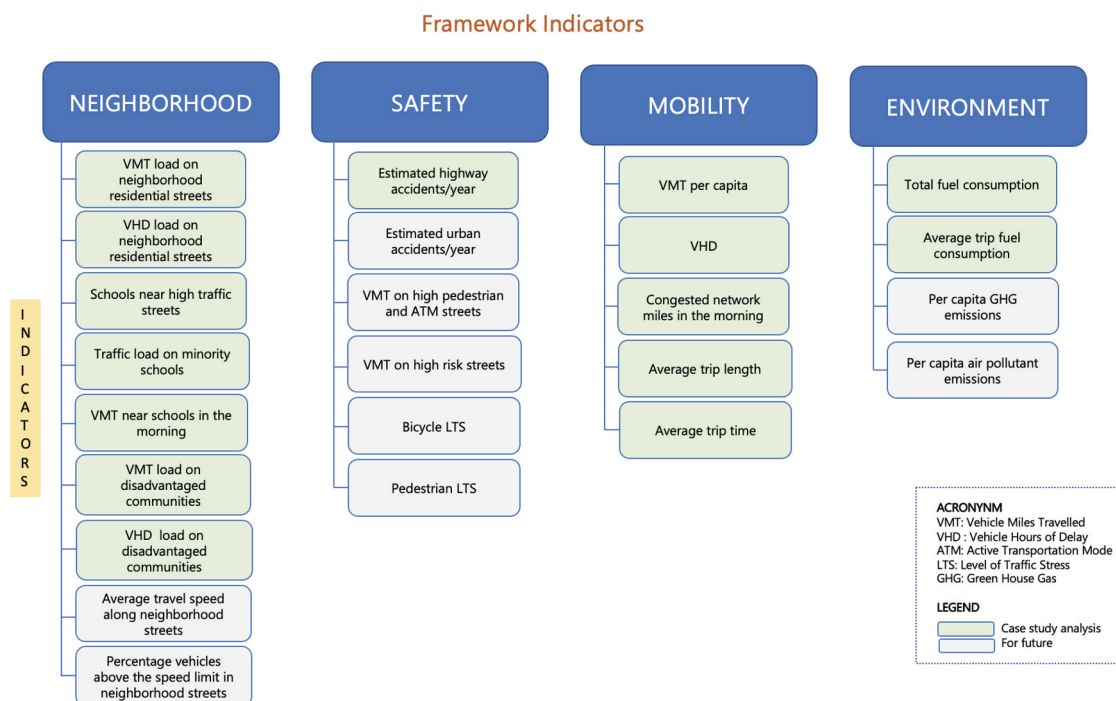
Figure 1. Themes in the framework.

Figure 2. Indicators for each theme.

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 environmental 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 toward long-term policy goals.

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 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 A, 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). 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
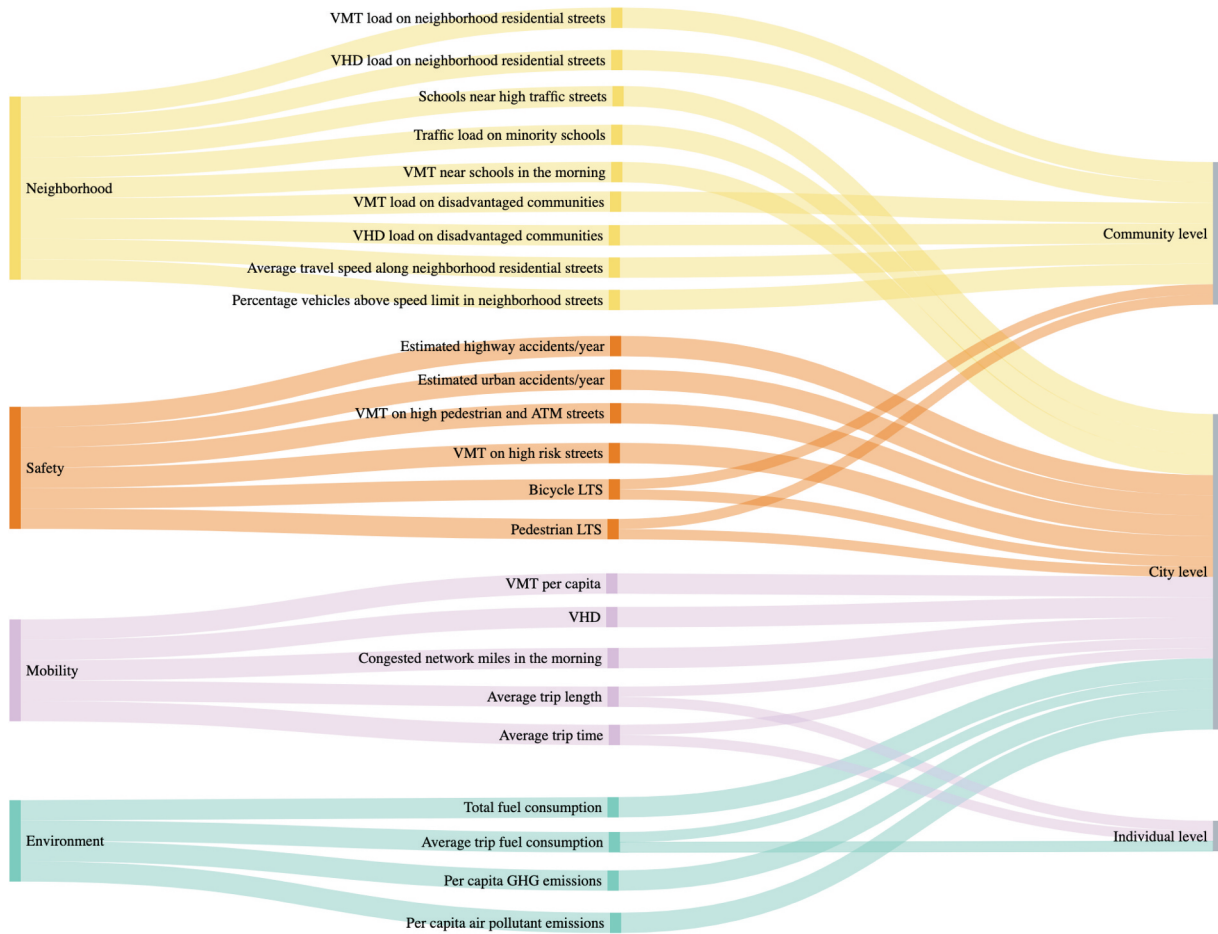
Figure 3. SAEF Indicators and their spatial levels.

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.

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 (Chan et al. 2018). Mobiliti is a mesoscopic urban-scale transportation simulation platform that implements parallel discrete event simulation on high-performance computers at Lawrence Berkeley National lab (2018) . 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 model accounting for ~ 19 million trips during a 24-hour period (2002). Mobiliti provides three optimization methods based on standard traffic assignment algorithms. Specifically, it implements a Quasi-Dynamic Traffic Assignment (QDTA) (Chan et al. 2021) followed by a discrete event simulation. The main components of the simulator are detailed in Figure 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 (Wardrop 1952). The optimization objectives are travel time or fuel (refer to Appendix B for the specific objective functions).
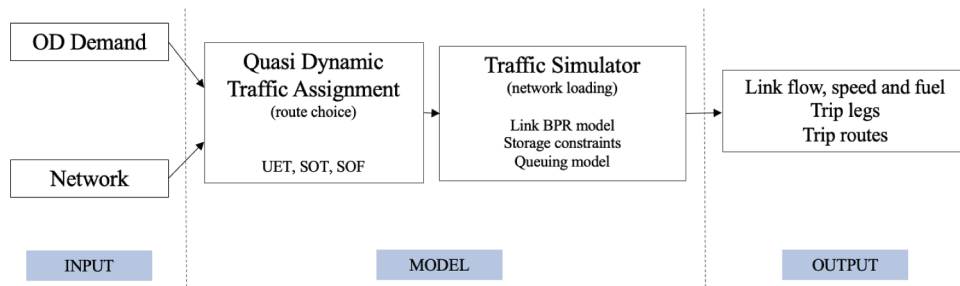

Figure 4. Mobiliti simulation framework.

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 (Table 1). Figure 5 shows all Bay area cities with the chosen four case study cities highlighted.

Table 1. Case study cities.

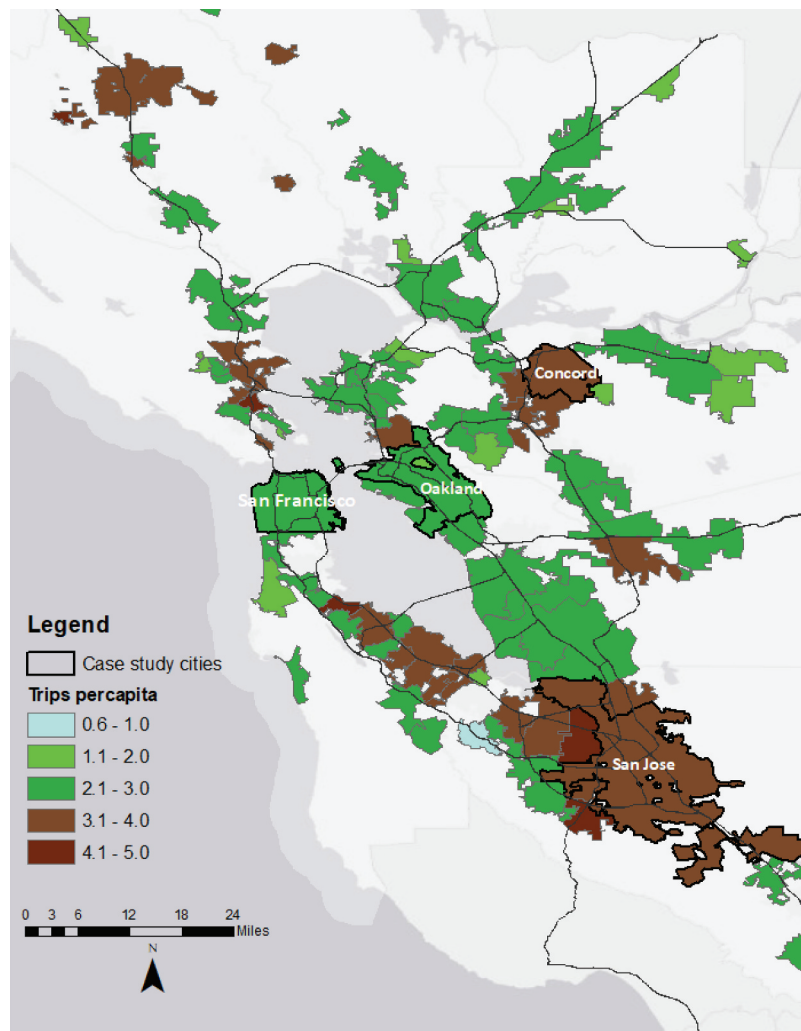| City	Area (sq.mile)	Population	Population density (person/sq.mile)	Trips per capita
San Jose	185	1,021,795	5,524	3.1
San Francisco	49	874,961	17,847	2.2
Oakland	58	425,097	7,333	2.7
Concord	31	129,183	4,105	3.5

Figure 5. Bay area cities colored by per capita trips.

Network typologies

Depending on the goals of the routing strategy, the distribution of traffic on the roads may change. Therefore, it is important to quantify these variations among different types of roads when assessing impact. Traditionally, road classification systems are based on mobility, and access for vehicular use (2000). 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 (2015). 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. This resulted in 16 classes designed using extensive community surveys and manual labeling (e.g., downtown residential streets, downtown commercial streets, mixed-use streets, etc.) (2010). Similarly, San Jose classified streets into eight types based on a street's primary function, and adjacent land use context (2018b). 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 (2019). The HERE technologies map includes definitions of five functional class roads defined in Appendix C Table A2. 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). The 1,956,207 parcels in the analysis region is grouped into five land uses – residential, commercial, industrial, public-semi public, and others. For each link, the side land 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.

Thus, 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 6. Appendix C Table A3 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 and manual labeling and can still provide a good understanding of the network typologies. Figure 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 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 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.

1) Neighborhood Indicators Vehicle Miles Traveled (VMT) and Vehicle Hours of Delay (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 the proportion of VMT or VHD on the neighborhood residential streets divided by the proportion of neighborhood residential streets. A load greater than one indicates disproportional impact.

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 (Yu and Zhu 2015). 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
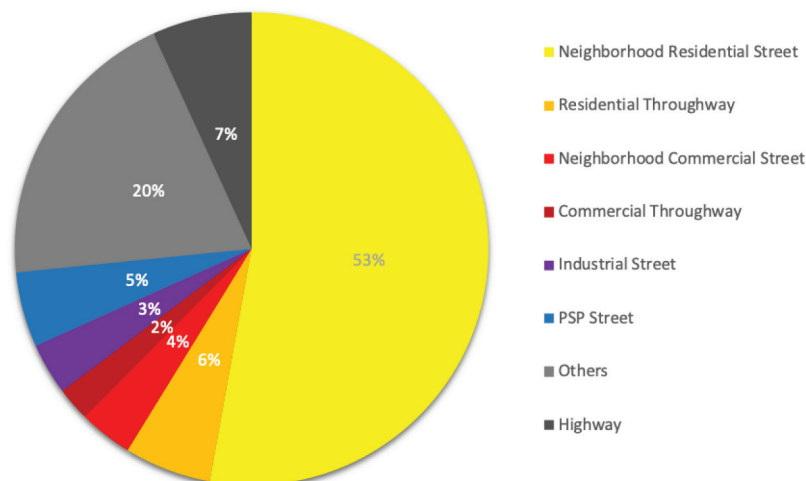

Figure 6. Network typologies for Bay Area. Neighborhood residential streets constitute the highest share, followed by highways. Individual cities reflect similar partitioning.
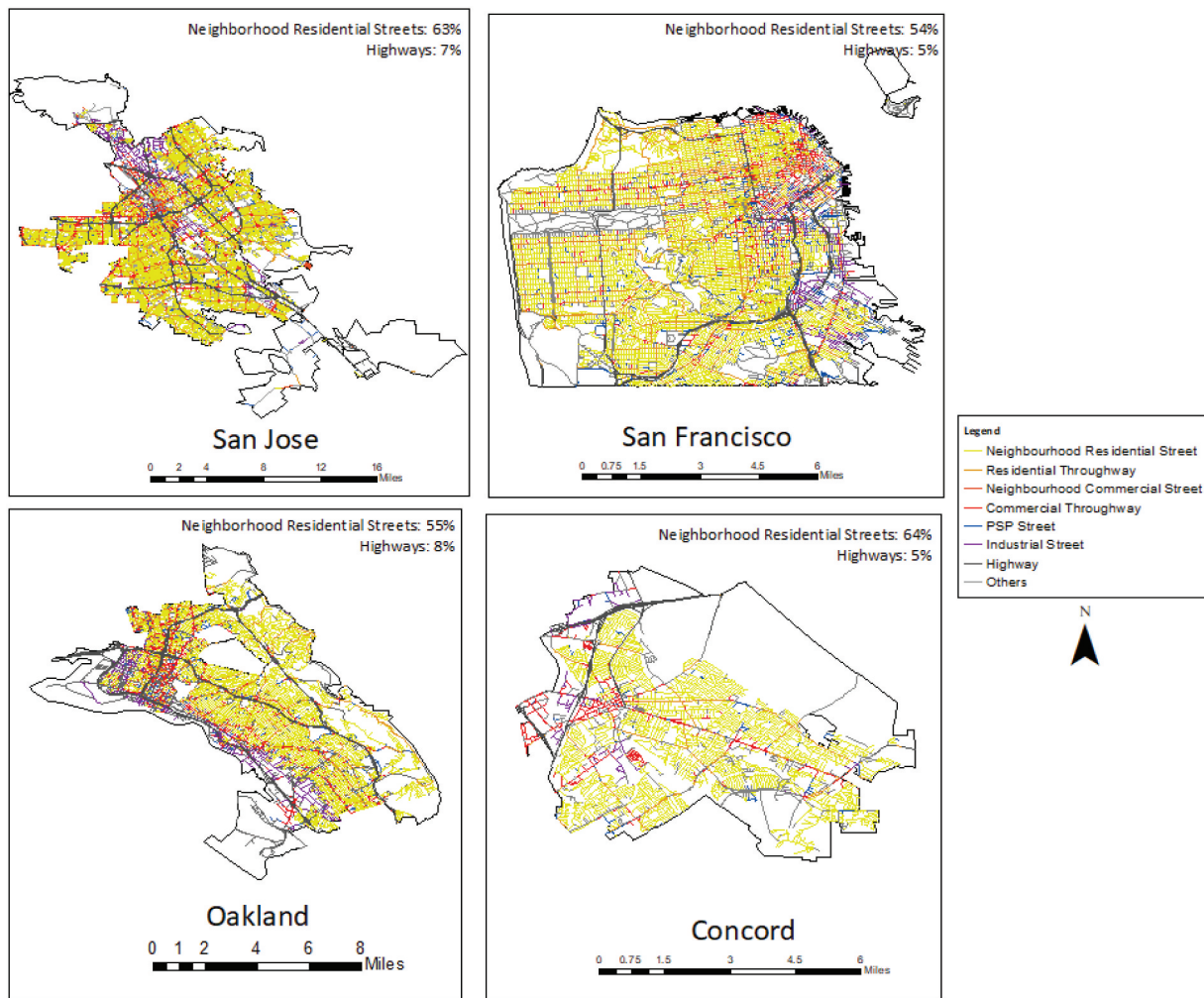
Figure 7. Network typologies for Oakland, San Jose, San Francisco, and Concord. Oakland has the highest percentage of highways, and Concord has the highest percentage of neighborhood residential streets.

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 Center for Education Statistics (NCES) using data from the Common Core of Data (CCD) for the year 2018–2019. We evaluated roads within a 250 m radius of each school (Kingsley et al. 2014). Studies suggest that Average Daily Traffic (ADT) greater than 50,000 creates high expo-

sure to traffic emissions, and between 25,000 to 50,000 is considered medium exposure (Green et al. 2004; Wu and Batterman 2006). For all links in the buffer of each school, ADT counts were calculated to determine if these thresholds were exceeded. Additionally, we identify the effects of increased traffic flow between 7 and 8 am, when children are likely to be present, by calculating the VMT for the links in the 250 m school 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

Table 2. Methods used to evaluate indicators.

Theme	Indicator	Method
Neighborhood	VMT load on neighborhood residential streets, VHD load on neighborhood residential streets	Section IV-B, IV-C1
	Schools near high traffic streets, Traffic load on minority schools, VMT near schools in the morning	Section IV-C1
	VMT load on disadvantaged communities, VHD load on disadvantaged communities	Section IV-C1
Safety	Estimated highway accidents/year	Section IV-C2
Mobility	VMT per capita, VHD, Congested network miles in the morning, Average trip length, Average trip time	Section IV-C3
Environment	Total fuel consumption, Average trip fuel consumption	Section IV-C3

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. We identify disadvantaged communities from the Metropolitan Transportation Commission's (MTC) Communities of Concern (CoC) classification to evaluate this. CoC classification is based on American Community Survey (ACS) 5-year census tract data. CoC is identified using eight demographic factors, namely minority population, low income, limited English proficiency, zero vehicle households, senior citizens, people with disability, single-parent families, and severely rent-burdened households (2016). All census tracts with concern classes categorized as high, higher, and highest are considered part of our disadvantaged group (Figure 8). Subsequently, we computed the VMT and VHD load on disadvantaged communities, similar to the neighborhood residential street load. The VMT or VHD load on disadvantaged communities is determined as the ratio between the proportion of VMT or VHD occurring on streets within the disadvantaged communities to the proportion of network miles in the disadvantaged communities.

2) Safety Indicators Numerous factors like traffic flow, road geometry, and road type (2020) must be taken into account while estimating the occurrence of accidents on highways and local roads. California Department of Transportation (Caltrans) has developed safety performance functions (SPF) to estimate the occurrence of accidents on highways (Shankar and Madanat 2015). The SPF 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:

$$\lambda_i = \alpha + ln(length)_i + \beta ln(ADT)_i \tag{1}$$

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 D.

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.

3) Mobility and Environment Indicators Mobility indicators used in the framework include key system performance metrics, e.g., Vehicle Miles Traveled (VMT) per capita, Vehicle Hours of Delay (VHD), congested urban VMT, and trip level metrics like average trip distance and trip 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 the difference between the actual and free flow travel times. 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 9 presents the results for San Jose. For added insights, we compare optimization scenarios for each of the indicators. We also compare our four focus cities to identify similarities and differences. Figure 13 shows the results for the other three cities and Appendix E provides the summary table for the results. For the rest of this section, we will discuss the results for San Jose. For comparison of routing strategies, we use UET optimized routes as our baseline.

1) 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 one for all three strategies, as neighborhood streets account for the majority of the total network.

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 (Figure 10). 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 250 m 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 one 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 for these communities are similar to the overall system VMT and VHD changes. VMT load in disadvantaged communities reduces with SOT and SOF routing. Delay load also shows similar trends to the overall system VHD.
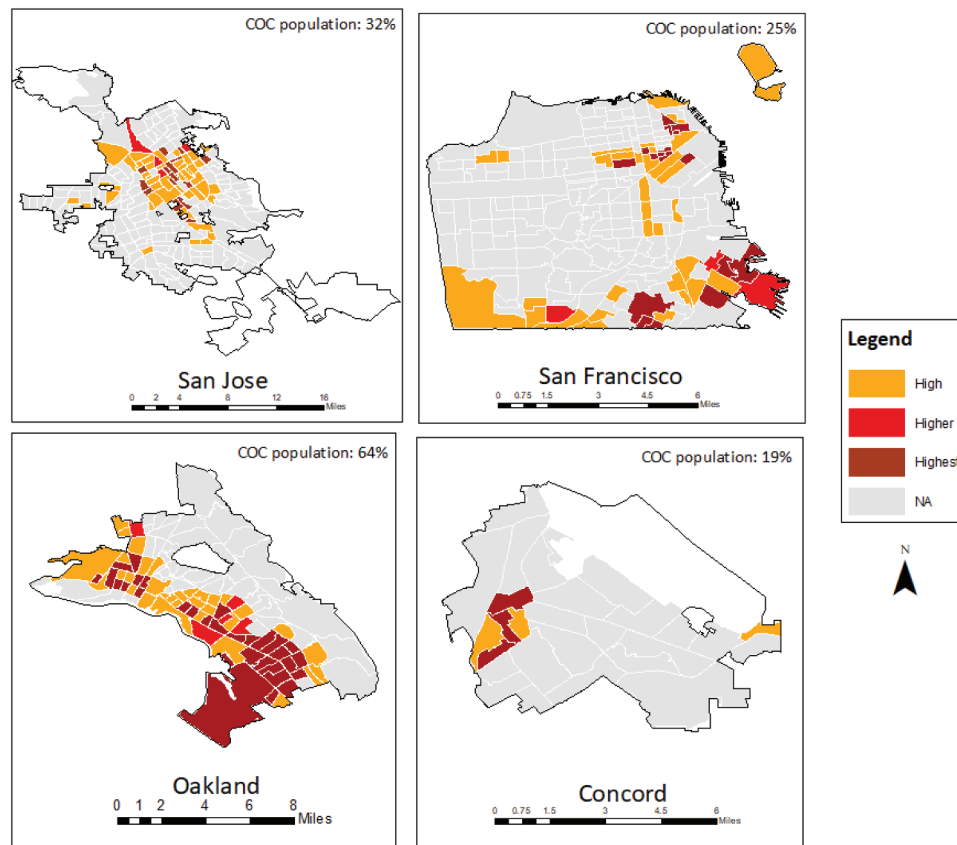
Figure 8. Theme Neighborhood: Communities of Concern census tracts in the case study cities. Oakland has the highest percentage of population living in these census tracts and Concord the least.

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 11, which has resulted in an increase in total delay. 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.

2) 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 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 with 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.

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 small, 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.

f. The VMT per capita decreases with SOT and SOF compared to the baseline for all cities.
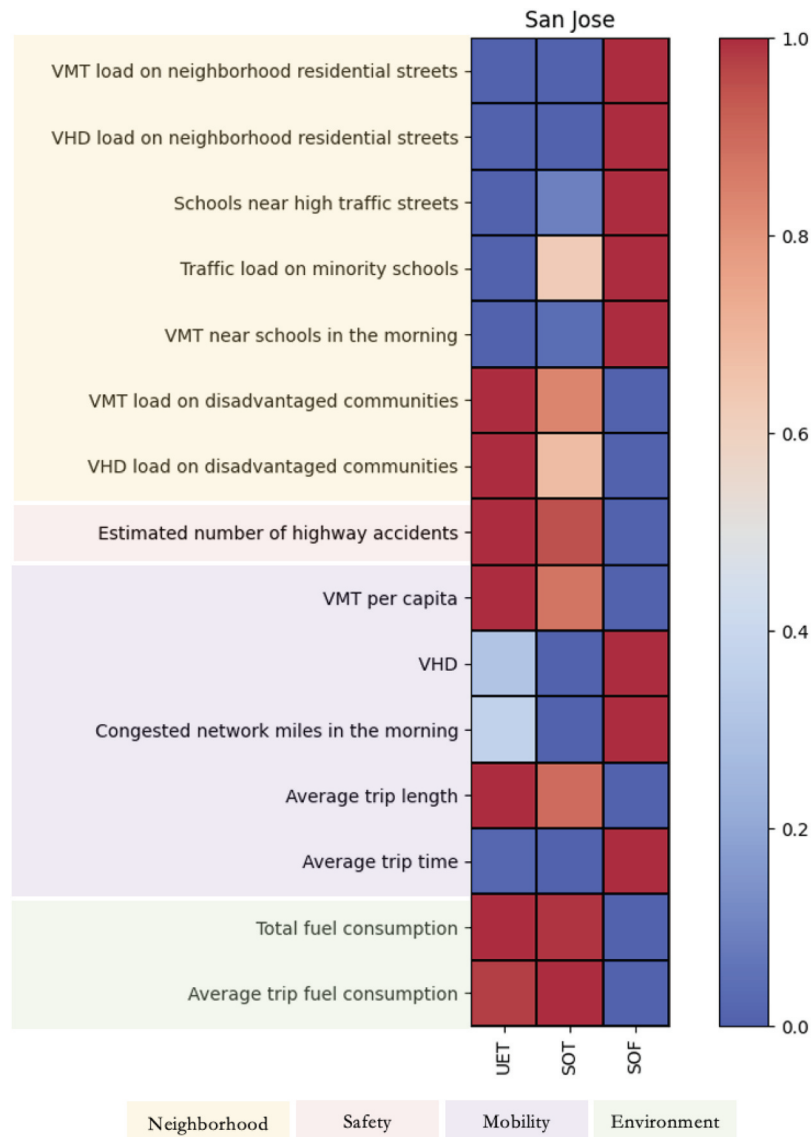
Figure 9. SAEF indicators for San Jose. Each metric is normalized to a scale between 0 and 1. Red and blue represent high and low, respectively. For instance, VHD indicator in the mobility theme is high for SOF and low for SOT

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. The VMT load on residential streets in Concord remains unchanged between the SOT and baseline, whereas it increases in all other cities. The baseline UET case in Concord showed very little congestion, indicating that system-level optimization had minimal impact. This is possibly due to the city's low density and spatial distribution.

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 underlying network and demand characteristics such as street layout, street composition, trip density etc.

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.
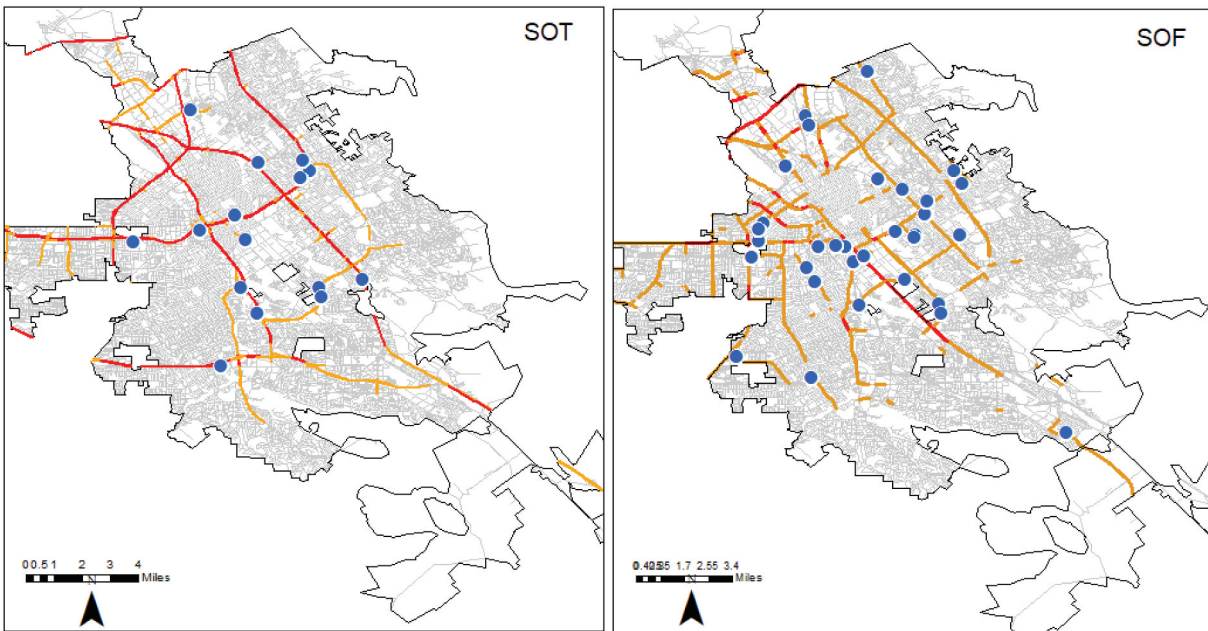
Figure 10. Theme Neighborhood: The figure illustrates the schools (blue circles) affected by high and medium traffic volume. Red links have an ADT greater than 50,000, and yellow links have ADT between 25,000 and 50,000. The number of impacted schools is higher with SOF routing.
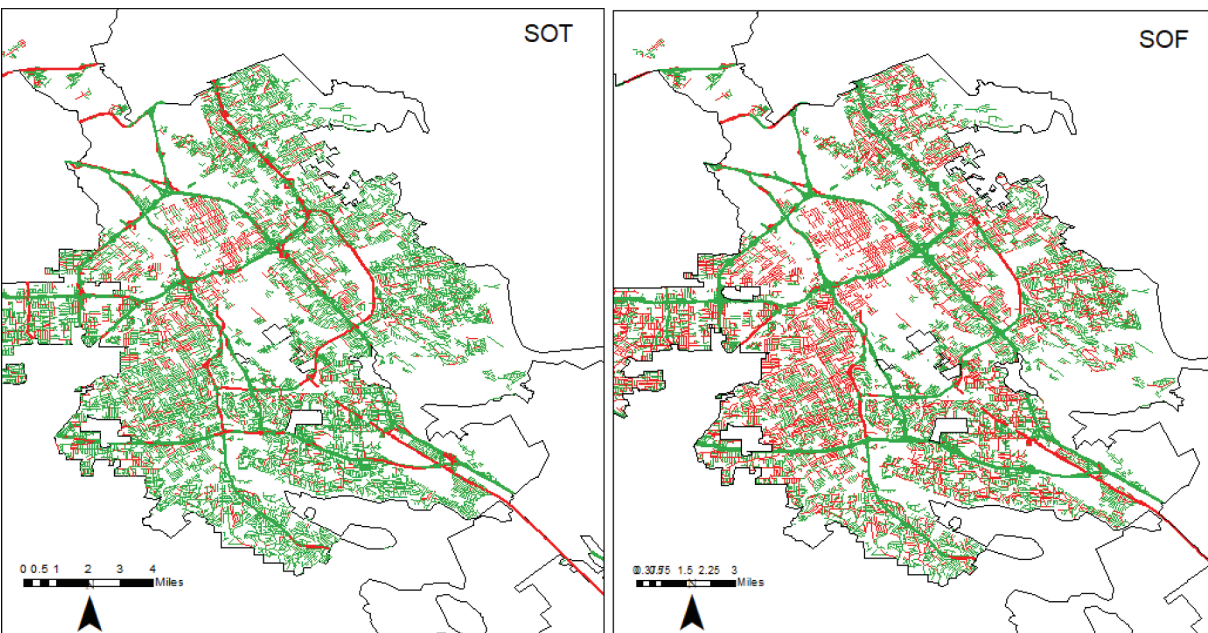

Figure 11. Theme Mobility: The figure shows the difference in VMT for SOT (left) and SOF (right) compared to baseline UET for San Jose. The red or green represents the increase or decrease in VMT, and the thickness represents the magnitude of the difference. Only highways and neighborhood residential streets are shown. It can be seen that SOF has shifted a significant amount of traffic from highways (broad green lines) to residential streets (thin red lines) in an attempt to reduce fuel consumption.

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 assignment 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.
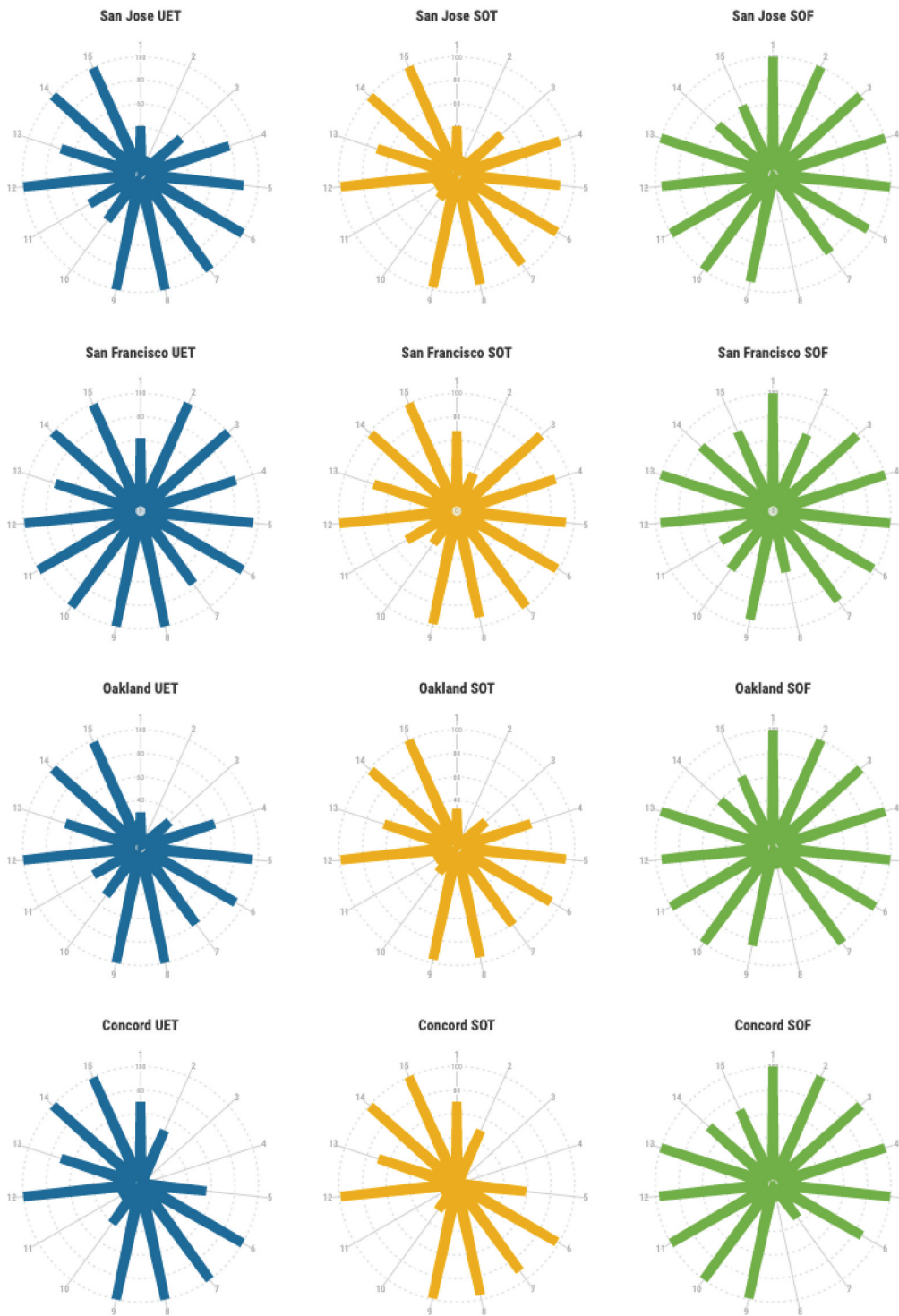
1 VMT load on neighborhood residential streets, 2 VHD load on neighborhood residential streets, 3 Schools near high traffic streets, 4 Traffic load on minority schools, 5 VMT near schools in the morning, 6 VMT load on disadvantaged communities, 7 VHD load on disadvantaged communities, 8 Estimated highway accidents/year, 9 VMT per capita, 10 VHD, 11 Congested network miles in the morning, 12 Average trip length, 13 Average trip time, 14 Total fuel consumption, 15 Average trip fuel consumption

Figure 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, 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.
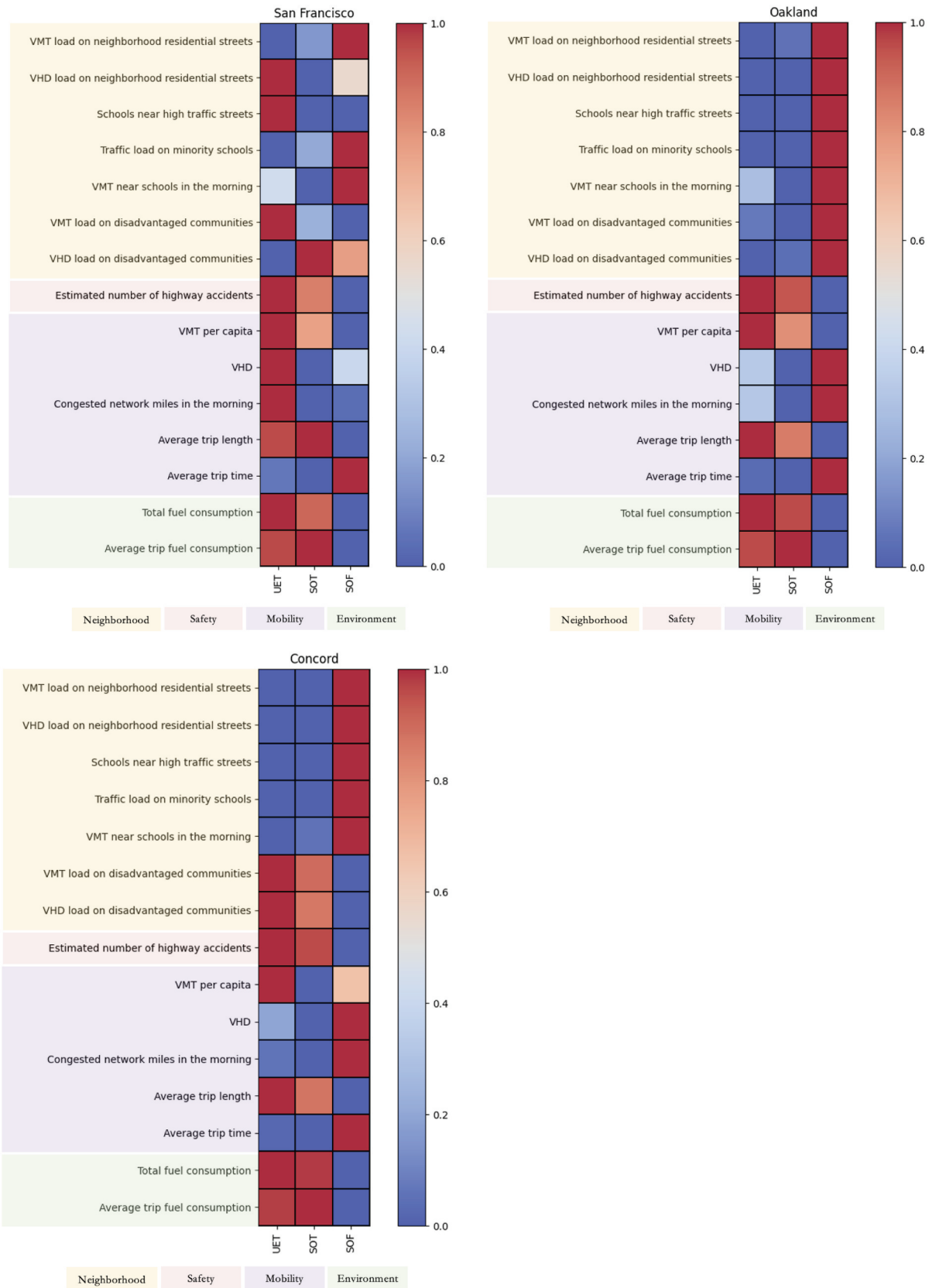
Figure 13. SAEF results for San Francisco, Oakland and Concord.

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.

Acknowledgments

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

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Appendix

A. SAEF Indicator Description
  B. QDTA Formulations

Table A1. 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 along 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
Neighborhood	Percentage vehicles 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 Transportation Mode (ATM) 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, steep slopes and sharp turns which can be dangerous when unknown drivers are routed through them.	Miles	City	Entire day/ Peak hours
Mobility	Bicycle level of traffic stress	Bicycle Level of Traffic Stress (LTS) rating can be calculated for road segments based on the type of facility, traffic volume and speed. Standard methods from literature can be adopted for calculation.		City/ Community	Peak hours
Mobility	Pedestrian level of traffic stress	Pedestrian LTS rating can be calculated for road segments based on the type of facility, traffic volume and speed. Standard methods from the literature can be adopted for calculation.		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 as the difference between the actual travel time and free flow travel time for all trips.	Hours	City	Entire day

(Continued)

Table A1. (Continued).

Theme	Indicator	Description	Unit	Spatial level	Temporal level
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.	Miles	City	Peak hours
Mobility	Average trip length	Average length of all the trips that start or end in a city. It can be segregated into work and nonwork trips.	Miles	Individual/ City	Entire day
Mobility	Average trip time	Average travel times for all the trips that start or end in a city. It can be segregated into work and nonwork trips .	Minutes	Individual/ City	Entire day
Environment	Total fuel consumption	Total fuel consumption for all vehicles in a city.	Liters	City	Entire day
Environment	Average trip fuel consumption	Average fuel consumption for all trips that start or end in a city.	Liters	Individual/ City	Entire day
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 meter	City	Entire day

$$UET : \sum_{a \in A} \int_0^{f_a} c_a(s)\, ds \qquad (5)$$

$$SOT : \sum_{a \in A} f_a c_a(f_a) \qquad (6)$$

$$SOF : \sum_{a \in A} f_a m_a(v_a) \qquad (7)$$

where:

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

$c_a(f_a)$ is the travel time on link a; f_a is the traffic flow assigned to link a; $c_{0,a}$ and C_a are the free-flow travel time and capacity associated with the link; α and β selected are BPR parameters 0.15 and 4 respectively.

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

$m_a(v_a)$ 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 (United States and Bureau of Public Roads 1964)); A, B, C are parameters estimated from Argonne National Laboratory drive cycle data $A = -0.00654170, B = 1.902150, C = 0.00001588$.

C. Bay Area Network
    Bay Area network functional classification is provided in Table A2 and the network typologies are provided in Table A3

D. 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 A4 (Shankar and Madanat 2015).

E. Summary of Results
    Summary of results is provided in Table A5 for the case study cities.

Table A2. 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 neighborhoods
5	Roads whose volume and traffic movement are below the level of any other functional class

Table A3. 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	Neighborhood or Throughway streets with adjoining industrial land use
6	PSP Street	2.5	Neighborhood 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 A4. 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

Table A5. Summary of Results: SAEF for case study cities.

City / 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	0.07	0.17	0.22	0.24	0.35	0.09	0.10	0.30	0.07	0.07	0.10
VHD load on neighborhood residential streets	0.01	0.01	0.06	0.14	0.05	0.10	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	2.30	0.86	0.86	1.30	0	0	2.55
VMT near schools in the morning	82,301	82,696	93,039	95,630	92,923	99,252	94,386	92,478	99,089	2,378	2,483	4,203
VMT load on disadvantaged communities	1.56	1.54	1.45	1.32	1.30	1.30	1.19	1.18	1.28	1.62	1.60	1.42
VHD load on disadvantaged communities	2.00	1.89	1.66	1.22	1.59	1.51	1.13	1.15	1.41	1.28	1.18	0.46
Estimated number of highway accidents	4,844	4,615	175	1,650	1,534	876	3,065	2,915	581	528	507	39
VMT per capita	18.57	18.35	16.78	11.22	11.08	10.63	23.57	22.94	20.25	17.74	17.65	17.71
VHD	10,665	5,682	21,857	16,947	5,919	10,366	9,298	4,873	18,268	578	382	1,399
Congested network miles in the morning	46.43	19.78	91.97	32.88	16.43	17.01	19.38	8.96	41.26	1.00	0.76	4.79
Average trip length	8.40	8.30	8.02	7.42	7.43	7.18	8.94	8.88	8.52	9.17	9.14	8.93
Average trip time	10.10	10.03	14.04	10.52	10.29	13.74	11.43	11.23	17.04	11.06	10.97	15.54
Total fuel consumption	2,883,657	2,871,752	1,828,504	995,748	979,577	816,895	1,441,556	1,418,620	872,783	328,744	327,188	240,779
Average trip fuel consumption	1.33	1.34	0.86	1.03	1.04	0.77	1.41	1.43	0.95	1.49	1.50	1.04