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MTI MINETA TRANSPORTATION INSTITUTE

Latent Active Transportation Methodology

Maria Chierichetti, PhD   Fatemeh Davoudi Kakhki, PhD

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16. Abstract
Understanding and estimating latent demand for active transportation, such as walking and cycling, is essential for designing infrastructure and policies that promote sustainable mobility. Unlike traditional demand models that focus on observed trips, latent demand estimation seeks to quantify the unrealized potential for active travel due to barriers such as inadequate infrastructure, safety concerns, or lack of connectivity. This study develops a comprehensive latent demand model tailored for California, integrating geospatial analysis and multimodal accessibility assessments. The methodology employs a GIS-based corridor analysis approach, utilizing spatial accessibility metrics and distance decay functions to evaluate potential demand. It incorporates employment and population data, school and university enrollments, and park and trail accessibility to estimate the likelihood of walking and cycling trips. To better capture behavioral patterns, the model also classifies cyclists into four categories: strong and fearless, enthused and confident, interested but concerned, and no way, no how. Case studies in Douglas City, El Centro, and downtown San Jose illustrate the model's application across urban, suburban, and rural contexts. Findings highlight that employment centers and commercial areas significantly contribute to bicycle demand, while schools and recreational spaces influence pedestrian activity. The results emphasize the need for targeted infrastructure improvements to convert latent demand into realized active transportation. This study provides a data-driven framework to guide investments in pedestrian and cycling infrastructure to ensure equitable and effective transportation planning in California.

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Executive Summary

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The methodology employs a GIS-based corridor analysis approach, utilizing spatial accessibility metrics and distance decay functions to evaluate potential demand. It incorporates employment and population data, school and university enrollments, and park and trail accessibility to estimate the likelihood of walking and cycling trips. To better capture behavioral patterns, the model also classifies cyclists into four categories: strong and fearless, enthused and confident, interested but concerned, and no way, no how.

Case studies in Douglas City, El Centro, and downtown San Jose illustrate the model's application across urban, suburban, and rural contexts. Findings highlight that employment centers and commercial areas significantly contribute to bicycle demand, while schools and recreational spaces influence pedestrian activity. The results emphasize the need for targeted infrastructure improvements to convert latent demand into realized active transportation.

The study is divided into five sections: (1) Introduction and Literature Review, (2) Methodology, (3) Geocoding Attractors and Generators, (4) Case Studies, and (5) Summary and Conclusions. The first chapter offers a review of relevant literature, focusing on studies of transportation demand and alternative models, in order to identify gaps and motivate the project. The second chapter describes the mathematical details of the methodologies and is followed by a description of the data sources used for the study.

The application of the Latent Demand Method to three case study areas in the state of California is demonstrated in Chapter 4 in order to demonstrate the use of the approach to identify where the latent demand for cycling and walking is higher. Transportation planning for active mobility should focus on the areas that are characterized by highest latent demand to be the most impactful.

1. Introduction and Literature Review

Understanding and estimating latent demand for active transportation, walking, and cycling is crucial for designing effective infrastructure and policies that promote sustainable mobility. Unlike traditional demand models that focus on observed trips, latent demand estimation seeks to quantify the potential for active travel that remains unrealized due to barriers such as inadequate infrastructure, safety concerns, or lack of connectivity.

Traditional demand models generally use recorded trips from surveys, GPS, or traffic counts for traffic and infrastructure planning. These models are based on real-world observed data, making them grounded in actual travel behavior. Since these models are based on historical trip data, these models can provide accurate predictions in areas where travel behavior remains relatively stable over time.

However, traditional models may struggle with predicting changes due to emerging travel behaviors (i.e., changes in active transportation due to non-existing infrastructures), new technologies (e.g., bicycle-sharing), and any other unobserved factors. Since these models rely only on recorded travel patterns, they do not account for trips that were desired but not taken due to barriers (latent demand). As a result, they might underestimate the actual demand for transportation if infrastructure were improved.

Over the years, researchers and practitioners have developed a range of methodologies, including spatial analysis, behavioral modeling, multimodal integration, and stated preference surveys, to better capture and predict this latent demand. This literature review synthesizes key studies and methodologies used in latent demand estimation, comparing different approaches and highlighting gaps that need to be addressed. By examining past research, this review provides a foundation for developing a latent demand model for active transportation in California, ensuring that future investments in walking and cycling infrastructure align with true mobility needs rather than just existing travel patterns.

Latent demand estimation for active transportation has gained significant attention in transportation research and planning due to its role in identifying unrealized travel potential. Traditional travel demand models have often underestimated walking and cycling trips due to data limitations and infrastructural constraints. Recent efforts have sought to refine methodologies for estimating latent demand by leveraging spatial modeling, behavioral analysis, and multimodal integration.

1.1 Methodologies for Latent Demand Estimations

The Latent Demand Method (LDM) has been a foundational approach for estimating non-motorized travel demand by evaluating trip generators and attractors in relation to travel impedances. Cambridge Systematics (2009) outlined the methodology in a technical appendix, describing how the model extends gravity-based principles to estimate potential pedestrian and bicycle activity along transportation corridors. This approach assumes that if certain infrastructural or environmental constraints were removed, latent bicycle and pedestrian trips would become realized trips. Several metropolitan areas, including Baltimore, Birmingham, and Philadelphia, have implemented variations of LDM to assess the potential demand for non-motorized travel.

The TAC Latent Demand Practitioner Survey (Transportation Association of Canada, 2019) reviewed the methods used by practitioners to estimate latent demand, highlighting key challenges such as data scarcity, multimodal trip misclassification, and model limitations. It categorized various approaches, including aggregate trip generation models, factor-based methods, and activity-based forecasting techniques. These methods provide a broad framework for estimating demand but often require refinement to align with the specific needs of active transportation planning.

Studies on active transportation demand have employed multiple techniques to capture both realized and unrealized trips. Beetham et al. (2021) examined various factors influencing walking and cycling, identifying stated preference models, GIS-based assessments (GIS: Geographic Information System), and demand typologies as essential components of robust forecasting. Their research emphasized the role of environmental and socio-demographic factors in shaping latent demand, particularly in areas where existing infrastructure does not support non-motorized travel. Clifton and Moura (2017) further developed a conceptual framework to understand latent demand by distinguishing between generative demand (previously unmade trips that become realized due to system improvements) and redistributed demand (trips shifting in mode, destination, or frequency). Their work emphasized the need for equity considerations, particularly in low-income and underserved communities where unmet transportation needs are often highest.

GIS-based accessibility models have been widely applied in latent demand estimation due to their ability to spatially quantify travel demand. The Active Transportation Network Utility Scores approach (Reardon et al., 2016) prioritizes investments in walking and cycling infrastructure by ranking road segments based on potential trip generation. Similarly, the Latent Demand Score (LDS) method used in Decatur, Atlanta (City of Decatur, 2018) applied GIS-based spatial modeling to identify high-demand areas for active transportation improvements. These methods provide practitioners with evidence-based tools to allocate resources effectively.

Multimodal integration is also a key consideration in estimating latent demand for active transportation. Shelat et al. (2018) analyzed the combined use of bicycles and transit, identifying distinct user groups through latent class analysis. Their findings suggested that bicycle-transit integration could significantly enhance last-mile connectivity and improve accessibility for longer commutes. Kroesen (2014) applied latent transition analysis to model changes in travel behavior over time, emphasizing the dynamic nature of transportation preferences and the potential for policy interventions to shift mode choice. The importance of transit-oriented development (TOD) in shaping non-motorized demand was further explored by Huang et al. (2021), who found that a significant portion of the population desires TOD features but lacks access to such neighborhoods.

Equity considerations have also been central to recent research on latent demand estimation. Chen et al. (2018) developed a Public Transport Supply Index (PTSI) and Public Transport Demand Index (PTDI) to quantify service gaps for seniors in Edmonton, Canada. Their GIS-based approach revealed significant spatial imbalances in transit accessibility, highlighting the importance of integrating social equity metrics into transportation demand modeling. Similarly, Fields et al. (2021) examined missed trips and latent demand among older adults, finding that mobility limitations significantly impact access to essential services such as healthcare and grocery stores. Addressing these gaps requires a more comprehensive approach to latent demand modeling that considers both physical infrastructure and demographic-specific needs.

The influence of built environment characteristics on active transportation demand has been extensively studied using latent class modeling. Oliva et al. (2018) analyzed cycling-inducing neighborhoods in Santiago, Chile, identifying distinct urban typologies that promote or hinder bicycle commuting. Their findings suggested that density, cycling infrastructure, and proximity to central activity hubs play a crucial role in shaping cycling behavior. Similarly, Hampshire et al. (2020) applied latent class segmentation to study shared mobility preferences in low-income communities, revealing that digital access, cost considerations, and prior exposure to shared mobility services significantly influence adoption rates.

Complete Streets analysis has provided additional insights into the relationship between street design and non-motorized travel. MacLeod et al. (2018) conducted a latent analysis of Complete Streets in Los Angeles, identifying key street typologies that impact pedestrian and cyclist safety. Their findings suggested that while Complete Streets initiatives improve pedestrian accessibility, additional safety countermeasures are necessary to mitigate conflicts between different modes of transportation.

Several studies have emphasized the need for improved behavioral models in latent demand estimation. Turner et al. (1997) conducted a literature review on bicycle and pedestrian travel demand forecasting, highlighting the limitations of traditional four-step models in capturing non-motorized travel behavior. The Bicycle and Pedestrian Trip Generation Workshop (Beltz & Huang, 1998) further underscored the challenges of integrating active transportation into regional demand models. The Guidebook on Methods to Estimate Non-Motorized Travel (Schwartz et al., 1999) provided an extensive review of demand estimation techniques, including discrete choice models, latent demand scores, and facility-based trip generation models.

1.2 Research Gaps and Future Considerations

Despite the advancements in latent demand estimation, several research gaps remain. Many models still rely on historical trip data, which fails to capture unrealized travel demand (Beetham et al., 2021). Additionally, there is a need for improved behavioral modeling techniques that can more accurately predict shifts in travel behavior over time (Kroesen, 2014). Few studies have explored how emerging micromobility trends, such as e-scooters and bike-sharing systems, influence latent demand for active transportation (Hampshire et al., 2020). Lastly, there is a growing recognition of the need to integrate equity-focused methodologies into latent demand models to ensure that infrastructure investments benefit all segments of the population, particularly low-income and mobility-impaired individuals (Chen et al., 2018; Fields et al., 2021).

In developing a latent demand model for estimating active transportation in California, it is essential to incorporate the insights gained from previous research. A successful model should combine GIS-based spatial analysis, latent class segmentation, multimodal integration, and behavioral modeling to provide a comprehensive and data-driven approach to forecasting active transportation demand. By leveraging statewide travel survey data, spatial accessibility metrics, and predictive analytics, such a model can inform policy decisions and infrastructure investments that better align with the unrealized potential for walking and cycling in California.

1.3 Bicycle and Walking as Modes of Transportation

Bicycling and walking are fundamental components of active transportation, contributing to sustainable mobility, public health, and urban livability. These modes play a crucial role in reducing traffic congestion, greenhouse gas emissions, and reliance on motorized transport, particularly in urban environments where infrastructure supports non-motorized travel. Understanding the trends and usage patterns of bicycle and walking trips is essential for transportation planning, infrastructure investment, and policy-making.

The 2022 National Household Travel Survey (NHTS) provides valuable insights into how bicycle and walking modes are utilized across different trip purposes and geographic settings. Table 1 examines urban and rural micromobility usage, highlighting key differences in the frequency and adoption of bicycling and walking. Meanwhile, Table 2 presents the distribution of person trips by trip mode and trip purpose, offering a comparative analysis of how active transportation modes fit within overall travel behavior. The data, as described in these two tables, underscores the importance of improving pedestrian and cycling infrastructure, especially in rural areas, to encourage higher rates of active transportation and reduce dependency on personal vehicles.

Micromobility, including e-scooters, bicycles, bikeshare, and walking, exhibited clear differences in usage between urban and rural areas in 2022 (Table 1). The survey results indicate that urban dwellers were significantly more likely to use micromobility modes compared to their rural counterparts. Specifically, bicycle usage among urban residents was more than twice that of rural residents, with 11.6% of urban dwellers reporting riding a bicycle in the past 30 days, compared to only 5.7% in rural areas. Similarly, walking was reported by 45.8% of urban residents, whereas only 30.1% of rural residents walked in the past 30 days. The average number of days these modes were used also varied between urban and rural settings. Bicycles were used for an average of 6.2 days in urban areas and 4.2 days in rural areas, suggesting a higher dependency or preference for cycling in city environments. Walking, though prevalent in both settings, also demonstrated a higher frequency in urban areas, with an average of 9.8 days compared to 7.6 days in rural regions. These trends highlight the greater availability and suitability of infrastructure for non-motorized travel in urban settings compared to rural environments (Federal Highway Administration, 2023).

Table 1. Urban and Rural Micromobility Usage in 2022
(Federal Highway Administration, 2023)

Travel Mode	Persons 16+ who used mode in past 30 days [%]		
	Urban	Rural	Total
E-scooter	2.3	0.5	1.9
Bike	11.6	5.7	10.5
Bikeshare	6.8	2.6	6.4
Walk	45.8	30.1	42.7

The distribution of person trips by trip mode and purpose in 2022 (Table 2) reflects broader travel patterns in the United States. Walking, as a mode of transport, accounted for a notable portion of trips across various purposes, although it remained secondary to private vehicle travel, which dominated most trip types. Walking played a minor role in most trip purposes, with work-related travel showing particularly low usage, as only 1.4% of trips to or from work were made on foot, while private vehicles dominated with 92.9% of these trips. Similarly, walking accounted for just 1.1% of shopping and personal errand trips, compared to 65.9% completed by private vehicles. For school and church travel, walking was even less common, representing only 0.8% of trips. However, walking had a relatively higher share in social and recreational trips, contributing 6.2%, indicating that people are more likely to walk for leisure and discretionary activities rather than for essential travel needs. Overall, walking comprised a modest percentage of total trips, highlighting the continued reliance on private vehicles for most daily travel needs. However, the data suggests that walking remains a viable mode for short, non-work-related trips, particularly in urban areas where infrastructure supports pedestrian travel (Federal Highway Administration, 2023).

Table 2. Distribution of Person Trips by Mode and Trip Purpose in 2022
(Federal Highway Administration, 2023)

Category	Trip Purpose					
	To/From Work	Work Related Business	Shopping and Personal Errands	School or Church	Social and Recreational	Other
Private Vehicle	92.9	92.6	92.1	65.9	85.6	70.8
Public	2.5	0.7	1.4	1.1	0.8	6.2
Walk	2.5	2.9	5.1	9.7	10.6	12.7

The 2012 National Survey of Bicyclist and Pedestrian Attitudes and Behavior, conducted by the National Highway Traffic Safety Administration (NHTSA), provides key insights into the prevalence and perceptions of bicycle and walking modes of transportation. The survey found that a majority of respondents who rode a bicycle in the past year reported using it at least once a week during the summer months, highlighting seasonal trends in cycling behavior (2012). Walking was also a significant mode of transportation, with 81% of respondents reporting that they walked at least once a week during the summer, demonstrating the importance of walking for short trips. Infrastructure availability played a major role in bicycle use, as nearly 46% of respondents had bicycle paths available within a quarter mile of their home, while 39% had access to dedicated bicycle lanes. Safety concerns remained a key issue, with 12% of bicyclists feeling threatened for personal safety on their most recent trip. Additionally, about 3% of bicyclists and pedestrians reported experiencing an injury requiring medical attention within the past two years, further emphasizing the need for improved infrastructure and pedestrian-friendly urban planning. Helmet usage was another area of concern, as only 28% of bicyclists reported wearing a helmet on all rides, highlighting the importance of helmet laws and public awareness campaigns (National Highway Traffic Safety Administration, 2012).

A separate study by Kellstedt et al. (2019) analyzed the impact of a free-floating bicycle-share program on active transportation and public health at a university campus. Within three months of the program's launch, there were 19,504 registered users, 24,371 different riders, and 165,854 rides covering 85,778 miles. The average bicycle trip was 0.52 miles and lasted 8.3 minutes, indicating that bicycle-share systems primarily facilitate short-distance, last-mile connectivity. The study also found that 33.6% of students, faculty, and staff surveyed had used the bicycle-share program, with younger individuals and students living on campus being more likely to participate than faculty and staff. The findings suggest that bicycle-sharing programs have a high potential for adoption in urban, student, and commuter populations. However, safety concerns, cost, and infrastructure limitations were identified as major barriers to further adoption, emphasizing the need for dedicated bicycle lanes, clear regulations, and improved helmet availability (Kellstedt et al., 2019).

Based on these studies, bicycle and walking modes of transportation are essential components of sustainable urban mobility. While walking remains a dominant mode for social and recreational trips, cycling adoption is influenced by safety perceptions, infrastructure availability, and ease of access through bicycle-sharing programs. The insights from these studies stress the need for improved pedestrian and cycling infrastructure, enhanced safety measures, and policy interventions to promote active transportation as a viable alternative to motorized travel.

1.4 The Four Types of Cyclists

The concept of the "Four Types of Cyclists" was introduced in 2006 by Roger Geller, the bicycle coordinator for the City of Portland, Oregon. Geller proposed that cyclists can be categorized into four distinct groups based on their level of comfort and willingness to ride a bicycle under various roadway conditions. This classification provides a valuable framework for understanding cycling behavior and serves as a basis for estimating the percentage of individuals who may choose to cycle if optimal cycling facilities are provided (Geller, 2006).

The first category, "the strong and the fearless," consists of cyclists who will ride regardless of roadway conditions. These individuals are highly confident and comfortable in traffic, making up a small but committed group of riders. The second category, "the enthused and confident," includes cyclists who are comfortable riding alongside motor vehicles but strongly prefer dedicated cycleways and cycling infrastructure to enhance their riding experience. The third and largest category, "the interested but concerned," represents individuals who are curious about cycling but are hesitant due to safety concerns. This group holds significant potential for increasing cycling participation if proper infrastructure and safety measures are in place. Finally, "the no way, no how" category includes those who have no interest in cycling due to physical, personal, or safety concerns and are unlikely to cycle regardless of available infrastructure (Geller, 2006).

While "the strong and the fearless" will cycle under any conditions, and "the no way, no how" group will not cycle under any circumstances, the key focus for cycling infrastructure improvements should be on "the enthused and confident" and "the interested but concerned" groups. These two categories represent individuals who may cycle more frequently if safer, well-connected, and high-quality cycling facilities are developed.

Geller's classification has been widely adopted and expanded beyond Portland to provide insights into cycling trends in other regions. In 2016, Dill and Neil (2020) conducted a comprehensive study analyzing cycling preferences across 50 of the largest metropolitan areas in the United States, including major cities in California such as Los Angeles, San Diego, San Francisco, Sacramento, and San Jose. The study, based on a phone and online survey of adults, aimed to capture community and transportation preferences, offering valuable insights into cycling behavior at a national scale.

The results of the study revealed that 7% of the population falls into the “strong and fearless“ category, while 5% are “enthused and confident“ cyclists. The largest segment, comprising 51% of the population, belongs to the “interested but concerned“ category, indicating that a majority of people might consider cycling if safety concerns are addressed through improved infrastructure. The remaining 37% of the population falls into the “no way, no how“ category and is unlikely to cycle under any circumstances (Dill & Neil, 2020).

For the purpose of transportation planning and infrastructure investment, only the first three categories are considered as potential cyclists, accounting for a total of 63% of the population that could be encouraged to cycle under favorable conditions. The focus on improving cycling facilities should be directed toward the enthused and confident and interested but concerned groups, as these individuals represent the greatest opportunity to expand bicycle ridership and promote sustainable, active transportation.

2. Methodology

The Latent Demand Method quantifies latent demand and its impact on transportation systems. The approach aims at estimating the latent demand in either cycling or pedestrian traffic by calculating the potential number of trips within a certain area in the presence of optimal cycling or pedestrian Infrastructure.

This method assumes that travel patterns may be described by the law of universal gravitation applied to trip interchanges due to the similarity in the way movement occurs between objects in physics and human travel behavior. The gravity model of trip distribution, which is widely used in transportation planning, is inspired by Newton's law of universal gravitation, where the attraction between two bodies is proportional to their masses and inversely proportional to the square of the distance between them. In travel patterns, the "attraction" between two locations depends on their size or importance (e.g., population, employment) and are characterized by an inverse relationship with distance because travelers generally prefer shorter trips over longer ones. While in physics, gravity forces govern the movement of objects and balance different forces, in transportation, people's travel choices balance between attraction (economic and social opportunities) and resistance (cost, time, congestion).

The latent demand model assumes that travel distance (and consequently time) is an impedance to cycling or walking. Therefore, if the distance between zones increases, the number of trips decreases. The method analyzes a geographical area using a corridor-based, GIS algorithm to quantify potential bicycle and trip activities. The analyses have been conducted with ArcGIS software, but the methodology can be generalized to any GIS software.

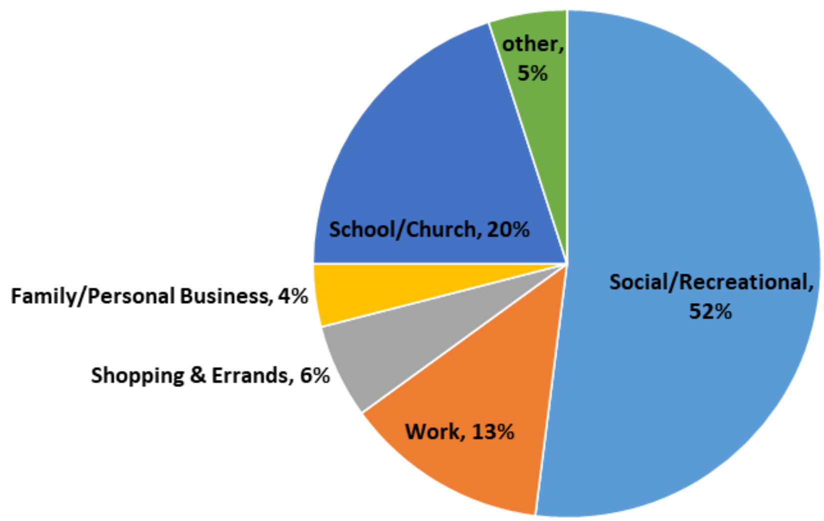
The method is based on aggregated data, such as employment and population, and does not generally consider the physical location of every residential or business establishment to estimate the latent demand because its primary goal is to estimate unrealized or suppressed travel demand rather than just mapping observed trip patterns.

As the goal of the approach is to estimate the latent demand under optimal infrastructure, the method does not provide an actual count of current active transportation trips.

2.1 Purpose of Trips – Four General Purposes

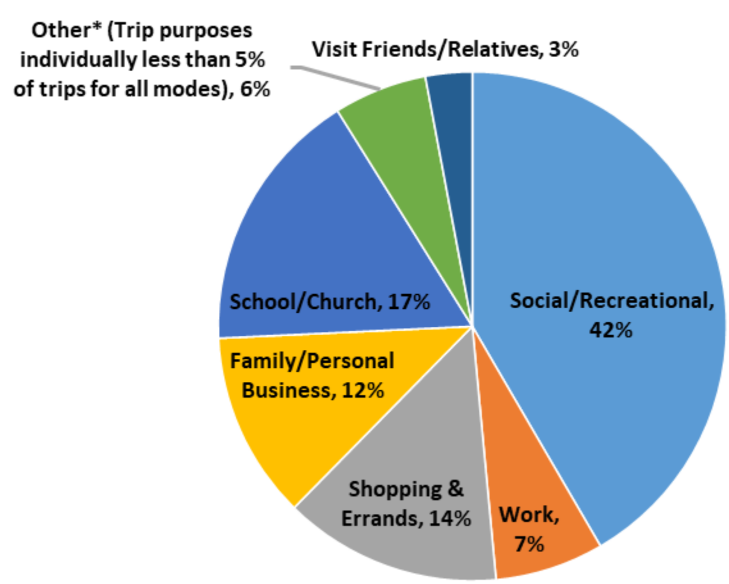
People take a cycling or walking trip for a variety of reasons. Based on the 2022 National Household Travel Survey (US Department of Energy, 2024), people mostly bicycle to commute to work (13%), to go to school or church (20%), for social and recreational purposes (52%), for shopping and errands (6%), and for family/personal business (4%), as shown in Figure 1.

Figure 1. Bicycle Trips by Purpose (US Department of Energy, 2024)



Similarly, individuals mostly walk to commute to work (7%), to go to school or church (17%), for social and recreational purposes (42%), for shopping and errands (14%), to visit friends and family members (3%) and for family/personal business (12%), as shown in Figure 2.

Figure 2. Walking Trips by Purpose (Bricka, 2022)



Based on these recognized categories, the latent demand method groups all potential trips into four different trip purposes: "work trips," "shopping and errands" trips, "school trips," and "social and recreational trips."

Each highway in the area of consideration is divided into road segments of 0.4 miles. For each of the road segments, the method identifies the potential trips that can be generated for each purpose; the sum of the individual trip purposes for each roadway corridor is the Latent Demand Score (LDS) for the given roadway segment.

$$LDS = \sum_{i=1}^{4} Q_i$$

In the rest of the report:

- Q_{Wk} is the total trip interchange potential for work trips.
- Q_{SE} is the Total trip interchange potential for shopping and errands trips.
- Q_{Sc} is the Total trip interchange potential for home-based school trips.
- Q_{RS} is the Total trip interchange potential for social/recreational trips.

Each Q_i is calculated based on the universal gravitation law applied to trip interchanges. The model assumes that travel distance (and consequently time) is an impedance to cycling or walking. Therefore, if the distance between zones increases, the number of trips decreases. The effect of distance and the trip elasticity function are described in the next section (2.2).

The method analyses a geographical area using a corridor-based, GIS algorithm to quantify potential bicycle and walking trip activities. Depending on the trip's purpose, the method uses a segment-based and/or an attractor-based approach to calculate each Q_i, as described in section 2.3.

2.2 Effect of Travel Distance on Trip Interchange and Buffer Zones

The calculation of each Q_i takes into account the effect of distance, which is considered an impedance to whether someone is willing to travel by bicycle or walking. A probability function P_d is included in the calculations and is defined as a distance decay function, which models how the likelihood of making a trip decreases as the travel distance increases. Essentially, the trip probability of each person varies according to the distance between origins and destinations. For this work, the probability distance is defined as

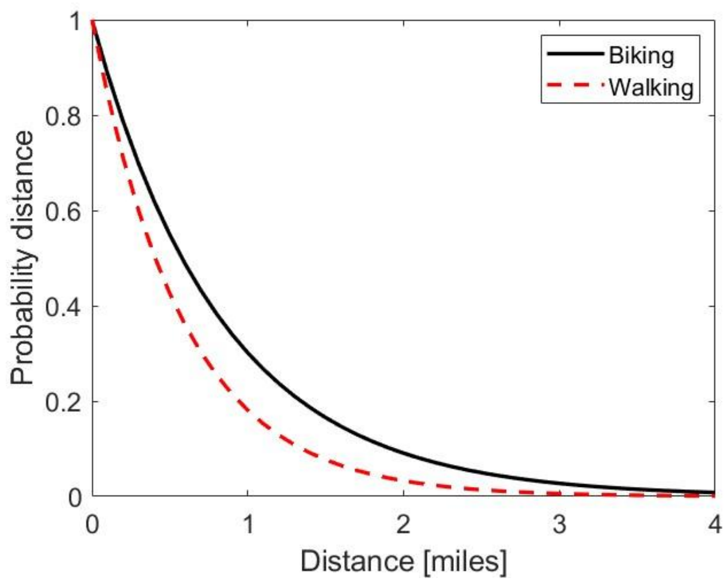
$$P_d = e^{-\beta d}$$

where β is a decay constant that reflects how sensitive trip-making is to distance, and d is the distance.

Larsen (2010) estimates the distance decay rate for cycling trips for different trip purposes; based on this data, the average distance decay rate for cycling purposes is $\beta_{biking} = 1.20 \frac{1}{miles}$.

Yang (2012) estimates the overall distance decay rate for walking trips to be $\beta_{walking} = 1.71 \frac{1}{miles}$.

Figure 3. Distance Decay Function



To take into account distance in the calculation of the latent demand method, buffer zones are identified around the highway corridor of interest. The buffer zones help evaluate the effect of distance on trip generation. Buffer zones are differently defined for cycling and pedestrian travel as travelers are willing to travel different distances based on their mode of transportation. The following buffer widths are considered as part of this report:

- for cycling trips: 0.5 mi, 1 mi, 1.5 mi, 2.5 mi[1]
- for pedestrians trips: 0.25 mi, 0.5 mi, 0.75 mi

The number and distance of each buffer zone can be easily modified in the analysis; as the calculations are very time-consuming, the analysis presented in this report will be limited to four buffer zones for cycling trips and three buffer zones for walking trips.

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1 More buffers can be added to the analysis, but for dense areas they will result in multiple days of computational time.

2.3 Segment-based Versus Attractor-Based Approach

The evaluation of each Q_i is based on spatial queries into a GIS software (Arc-GIS is used for this project) and is performed using either a segment-based or an attractor-based approach.

A segment-based approach means that the buffers are centered on an individual road segment. The buffer widths are defined in Section 3.2.

An image of the segment-based buffer zones is found in Figure 4. Once a buffer zone is defined around a tract of highway, the percentage of each block group contained in the buffer zone is calculated. This quantity is then used to evaluate the portion of population that lives/works within a certain buffer zone.

Figure 4. Segment-Based Buffer Zones

An example of segment-based buffer zones for a tract of highway for cycling is represented in Figure 5; for the same tract of highway, an example of segment-based buffer zones for walking is represented in Figure 6.

Figure 5. Example of Segment-Based Buffer Zones for Cycling

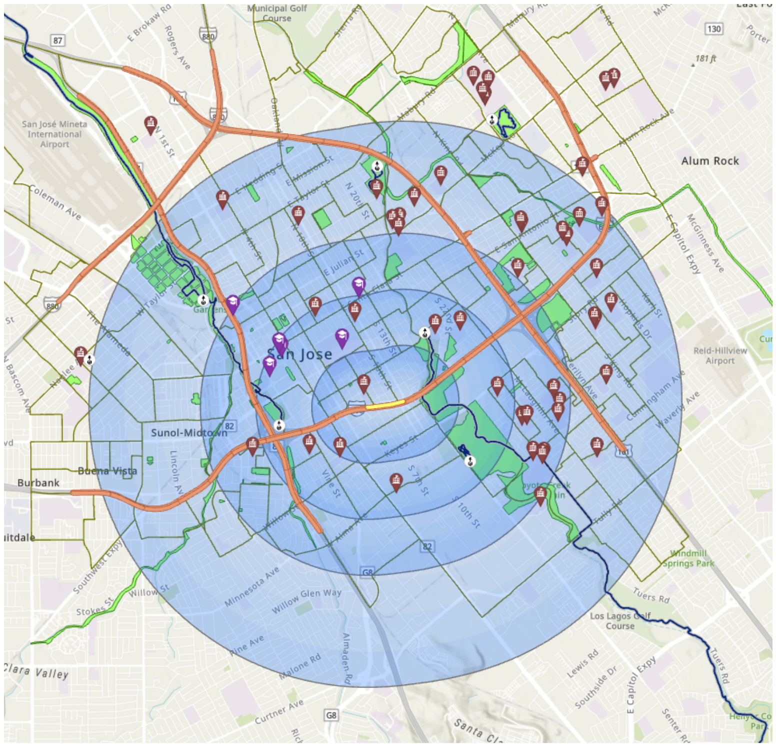
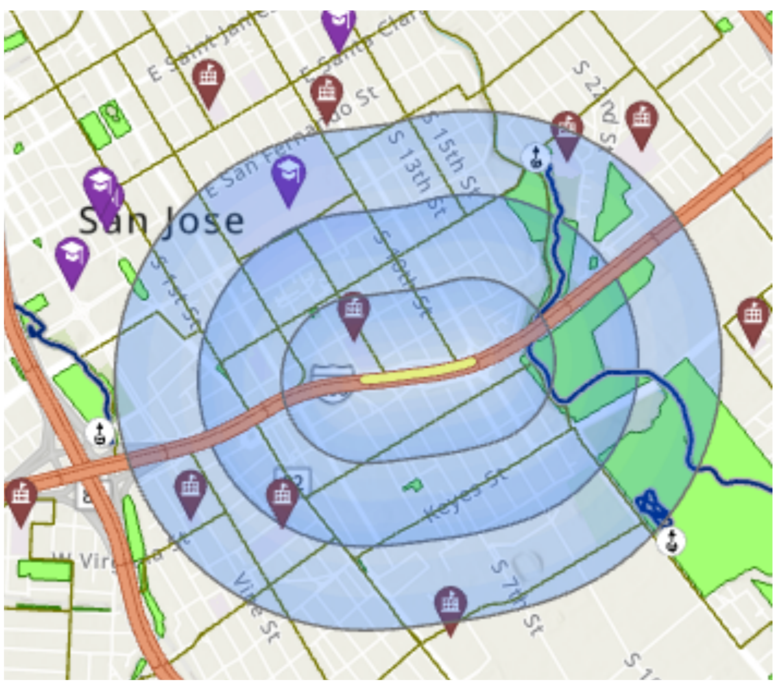


Figure 6. Example of Segment-Based Buffer Zones for Walking



An attractor-based approach means that the buffers are centered on an individual point of interest (i.e., a school) rather than on a road segment. An image of the attractor-based buffer zones is found in Figure 7. Once the buffer zone is created around an attractor, the portion of tract of highway that is contained in the buffer zone is calculated as a percent base (Figure 8). In the example in Figure 8, 23% of the tract is contained in the buffer zone. This percentage, corresponding to parameter S, is then used in the analysis as described in the following sections.

Figure 7. Example of Attractor-Based Buffer Zone Around a School

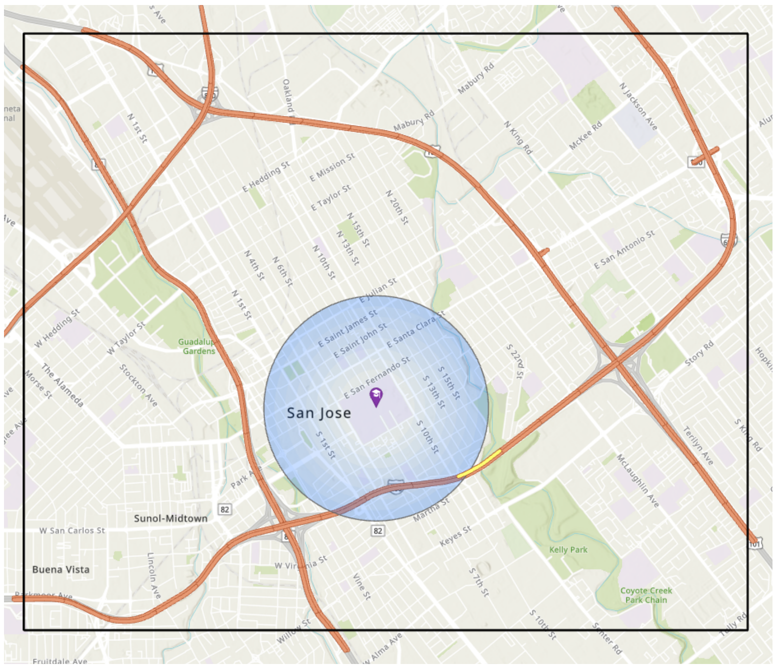
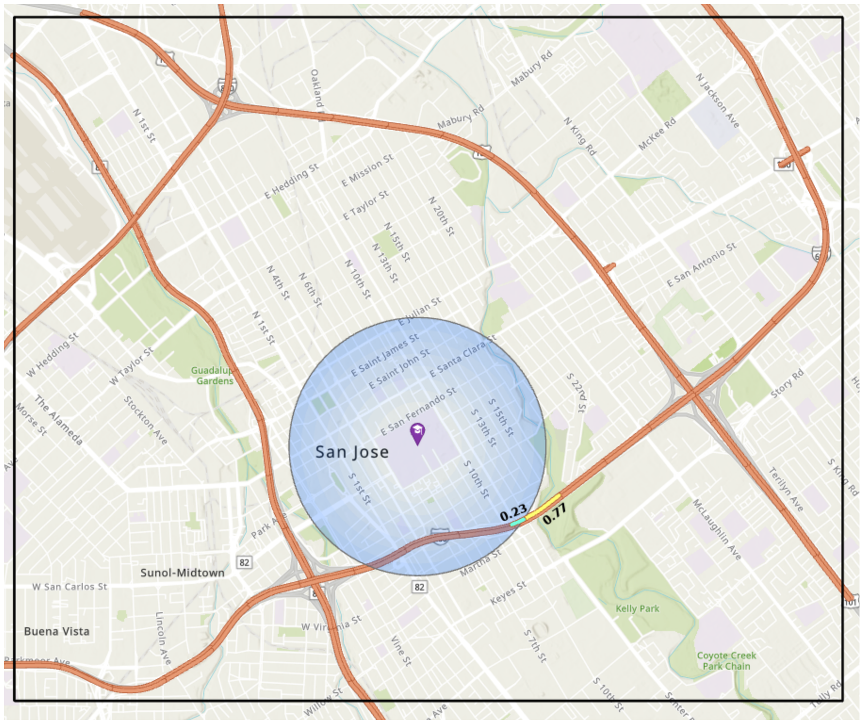


Figure 8. Example of Calculation of Attractor-Based Quantities



2.4 Work Trips

The latent demand for work trips is determined by defining the total trip interchange potential for work trips Q_{Wk}; for trips to work, employment data is used to estimate trip demand. Universities are also considered as work destinations, with trip calculations incorporating the number of university enrollments. Q_{Wk} has therefore two components: Q_E, which identifies the potential trips to commute to a work place and depends on local employment data, and Q_{CU}, which includes the trips generated to commute to colleges and universities.

$$Q_{Wk} = Q_E + Q_{CU}$$

Commuting to work trips:

The calculation of work trips for commuting to work Q_E uses a segment-based approach, which means that the buffers are centered on the individual road segments as in Section 2.3. The latent demand due to employment is determined by considering that a certain percentage k_{wk} of all employees working in a certain zone could potentially bicycle or walk to work, should optimal facilities be present in the area.

$$Q_E = \sum_{d=1}^{n} P_d \left(\sum_{z=1}^{n} k_{wk} \cdot E_z \right)$$

The following quantities define the total trip interchange potential for commuting to work Q_E:

- d: Spatial query buffer
- n: Total number of buffers
- P_d: Effect of travel distance on trip interchange, expressed as a probability
- z: BG adjacent to roadway segment
- E_z: Total employment within buffer
- k_{wk}: Percentage of people who either bicycle or walk to work

The percentage of employees that either bicycle or walk to work is determined to be:

- $k_{wk} = 63\%$ for cycling trips based on the four types of cyclists (Section 1.4)
- $k_{wk} = 100\%$ for walking trips (every employee has the potential to walk)

Trips to colleges and universities:

Trips to colleges and universities are considered a part of the "work trips" purpose due to the similarity of their trip characteristics with commuting to work trips (primarily trip length). The calculation of the total trip interchange potential for college and university trips Q_{CU} uses colleges and universities as attractors and uses an attractor-based approach to the spatial queries. It is based on the number of students enrolled, which is represented by the parameter FTE (full-time enrollment of the college or university).

$$Q_{CU} = \sum_{d=1}^{n} P_d \sum_{A=1}^{N_a} FTE_A \, S \, k_{CU}$$

- d: Spatial query buffer
- n: Total number of buffers
- P_d: Effect of travel distance on trip interchange, expressed as a probability
- N_a: Number of attractors
- FTE: Full-time enrollment of the college or university
- S: Percent of segment within buffer zone

- k_{CU}: Percentage of students that either bicycle or walk to college and university

The percentage of students that either bicycle or walk to work is determined to be:

- $k_{CU} = 22\%$ for cycling trips based on the data from the UC Davis campus
- $k_{CU} = 100\%$ for walking trips (every student has the potential to walk around campus)

The potential percentage of students that bicycle to campus is estimated based on existing data from the University of California, Davis campus (UC Davis). UC Davis is considered to be the best California campus for cycling infrastructure, and the town of Davis itself has been designated as a bicycle friendly community (City of Davis, 2021). UC Davis self-reports a 22% share of commuters who bicycle (University of California Davis, 2024).

2.5 Shopping and Errands

The latent demand for shopping and errands uses a segment-based approach and is determined by defining the total trip interchange potential Q_{SE}; as individuals can conduct shopping and errands trips either from home or work (i.e., during a break), the sum of employment and population data is used to estimate trip demand.

$$Q_{SE} = \sum_{d=1}^{n} P_d \sum_{z=1}^{n} (R_z + E_z)\, k_{SE}$$

- Q_{SE} = Total trip interchange potential for shopping and errands trips
- d = Spatial query buffer
- n = Total number of buffers
- P_d = Effect of travel distance on trip interchange, expressed as a probability
- z = BG adjacent to roadway segment
- R_z = Total population within buffer
- E_z: Total employment within buffer
- k_{SE} = Percentage of people that either bicycle or walk for shopping and errands trips

The percentage of people that either bicycle or walk for shopping and errands trips is determined to be:

- $k_{SE} = 63\%$ for cycling trips based on the four types of cyclists
- $k_{SE} = 100\%$ for walking trips (every person has the potential to walk)

2.6 Schools

The latent demand for trips to school uses an attractor-based approach centered on each school and is determined by defining the total trip interchange potential Q_{Sc}. It is based on the number of students enrolled, which is represented by parameter ASE (average school enrollment). As each individual who bicycles from home to school usually needs to bicycle back home, a constant parameter of "2" is added to the formula.

$$Q_{Sc} = \sum_{d=1}^{n} \quad P_d \sum_{A=1}^{N_a} \quad 2\ ASE\ S\ k_{sc}$$

- Q_{Sc} = Total trip interchange potential for home-based school trips
- d = Spatial query buffer
- n = Total number of buffers
- P = Effect of travel distance on trip interchange, expressed as a probability
- N_a = Number of attractors
- ASE = Average School enrollment
- S = Percent of segment within BG
- 2: Return trip
- k_{sc} = Percentage of students that either bicycle or walk to school

The percentage of people that either bicycle or walk to school is determined to be:

- $k_{sc} = 63\%$ for cycling trips based on the four types of cyclists
- $k_{sc} = 100\%$ for walking trips (every student has the potential to walk to school)

2.7 Recreational and Social (RS) Trips

The latent demand for recreational trips uses an attractor-based approach centered on each park and/or trail and is determined by defining the total trip interchange potential Q_{RS}. Parameter Q_{RS} is obtained by adding the contribution on parks (city, state, or federal parks) and walking/cycling trails:

$$Q_{RS} = \sum_{d=1}^{n} P_d \left(T_t + \frac{R_z}{T_t} \right)$$

- Q_{RS} = Total trip interchange potential for social/recreational trips
- d = Spatial query buffer
- n = Total number of buffers or BG's
- P_d = Effect of travel distance on trip interchange, expressed as a probability
- T_t = Total number of park trips + total number of urban trail trips
- R_z = Total population within buffer

The sum of the total number of park trips and urban trail trips T_t requires the identification of all the parks in the vicinity of a road segment. The spatial queries for urban trails are attractor-based, whereas the spatial queries for parks are segment-based. Once all parks and trails are identified as important to a road segment, the number of trips that each park generates is specified based on the classification of each park as "Small," "Medium," or "Large." Parks are classified using a weighted average based on the number of amenities present in each park; in fact, a park that has ball fields and a playground generally attracts more users than a park of equal size with fewer amenities. A list of possible amenities is presented in Table 3 and is divided into general amenities and sports related amenities.

Table 3. List of Possible Park Amenities

Amenities	Sports/Activities
BBQ	softball/baseball field
picnic area	soccer field
concession stand	basketball court
water features	handball court
walking trail	bocce ball court
bicycle trail	tennis court
	pickleball court
	fitness equipment
	skate park
	swimming pool
	tot lot
	playground
	restroom
	historical monument
	visitor center
	botanical garden
	nature center
	dog park
	amphitheater
	carnival ride
	wi-fi access
	parking lot
	nearby facility

Each amenity in a park is attributed a popularity rating (0–5) which defines how much each amenity is likely to attract cycling or walking traffic, as shown in Table 4.

Table 4. Popularity Rating and Weights for Each Amenity in A Park

	BIKING	WALKING
Amenity	Popularity Rating	Popularity Rating
BBQ	2	2
picnic areas	2	2
concession stand	4	4
water feature	3	3
walking trail	5	5
bicycle trail	0	0
softball/baseball field	1	1
soccer field	1	1
basketball court	3	3
handball court	1	1
bocce ball court	4	4
tennis court	2	2
pickleball court	2	2
fitness equipment	2	2
skate park	2	2
swimming pool	1	1
tot lot	5	5
playground	5	5
restroom	1	1
historical monument	1	1
visitor center	1	1
botanical garden	3	3
nature center	2	2
dog park	5	5
amphitheater	3	3
carnival ride	2	2
wi-fi access	1	1
parking lot	0	0
nearby facility	0	0
TOTAL		64

Once the amenities in each park are identified, counted, and multiplied by its own popularity rating, a total score for the park is calculated by summing all the contributions for each amenity. A total score of 0–29 corresponds to a small park, 30–50 to a medium park, and 51–100 to a large park; see Table 5. Based on Landis (2001), a small park generates 28 trips, a medium park generates 375 trips, and a large park generates 3,058 trips.

Table 5. Park Classification Scores, Based on Landis (2001)

Possible Points		Park Classification	Trip Generation
0	29	Small	28
30	50	Medium	375
51	100	Large	3,058

Based on Landis (2001), a trail is considered a large park and generates 3,058 trips.

3. Geocoding Attractors and Generators

The latent demand analysis is based on the ability to geocode the highway corridors as well as a division in smaller areas (block groups) within an area of interest. Several data need to be determined to perform the analysis, such as the total population and employment for each block zone, the location and enrollment of schools and colleges / universities, and the location and amenities for parks and trails. All this information needs to be collected in Shapefiles or .csv tables that are then imported into the GIS software. This chapter describes the sources of this data, which are summarized in Table 6.

3.1 State Highway System

The State Highway system information was obtained from the California State Geoportal (2022), and it contains a record of the state highways based upon the Caltrans Linear Referencing System. Each record represents a highway segment where the county, route, postmile prefix, and postmile suffix are the same. This geometry was downloaded in December 2023 and is depicted in Figure 9.

Figure 9. State Highway System (California State Geoportal, 2022)

3.2 Block Groups

The geographical division of the state of California into smaller areas (block groups) was obtained from the U.S. Census Bureau, Department of Commerce (2021).

This database is an extract of selected geographic and cartographic information from the U.S. Census Bureau's Master Address File / Topologically Integrated Geographic Encoding and Referencing (MAF/TIGER) Database (MTDB). The MTDB represents a seamless national file with no overlaps or gaps between parts.

Block groups (BGs) are defined clusters of blocks within the same census tract (U.S. Census Bureau, Department of Commerce, 2021). Each census tract contains at least one BG, and BGs are uniquely numbered within census tracts. BGs generally contain between 600 and 5,000 people. A BG usually covers a contiguous area but never crosses county or census tract boundaries. They may, however, cross the boundaries of other geographic entities such as county subdivisions, places, urban areas, voting districts, congressional districts, and American Indian / Alaska Native / Native Hawaiian areas. The BG boundaries in this release are those that were delineated as part of the Census Bureau's Participant Statistical Areas Program (PSAP) for the 2010 Census. The database was created in 2019.

3.3 Total Population for each Block Group

The total population residing in each block group was obtained from the U.S. Census Bureau (2019), and it is based on data from 2019.

3.4 Total Employment for each Block Group

The total population residing in each block group was extracted from ArcGIS Business Analyst. This platform contains all businesses in an area of interest, with their employee count and geographical coordinates; from there, the team determined the number of employees in each BG through the ArcGIS software (ESRI, 2024).

3.5 College and University Location and Enrollment

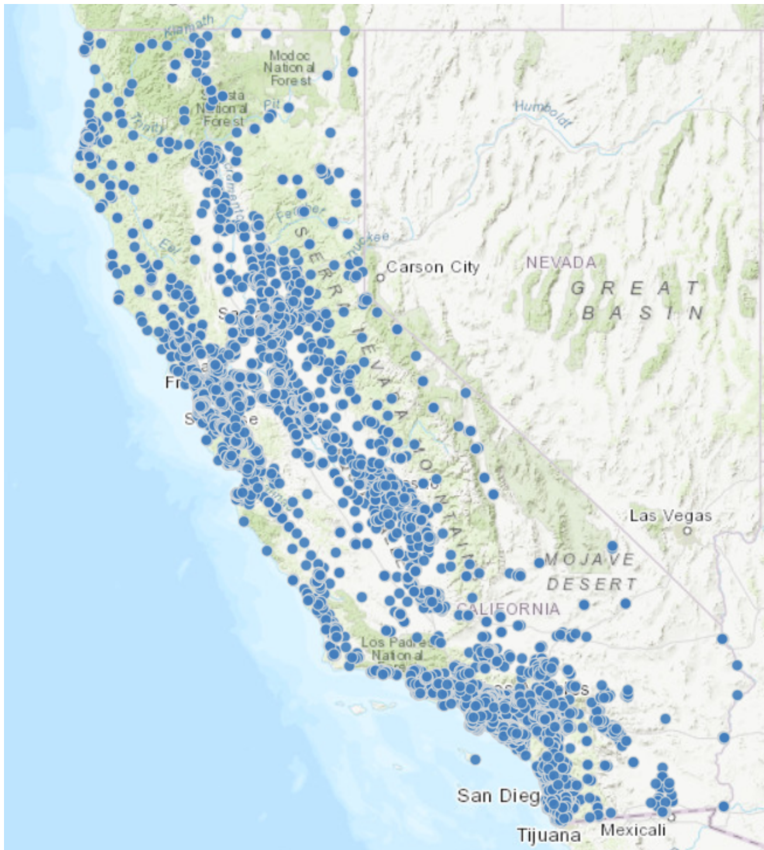
The data regarding colleges and universities was obtained from the National Center for Education Statistics (IPEDS, 2022). The team considered all type of colleges and universities (public, private for-profit, and private non-profit) and used the enrollment from Fall 2022, which was the most recent that was available. A map of all available colleges and universities in California is depicted in Figure 10.

Figure 10. Map of California Colleges and Universities (IPEDS, 2022)

3.6 Schools Location and Enrollment

The location of K–12 schools and their enrollment was obtained from the California State Geoportal (Dixon, 2023). Data is available for school year 2022–2023. The team cleaned the dataset by manually checking whether schools with zero enrollment were still in existence.

Figure 11. Map of California K–12 Schools (Dixon, 2023)



3.7 Parks and Trails

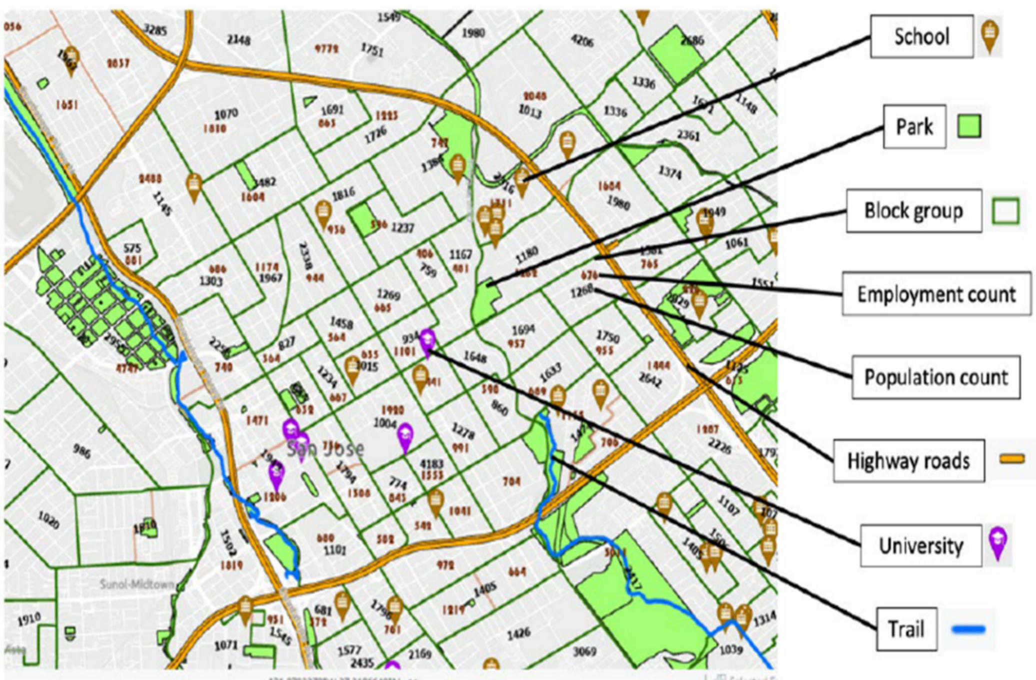
Parks and trails were extracted from a variety of sources. Information about parks was obtained from the Parks for All Californians website agency (Parks for All Californians, 2021), sponsored by the California Department of Parks and Recreation. The tool provides 2020 neighborhood-level park access and demographic information and is updated every five years. Information about the amenities in each park are manually collected from city websites for the areas of interest. Urban trails information was collected from the website Alltrails.com (All Trails, 2024). Coastal trails information was extracted from the California Coastal Trail (CCT) mapping website (California Coastal Commission Mapping Unit, 2023).[2] A summary of all data sources is contained in Table 6; a sample representation of a data for an area of interest is shown in Figure 12.

[2] When running an analysis, please make sure a folder is created for the study area even if there are no trails (empty folder).

Table 6. Summary Of Data Geocoded into ArcGIS and their Sources
Data Downloaded between December 2023–April 2024

List of Raw Data	Source
State highway system in GIS format	California State Geoportal (2022)
Block groups	U.S. Census Bureau, Department of Commerce (2021)
BG population density	Census Block 2019, US Census Bureau (2019)
BG total employment	ArcGIS Business Analyst, ESRI (2024)
College location & FTE	National Center for Education Statistics, IPEDS (2022)
K–12 schools & enrollment	California State Geoportal (Dixon, 2023)
Parks	California Department of Parks and Recreation (Parks for All Californians, 2021)
Urban trails	Alltrails.com (All Trails, 2024)
Coastal trails	California Coastal Trails (California Coastal Commission Mapping Unit, 2023)

Figure 12. Summary of Data Imported into Analysis



4. Case Studies

Three case study areas are selected to demonstrate the approach. The areas are distributed across the state of California and are selected in an attempt to represent different areas in the state. Of the selected areas, Douglas City in Trinity County (Northern California) is a rural area, El Centro in Southern California is considered as a suburban area, and downtown San Jose in Santa Clara County is selected to represent an urban area. A representation of these areas is found in Figure 13. Each case study is separately described in the following sections.

Figure 13. Case Study Areas

It is also worth noting that the latent demand analyses described in this report are computationally demanding and require multiple hours to complete (Table 7).

Table 7. Computational Time for Case Studies

Study area	Computational time
Douglas City	7 hours 5 minutes
El Centro	11 hours 10 minutes
San Jose downtown	30 hours

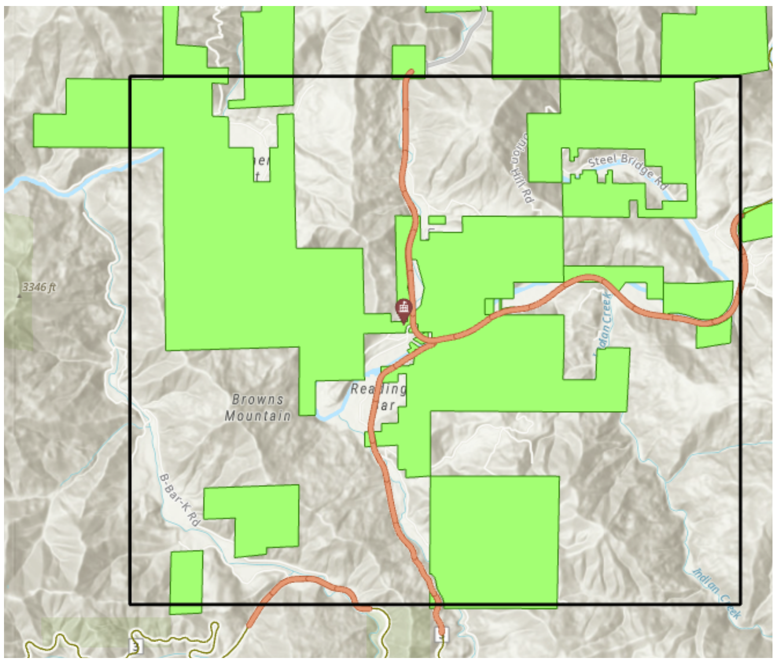
4.1 Douglas City

Douglas City is an unincorporated community in Trinity County, California, located in the northern part of the state. It was first settled during the California Gold Rush. Douglas City sits at an elevation of 656 m feet (Wikipedia, 2025, 1).

Description of study area:

The area considered in the analysis (Figure 14) is 9.1 km wide and long, for a total area of 82.5 km^2.

Figure 14. Area of Study in Douglas City

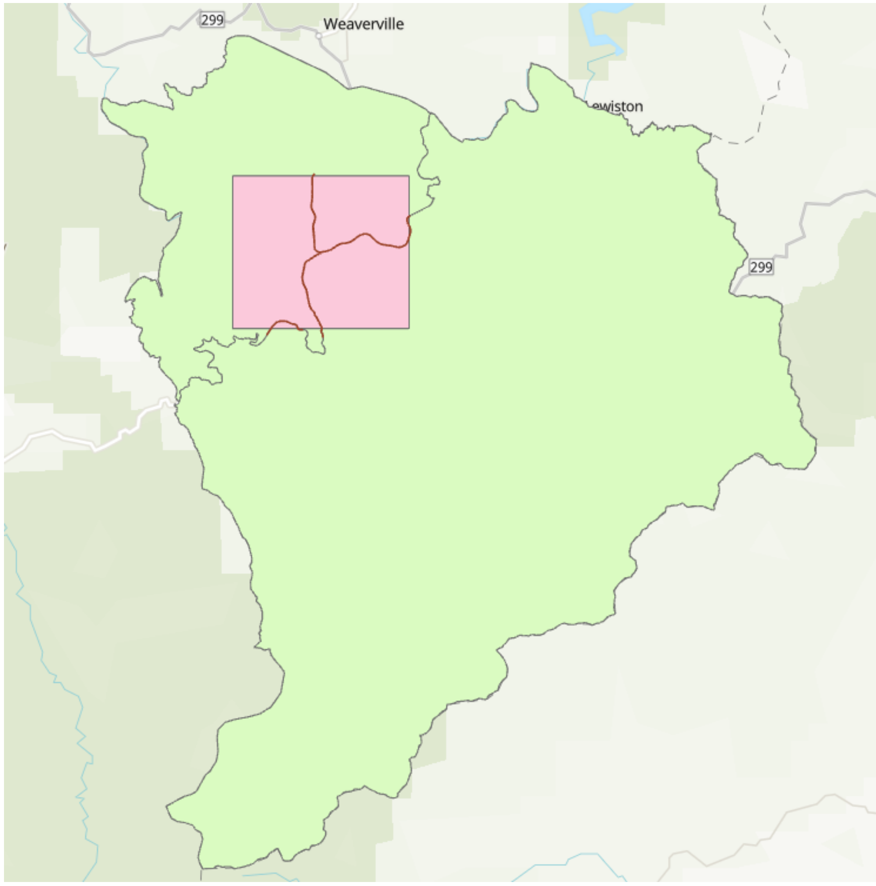


There are two block groups in this area of study. Figure 15 shows that both block groups (green) are larger than the area of study (pink). A total population of 2,092 people live in the two block groups combined and a total of 307 people are employed in the two block groups.

The highway system in this area consists of a piece of California State Routes 3 and 299, for a total length of 38.9 km. It is divided into 30 segments, whose lengths vary from a minimum of 84 m to a maximum of 996 m (mean: 648 m, standard deviation: 126 m, median: 662 m).

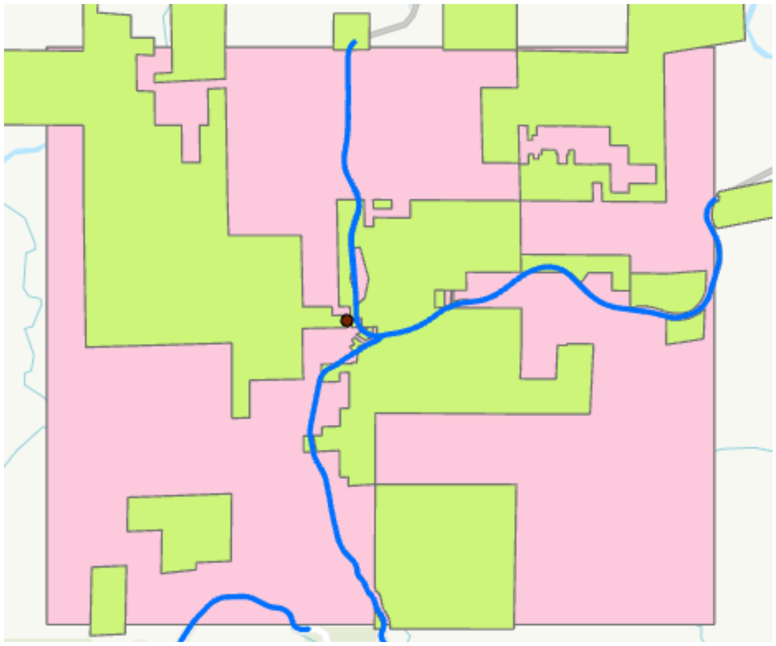
Only one school is located in this area (Figure 14): Douglas City Elementary, a K–8 school with approximately 162 students enrolled in 2022–2023. There are no colleges or universities.

Figure 15. Area of Study in Douglas City (pink) with Block Groups (green)



The parks in this area occupy about 29 km^2 (Figure 16) and can be classified into four parks: BLM (size: 28.6 km^2), Indian Creek (size: 0.3 km^2), Trinity River (0.03 km^2), and a United States Bureau of Reclamation park (size: 0.02 km^2). All parks are characterized as “Small” both for pedestrian and cycling amenities, as they do not offer the amenities described in Section 2.7.

Figure 16. Parks (green) in the Area of Study in Douglas City (pink) with Highway (blue) and School (black dot)



There are no trails in this area.

Latent demand for cycling traffic:

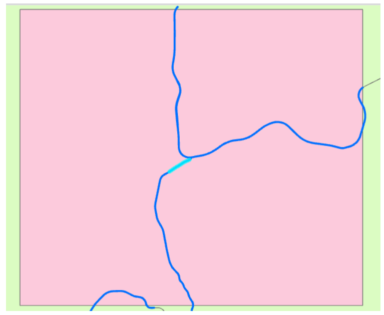
The latent demand score for each tract of highway is calculated with the contribution of the "work trips," "shopping and errands" trips, "school trips," and "social and recreational trips." The work trips also contain contributions from colleges and universities, which are zero in the area under study.

Focusing on cycling latent demand, the contribution of work trips Q_{wk} ranges from 4.04 to 11.35; the contribution of shopping and errand trips Q_{SE} ranges from 28.9 to 38.5; the contribution of school trips Q_{Sc} ranges from 0 to 217.4; and the contribution of social and recreational trips Q_{RS} ranges from 32.7 to 119.8. The final LDS score ranges from 78.3 to 388.7.

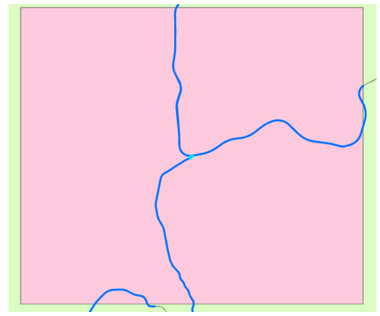
The three highest LDS scores for cycling are obtained by the segments in Figures 17 and 18, with values of 388.7, 370.0, and 362.9, respectively. The major contributors to LDS scores in this area are school trips and social and recreational trips. The distribution of LDS scores for cycling is depicted in Figure 19.

Figure 17. Top three LDS Segments for Cycling in Douglas City Area (Highlighted) – One by One

(1) $LDS = 388.7$ – segment length 0.99 km



(2) $LDS = 370.0$ – segment length 0.67 km



(3) $LDS = 362.9$ – segment length 84 m

Figure 18. Top three LDS Segments for Cycling in Douglas City Area (Highlighted)

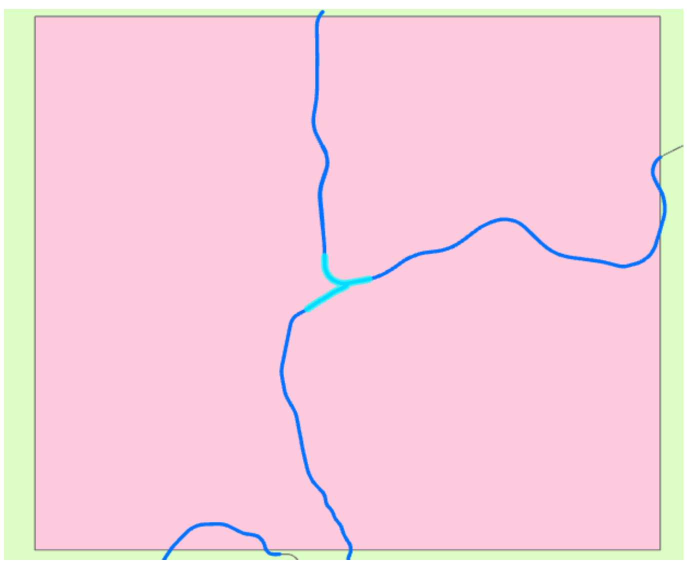
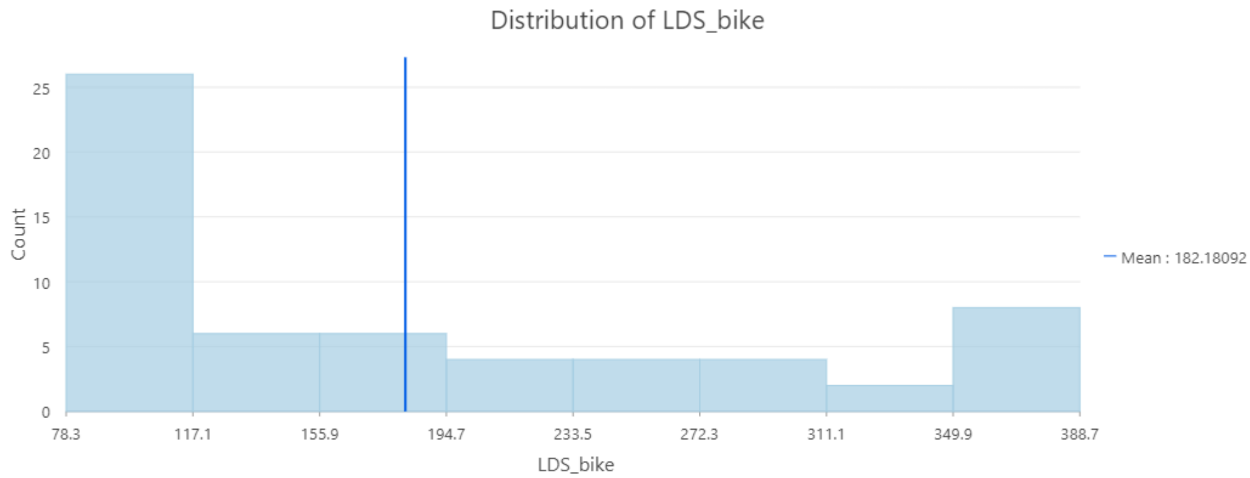


Figure 19. Distribution of Latent Demand Score for Cycling in Douglas City Area

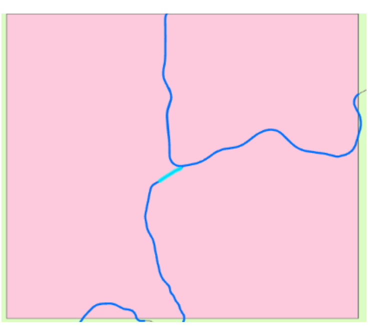


Latent demand for pedestrian traffic:

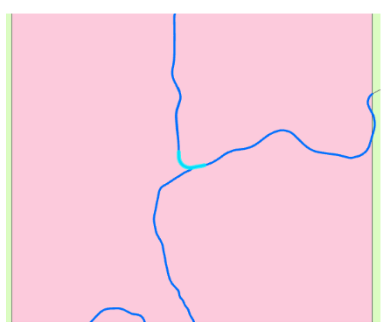
Focusing on pedestrian latent demand, the contribution of work trips Q_{wk} is 3.59; the contribution of shopping and errand trips Q_{SE} is 19.2; the contribution of school trips Q_{Sc} ranges from 0 to 377.0; and the contribution of social and recreational trips Q_{RS} ranges from 20.1 to 151.9. The final LDS score ranges from 42.9 to 503.3.

The three highest LDS scores for pedestrian facilities are obtained by the segments in Figures 20 and 21, with values of 503.3, 498.8, and 444.2, respectively. Similar to cycling trips, the major contributors to LDS scores for walking trips are school trips and social and recreational trips.

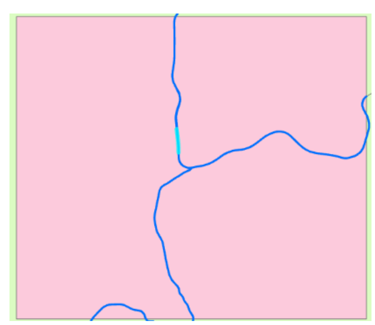
Figure 20. Top Three LDS Segments for Walking Trips in Douglas City Area (Highlighted) - One by One



(1) LDS = 503.3 – segment length 0.67 km

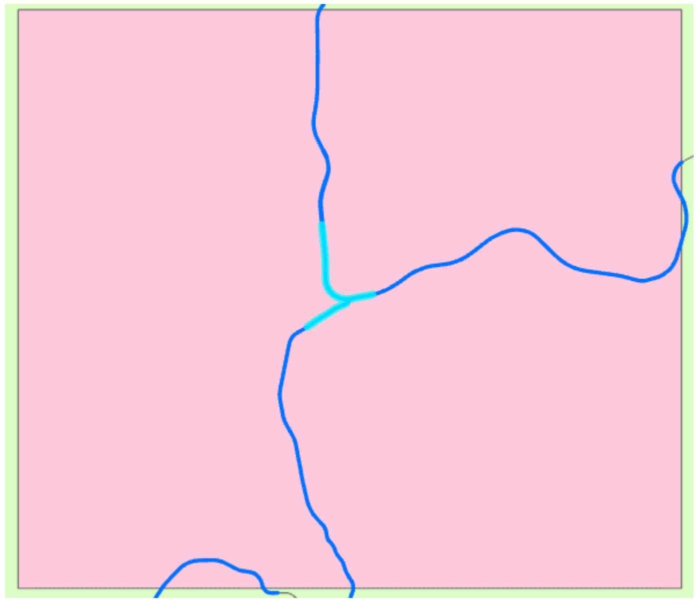


(2) LDS = 498.8 – segment length 0.99 km



(3) LDS = 444.2 – segment length 0.66 km

Figure 21. Top Three LDS Segments for Walking Trips in Douglas City Area (Highlighted)



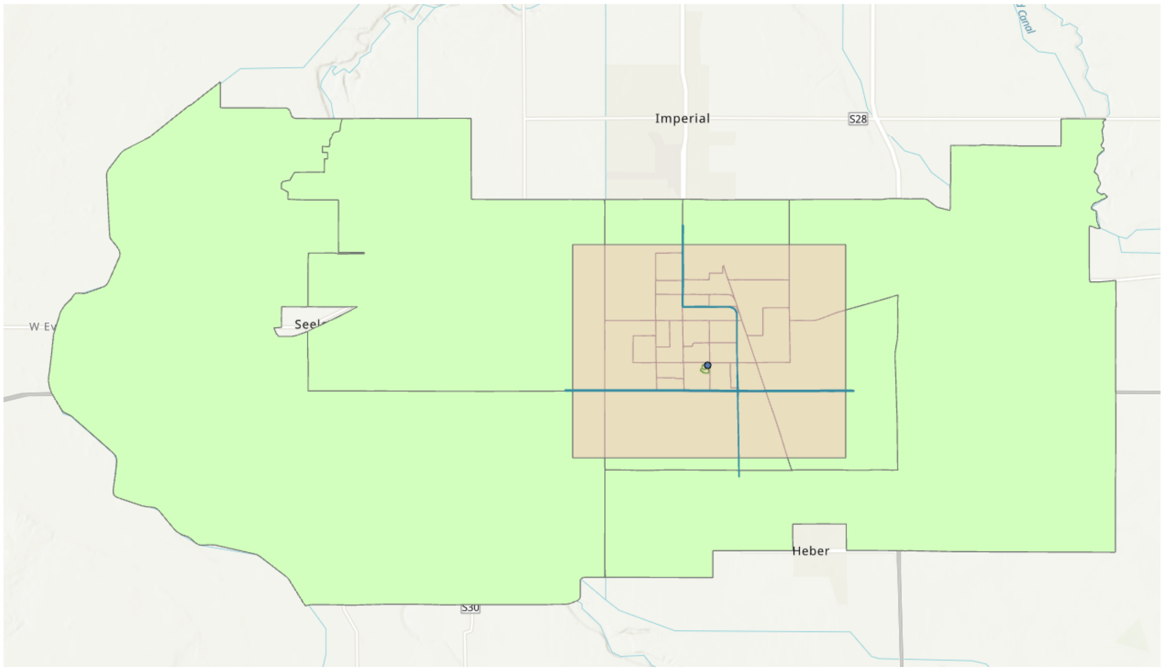
4.2 El Centro

El Centro is a city in Imperial County, California, United States. El Centro is the most populous city in the Imperial Valley, and the core urban area and principal city of the El Centro metropolitan area which encompasses all of Imperial County. El Centro lies entirely below sea level at −13 meters. The city, located in southeastern California, is 113 miles (182 km) from San Diego and less than 20 miles (32 km) from the Mexican city of Mexicali (Wikipedia, 2025, 2).

Description of study area:

The area considered in the analysis (Figure 14) is 8.6 km wide and long, for a total area of 74.5 km^2.

Figure 22. Area of Study in El Centro (Pink) with Block Groups (Green)

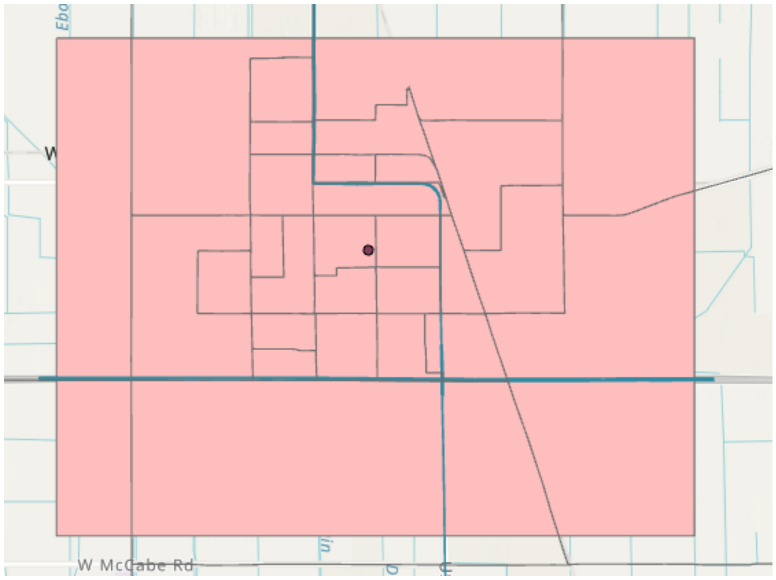


There are 30 block groups in this area of study, as shown in Figure 22. A total population of 19,006 people live in these block groups, and a total of 29,038 people are employed due to commuters from outside the area under consideration.

The highway system in this area consists of a piece of California State Routes 863 and Interstate 8, for a total length of 42.2 km. It is divided into 32 segments, whose lengths vary from a minimum of 19 m to a maximum of 776 m (mean: 659.9 m, standard deviation: 124 m, median: 644.7 m).

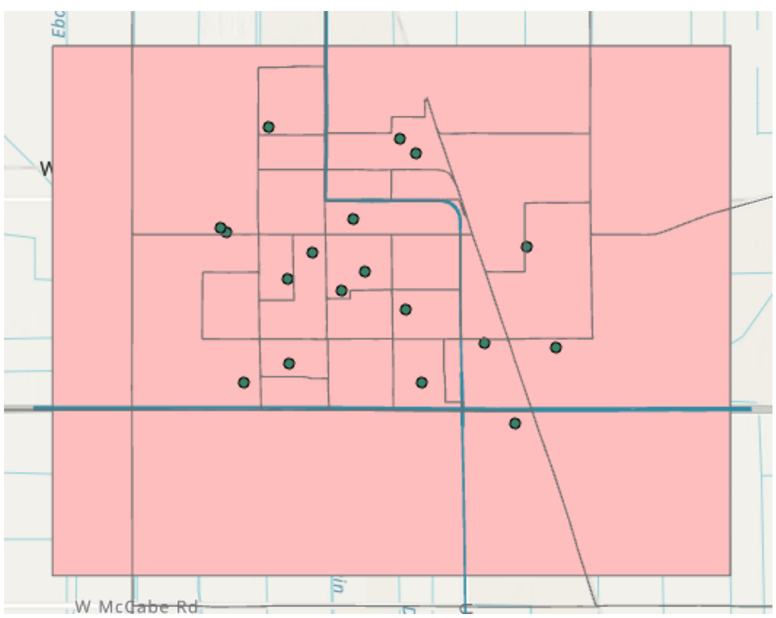
There is one university in the area, CET-El Centro, with a total FTE of 212 students (Figure 23).

Figure 23. Location of CET-El Centro



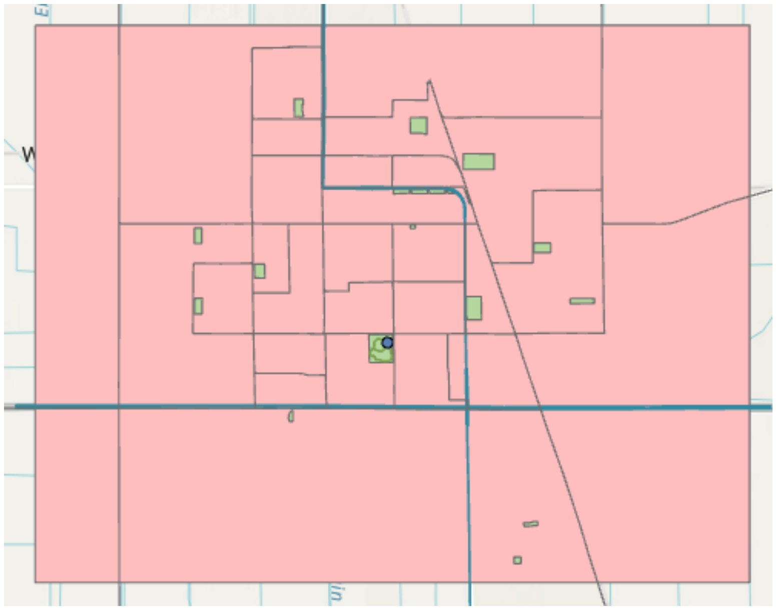
There are 11 elementary schools, 2 middle schools, and 6 high schools, for a total of 19 K–12 schools and a total enrollment of 9,746 students in 2022–2023 (Figure 24).

Figure 24. K–12 Schools Located in El Centro Study Area



There are 15 parks in the area under consideration, covering a total area of about 0.4 km^2 (Figure 25). All parks are characterized as "Small" both for pedestrian and cycling amenities, as they do not offer the amenities described in Section 2.7.

Figure 25. Parks (Green) in the Area of Study in El Centro (Pink)
with Highway (Blue)



There is one trail in the area (Buckling Park trail – Figure 26).

A summary of the features in the El Centro area of study is shown in Figure 27.

Figure 26. Trail (Green) in the Area of Study in El Centro (Pink)
with Highway (Blue)

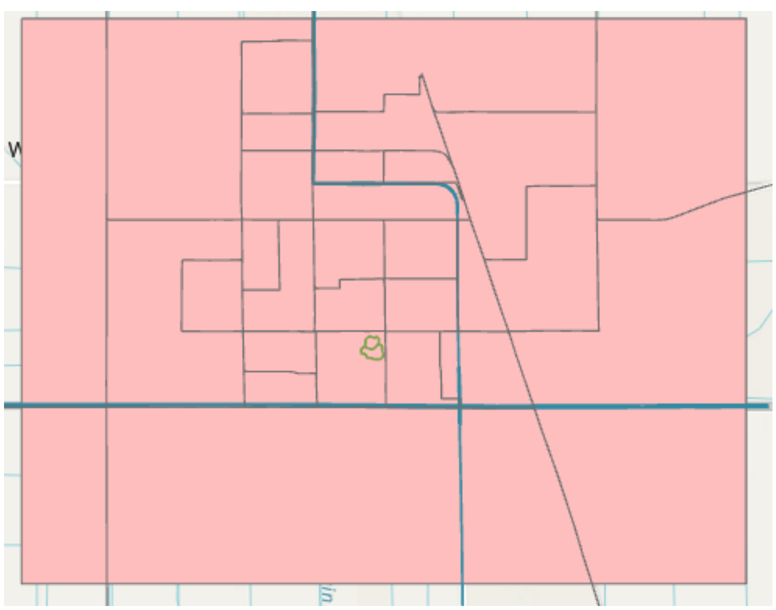
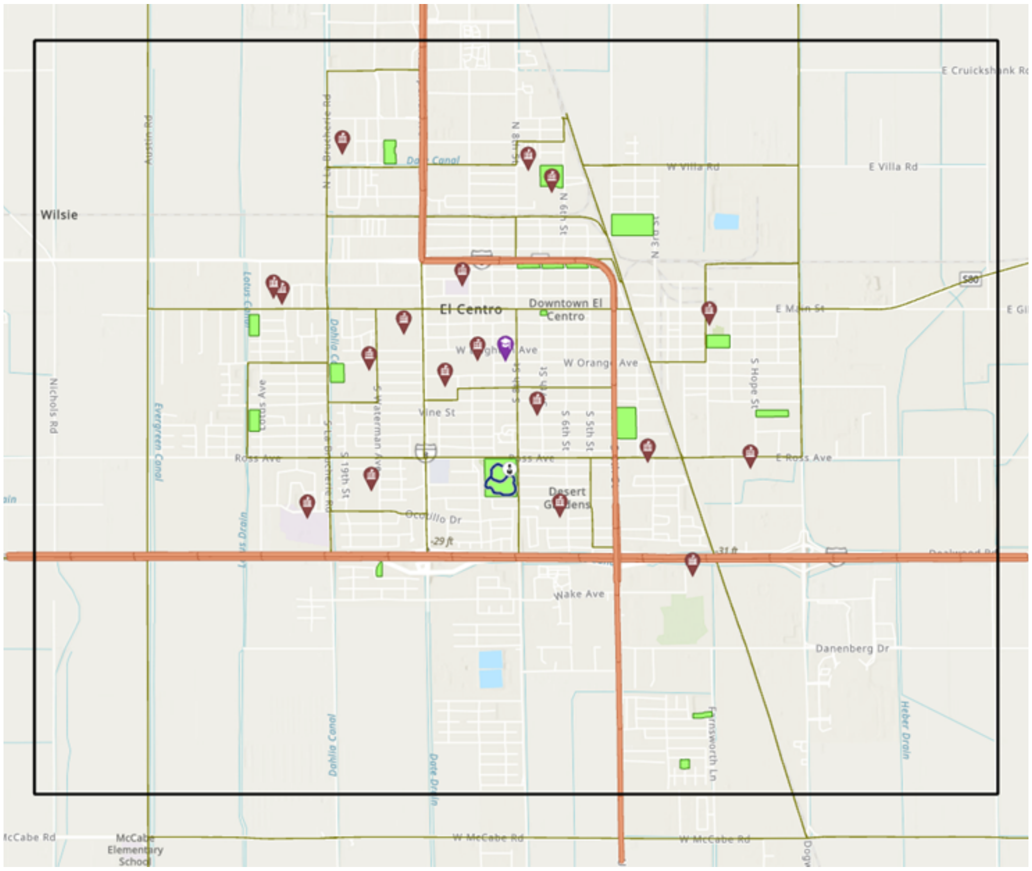


Figure 27. Summary of Features in El Centro Area of Study



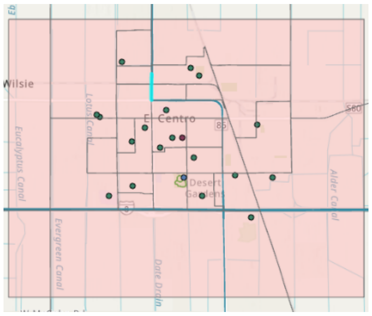
Latent demand for cycling traffic:

The latent demand score for each tract of highway is calculated with the contribution of the "work trips," "shopping and errands" trips, "school trips," and "social and recreational trips." The work trips also contain contributions from colleges and universities.

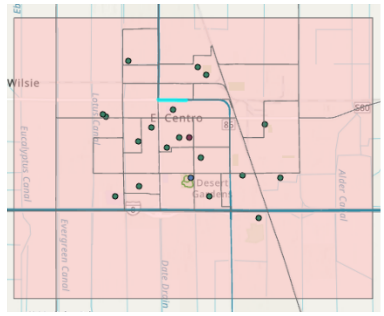
Focusing on cycling latent demand, the contribution of work trips Q_{wk} ranges from 499.4 to 6,099.6; the contribution of college and university trips Q_{CU} ranges from 0 to 24.6; the contribution of shopping and errand trips Q_{SE} ranges from 1,509.3 to 10,810; the contribution of school trips Q_{Sc} ranges from 119.9 to 5,073.4; and the contribution of social and recreational trips Q_{RS} ranges from 174.3 to 3,781. The final LDS score ranges from 2,903.9 to 2,2717.7.

The three highest LDS scores for cycling are obtained by the segments in Figures 28 and 29, with values of 22,717.7, 21,487.7, and 21,073.9, respectively. The major contributors to the LDS score in this area are shopping and errands and work.

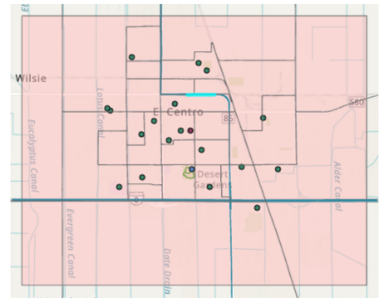
Figure 28. Top Three LDS Segments for Cycling in El Centro Area
(Highlighted) - One by One



(1) $LDS = 22{,}717.7$ – segment length 0.72 km

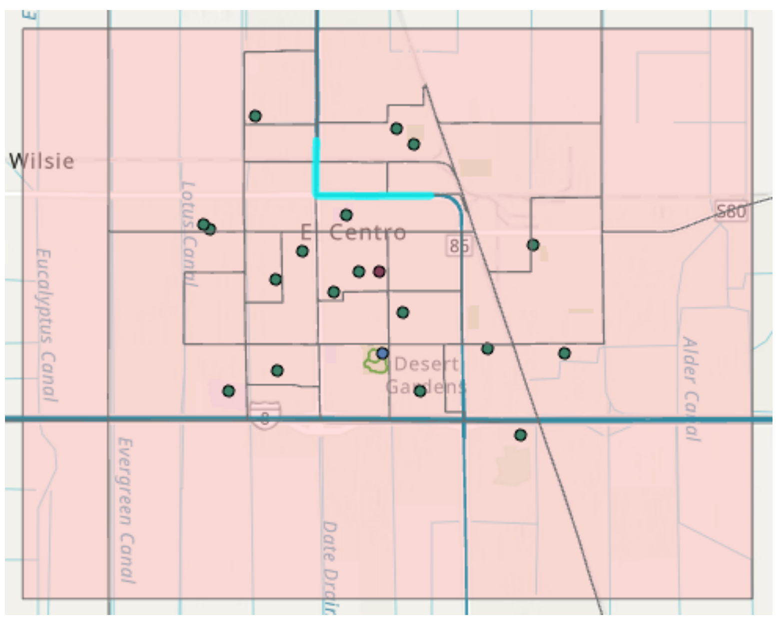


(2) $LDS = 21{,}487.67$ – segment length 0.77 km



(3) $LDS = 21{,}073.9$ – segment length m

Figure 29. Top Three LDS Segments for Cycling in
El Centro Area (Highlighted)

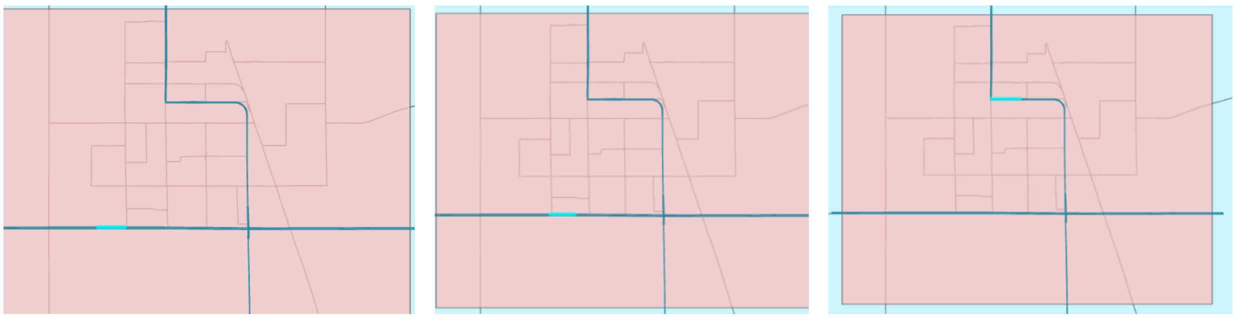


Latent Demand for Pedestrian traffic:

Focusing on pedestrian latent demand, the contribution of work trips Q_{wk} is 1,407.8; the contribution of college and university trips Q_{CU} ranges from 0 to 60.2; the contribution of shopping and errand trips Q_{SE} is 2,683.8; the contribution of school trips Q_{Sc} ranges from 0 to 5,089.5, and the contribution of social and recreational trips Q_{RS} ranges from 0 to 2,451.9. The final LDS score ranges from 4,091.6 to 9,275.8.

The three highest LDS scores for pedestrian facilities are obtained by the segments in Figures 30 and 31, with values of 9,275.8, 8,152.3, and 7,869.7, respectively. The major contributors to the LDS score in this area are shopping and errands and school trips.

Figure 30. Top Three LDS Segments for Walking Trips in El Centro Area (Highlighted) - One by One

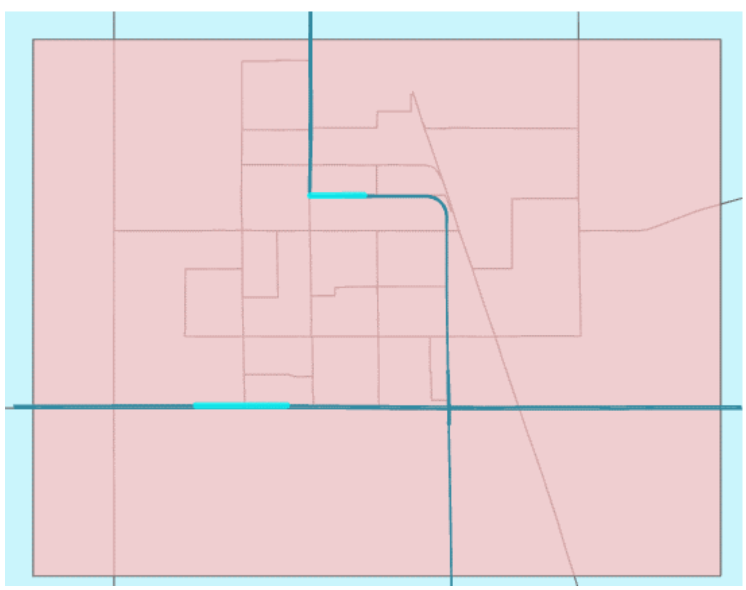


(1) $LDS = 9{,}275.8$ – segment length 0.64 km

(2) $LDS = 8{,}152.3$ – segment length 0.64 km

(3) $LDS = 7{,}869.7$ – segment length 0.66 km

Figure 31. Top Three LDS Segments for Walking Trips in El Centro Area (Highlighted)



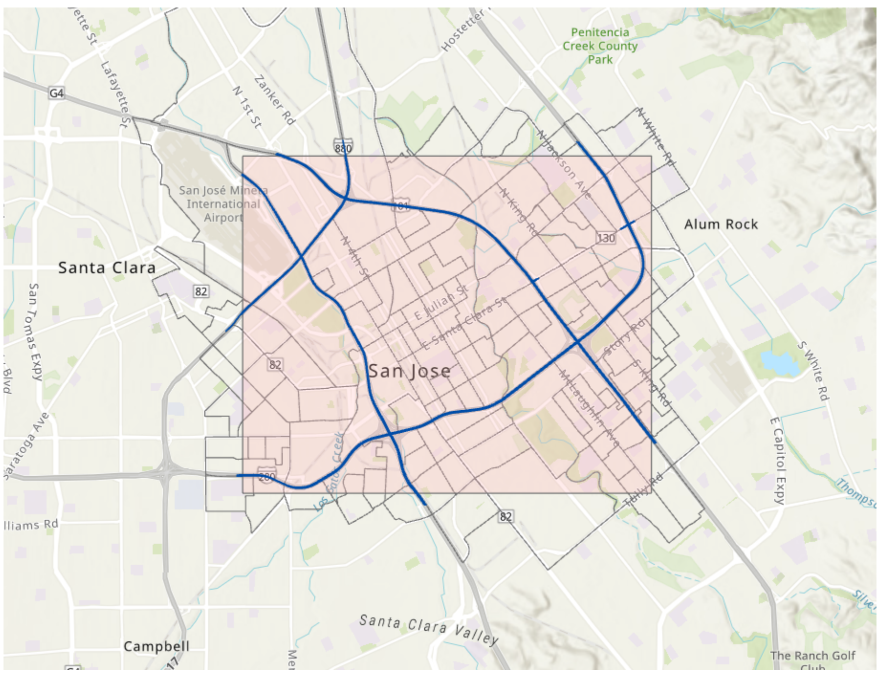
4.3 San Jose

San Jose is the largest city in Northern California by both population and area (Wikipedia, 2025, 3). With a 2022 population of 971,233, it is the most populous city in both the Bay Area and the San Jose–San Francisco–Oakland Combined Statistical Area. Located in the center of the Santa Clara Valley on the southern shore of San Francisco Bay, San Jose covers an area of 179.97 sq mi (466.1 km^2).

Description of study area:

The area considered in the analysis (Figure 32) is 8.9 km wide and long, for a total area of 78.8 km^2.

Figure 32. Area of Study of San Jose Downtown (Pink) with Block Groups and Highways (Blue)

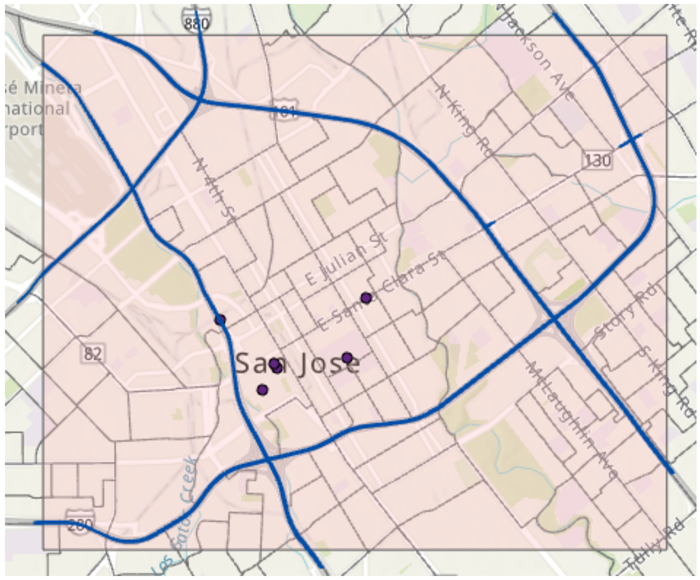


There are 145 block groups in this area of study, as shown in Figure 32. A total population of 222,955 people live in these block groups and a total of 214,556 people are employed.

The highway system in this area consists of a piece of Interstates 280, 880, US 101, and US 72, for a total length of 84 km. It is divided into 130 segments, whose lengths vary from a minimum of 166 m to a maximum of 692 m (mean: 647 m, standard deviation: 71 m, median: 658 m).

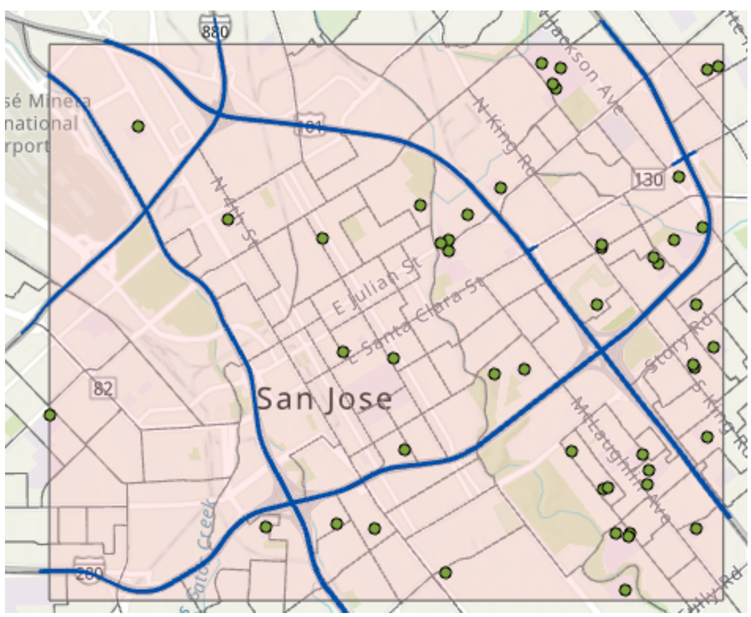
There are six universities in the area, with a total FTE of 36,456 students (Figure 33). The largest headcount is from San José State University, which accounts for 99% of FTES.

Figure 33. Location of Colleges and Universities in San Jose Downtown



There are 51 K–12 schools in the area under consideration, for a total enrollment of 22,614 students in 2022–2023 (Figure 34).

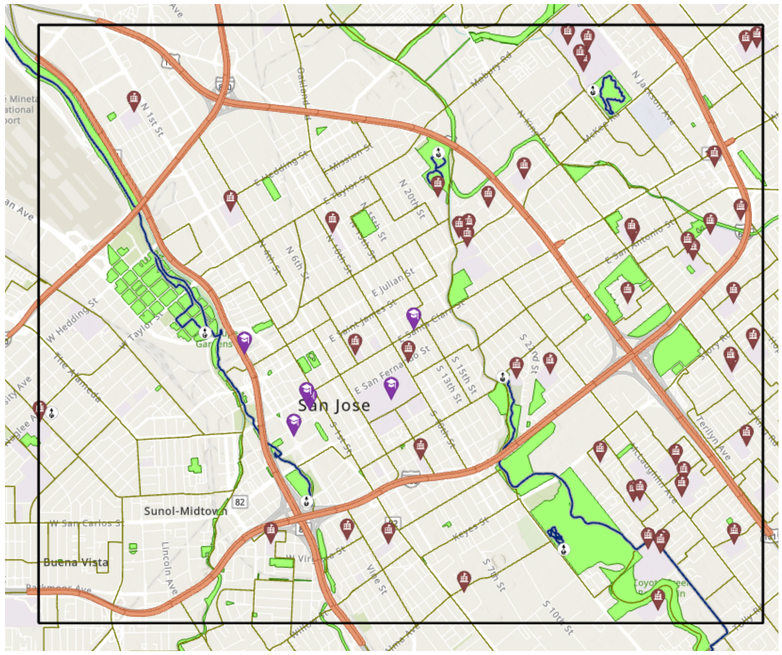
Figure 34. K–12 School Locations in San Jose Downtown Study Area



In the area under consideration, there are 63 parks for a total area of about 3.8 km^2 (Figure 35). All parks are characterized as “Small” both for pedestrian and cycling amenities, except for Backesto Park. There are also seven urban trails in the area (Figure 35).

A summary of the features in the San Jose downtown area of study is shown in Figure 35.

Figure 35. Summary of Features in San Jose Downtown Area of Study



Latent demand for cycling traffic:

The latent demand score for each tract of highway is calculated with the contribution of the "work trips," "shopping and errands" trips, "school trips," and "social and recreational trips." The work trips also contain contributions from colleges and universities.

Focusing on cycling latent demand, the contribution of work trips Q_{wk} ranges from 3,402 to 32,840; the contribution of college and university trips Q_{CU} ranges from 0 to 4,185; the contribution of shopping and errand trips Q_{SE} ranges from 15,596 to 52,875; the contribution of school trips Q_{Sc} ranges from 392.6 to 6,901; and the contribution of social and recreational trips Q_{RS} ranges from 841 to 8,536. The final LDS score ranges from 24,181 to 99,433.

The three highest LDS scores for cycling are obtained by the segments in Figures 36 and 37, with values of 99,433, 96,666, and 96,118, respectively. The major contributors to LDS scores in this area are work and shopping and errands.

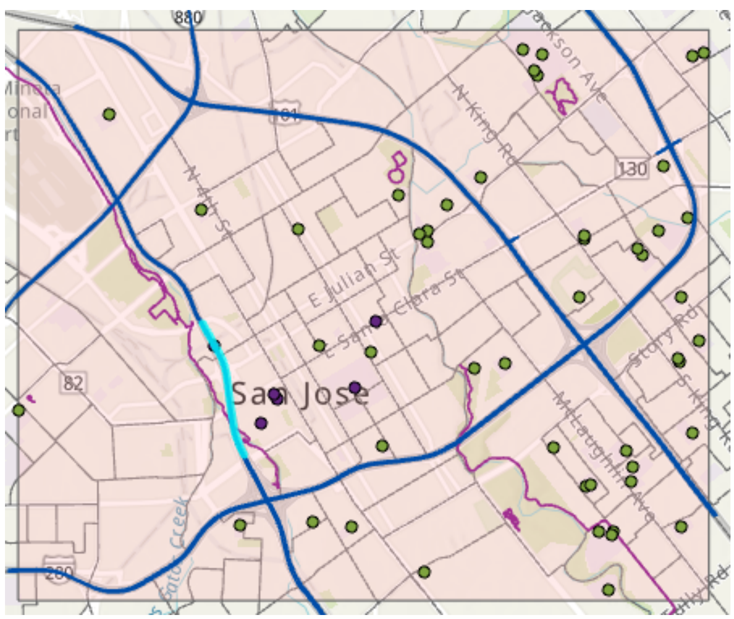
Figure 36. Top Three LDS Segments for Cycling in San Jose Downtown Area (Highlighted) - One by One

(1) $LDS = 99{,}433$ – segment length 0.66 km

(2) $LDS = 96{,}666$ – segment length 0.66 km

(3) $LDS = 96{,}118$ – segment length 0.66 km

Figure 37. Top Three LDS Segments for Cycling in San Jose Downtown Area (Highlighted)



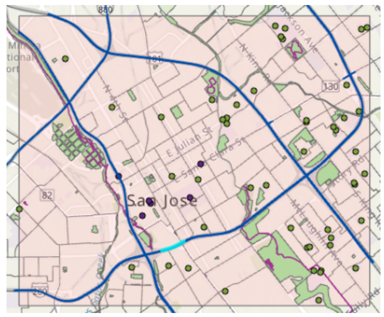
Latent demand for pedestrian traffic:

Focusing on pedestrian latent demand, the contribution of work trips Q_{wk} is 17,760.3; the contribution of college and university trips Q_{CU} ranges from 0 to 10,024.2; the contribution of shopping and errand trips Q_{SE} is 21,490.3; the contribution of school trips Q_{Sc} ranges from 0 to 4,770; and the contribution of social and recreational trips Q_{RS} ranges from 0 to 5,627.7. The final LDS score ranges from 39,250.7 to 53,446.8.

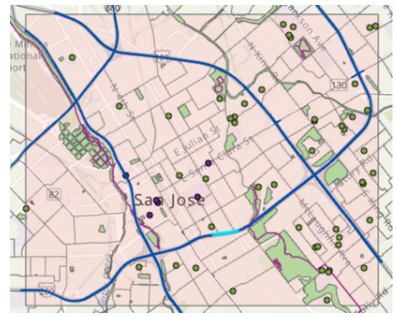
The three highest LDS scores for pedestrian facilities are obtained by the segments in Figures 38 and 39, with values of 53,446.8, 52,904.4, and 51,682.2, respectively. The major contributors to LDS scores in this area are work and shopping and errands trips.

Figure 38. Top Three LDS Segments for Walking Trips in San Jose Downtown Area (Highlighted) - One by One

(1) $LDS = 53{,}446.8$ – segment length 0.66 km



(2) $LDS = 52{,}904.4$ – segment length 0.66 km



(3) $LDS = 51{,}682.2$ – segment length 0.66 km

Figure 39. Top Three LDS Segments for Walking Trips in San Jose Downtown Area (Highlighted)

5. Summary and Conclusions

This report discusses the application of the Latent Demand Method to identify areas of potential high pedestrian and cycling traffic. The method estimates the potential trips (either walking or cycling trips) in the presence of optimal active transportation infrastructures. It allows urban planners to identify in which areas' optimal infrastructures will have higher impacts on walking and cycling.

The method needs to be implemented in GIS software. It assigns a Latent Demand Score to different segments of a highway based on potential active transportation traffic due to work, shopping and errands, presence of schools (including colleges and universities), and parks and trails. Three case studies in the state of California are presented for an urban area (San Jose – Downtown), a suburban area (El Centro), and a rural area (Douglas City). For each area, the three segments of highway in which active transportation infrastructures would have the most impact are identified, both for pedestrian and cycling traffic.

It is worth noting that the method provides a qualitative understanding of the impact of optimal infrastructure and future potential trips and does not quantify actual active transportation trips. Moreover, LDM does not consider the presence of existing infrastructure.

The method, in its current form, also does not consider the presence of places of worship, public transportation facilities, or actual shopping centers, which may serve as additional attractors for walking and cycling traffic. It also does not consider potential trips to visit family and friends, and non-destination trips, in which travelers are not focused on a specific destination. These additional features may be added in the future if the need arises.

Overall, the method provides a good indication of the potential impact of active transportation infrastructure. It provides an indication of the areas in which infrastructure would be more effective in enhancing active transportation. In making a decision, though, the urban planner is urged to consider existing active transportation infrastructure or infrastructure under development before planning for new facilities.

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