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Multi-dimensional Prioritization Tool for Capital Improvement of Hillside Streets in Los Angeles

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Multi-dimensional Prioritization Tool for Capital Improvement of Hillside Streets in Los Angeles

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16. Abstract
This report presents a comprehensive framework for prioritizing capital investment in urban road infrastructure, with a focus on resilience, safety, and equity. The framework addresses the growing challenges of aging road networks, increased traffic demand, and the risks posed by natural hazards such as landslides and wildfires. Using a multi-dimensional tool, the report evaluates road segments in Los Angeles hillside regions based on their importance within the transportation network, physical condition, and hazard exposure. Additionally, it incorporates demographics to ensure that infrastructure investments prioritize underserved communities. The results are further enhanced through a probabilistic framework designed to assess landslide risks in earthquake-prone regions. By combining structural importance with demographic data and hyperlocal assessments, cities can make more informed and equitable infrastructure investment decisions. Recommendations include prioritizing investments in critical roadways that serve vulnerable populations and incorporating advanced technology for road monitoring. This research provides a scalable, data-driven approach that can be applied to other urban regions to enhance road network resilience and ensure the fair distribution of resources.

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Executive Summary

Executive Summary

Maintaining urban road infrastructure faces increasing pressure from extreme weather events, aging components, and growing traffic demand. Ensuring equitable investment in road improvements is critical to guarantee the safety and continuity of essential services, especially during emergencies.

In response to the pressing need for resilient road infrastructure in urban areas, particularly in hazard-prone regions, this report introduces a comprehensive framework for prioritizing capital investments in urban roads. The approach not only focuses on road networks vulnerable to aging, inconsistent maintenance, and natural disasters like landslides, earthquakes, and wildfires but also provides a framework for the equitable allocation of funds to enhance resilience, safety, and fairness, particularly for underserved communities that have historically faced socio-economic disparities in infrastructure funding and improvements. This framework is designed to create a more just distribution of resources, ensuring that all populations benefit from safer and more resilient road networks.

Project Description

This report identifies critical road segments in the hillside region of Los Angeles not only based on their physical deterioration and exposure to natural hazards but also on addressing socio-economic disparities that have historically marginalized underserved communities. By placing equity at the core, this framework ensures that resource distribution mitigates the long-standing imbalances in infrastructure funding, empowering communities that are most vulnerable to adverse conditions and ensuring fair access to a safe and resilient transportation network.

By employing a multi-dimensional framework that integrates road condition, importance, hazard exposure, and an equity perspective, this methodology offers a robust solution for identifying critical road segments that require targeted investments. The holistic approach ensures that resource allocation not only addresses pressing infrastructure vulnerabilities but also equitably benefits underserved communities, promoting a more inclusive and fair transportation system.

A key element of the framework is a multi-dimensional tool for evaluating road “importance. ” This tool combines an evaluation of streets based on how they connect key destinations within the regional transportation network with analyses of demographic travel patterns to generate road importance scores that reflect both network-critical roles and social equity considerations. This approach provides a nuanced view of road usage across different population segments, ensuring that infrastructure improvements are equitably distributed to maximize social benefits and network efficiency.

The cornerstone of this approach lies in its use of advanced data collection and analytical techniques. Through the deployment of mobile mapping technologies, including LiDAR and panoramic imaging systems, fine-grained “hyperlocal” data on road conditions and hazards over small areas was collected and integrated into decision-making processes. This data collection strategy allows for unprecedented precision in capturing road network characteristics, revealing hidden vulnerabilities and enabling a detailed understanding of road performance, structural integrity, and associated risks. Such high-resolution data supports informed decision-making and enhances the reliability of infrastructure assessments.

The proposed framework further incorporates hazard rating techniques, focusing on the risk posed by landslides and other geological hazards, particularly in Los Angeles' complex hillside regions. Slope data and terrain analysis were utilized to identify high-risk areas, informing hazard mitigation strategies and retrofitting plans that enhance resilience to natural disasters. Integrating hazard ratings with road condition and importance metrics allows city planners to prioritize roads that are both essential to the network and most vulnerable to external threats.

Key Findings

1. **Data-Driven Prioritization:** The use of multi-dimensional tools and hyperlocal data collection provides a quantitative approach to systematically identifying critical roads in need of improvement.
2. **Equitable Resource Allocation:** Traditional infrastructure investments that focus solely on minimizing traffic delays can inadvertently widen the welfare gap between low- and high-income commuters. However, explicitly incorporating equity metrics—such as welfare loss—into the decision-making framework actively mitigates these disparities, ensuring that limited capital investments distribute resilience benefits fairly across diverse communities.
3. **Technology Integration:** The deployment of mobile mapping systems enhances the accuracy of road condition assessments, leading to more effective decision-making. Independent, hyperlocal data collection is essential for local governments to evaluate neighborhood road vulnerabilities often overlooked by state-level highway monitoring.

Recommendations

Prioritize Strategic Capital Investment. Policymakers should adopt this data-driven framework to prioritize critical road segments for infrastructure investment. This ensures that limited funds are used effectively to improve road resilience where they are most needed.

Center Equity in Infrastructure Decisions. Ensuring that vulnerable communities receive critical infrastructure improvements will promote transportation equity, fairness in transportation decision-making and transportation outcomes. Ignoring equity-focused considerations may lead to investment decisions that do not support the needs of vulnerable communities.

Adopt Advanced Data Collection Technologies. Local governments should invest in advanced mapping and data collection technologies to gain accurate insights into road conditions and hazards. This will enable more informed decisions for future infrastructure projects.

Conclusion

This report presents a comprehensive and data-driven approach for prioritizing capital investments in road networks, with a focus on enhancing resilience, safety, and equity in hazard-prone regions. By focusing on road condition, importance, and hazard risk, this equity-based framework offers a sustainable solution for enhancing road resilience in urban areas. Results from applying it to the Los Angeles Hillside region demonstrate the framework's efficacy in identifying and prioritizing critical road segments, ensuring that underserved communities receive fair attention.

Our framework emphasizes equitable resource distribution by prioritizing improvements for roads serving underserved and vulnerable communities. This involves integrating socio-economic data to ensure that infrastructure upgrades directly address disparities, providing fair access to safer and more resilient transportation networks.

The project also demonstrates the value of combining traditional engineering metrics with cutting-edge data science and machine learning techniques. The use of advanced models exemplifies how computational efficiency can be significantly improved in large-scale infrastructure projects. These models enable efficient assessment and optimization of retrofitting strategies, ultimately leading to more effective and equitable infrastructure enhancements.

Contents

Introduction

In today's rapidly urbanizing world, maintaining and improving roads is crucial for ensuring efficient transportation, public safety, and resilience to natural hazards. In regions prone to extreme weather events, aging infrastructure, and increasing traffic demands, building resilient road networks becomes even more urgent. As cities operate under budgetary constraints, making optimal capital investment decisions is essential for enhancing infrastructure resilience while efficiently using available resources. This report presents a data-driven approach for prioritizing road improvements through an equity lens, ensuring that resources are allocated where they will have the greatest impact, especially in underserved communities.

Resilient road networks are vital for ensuring the safety of commuters and the continuity of critical services during and after natural disasters. However, many urban road systems face challenges like aging infrastructure, inconsistent maintenance, and inadequate planning for fires, landslides, flooding, or other extreme events. Making sound capital investment decisions for infrastructure resilience involves evaluating multiple factors: physical road conditions, the road's importance in the network, hazard risks, and equitable resource distribution [1].

Including equity is especially important in this context. Ensuring that vulnerable or underserved communities receive adequate infrastructure improvements addresses historical under-investments and promotes fair access to safe, reliable transportation [2]. This report offers a systematic framework to help city planners and decision-makers identify critical roads for investment, enhancing resilience and addressing socioeconomic disparities in resource allocation.

Overview

Section 1: Multi-Dimensional Tool for Identifying Critical Roads

Section 1 introduces a multi-dimensional framework—developed as a part of an ongoing Los Angeles Hillsides Project funded by the City of Los Angeles Bureau of Engineering—that evaluates roads based on three key factors: condition, importance, and hazard risk. The condition rating assesses the physical state of the road, identifying those most in need of maintenance. The importance rating measures a road's role within the network, considering connectivity and traffic volume. The hazard rating highlights risks such as steep slopes or flood-prone areas that increase the likelihood of road failure during extreme weather events. Importantly, this section also describes how to incorporate an equity perspective by considering the travel demand of underserved communities. This is aimed at ensuring that investments are distributed fairly. This tool forms the basis for identifying critical roads in need of capital investment.

Section 2: Demographic Travel Pattern-Driven Road Importance Ranking

Section 2 introduces a new road importance rating system based on demographic travel patterns using the LODES (Longitudinal Employer-Household Dynamics) dataset. This approach builds on the ideas from Section 1 by integrating equity considerations and travel pattern information, prioritizing roads based on their value to different age groups, income levels, and employment sectors of commuters that use the streets. The LODES dataset helps ensure that infrastructure improvements address the needs of diverse groups, such as younger or older workers, lower-income communities, and various industries. The section details a method to calculate road importance by analyzing commuting patterns, shortest paths to and from key destinations, and accumulating trip data to provide a more equitable and comprehensive assessment of road infrastructure.

Section 3: Hyperlocal Data Collection for Accurate Road Assessments

Section 3 explores the use of “hyperlocal” data (data that refers to highly detailed, street-level information that captures the precise physical and geometric characteristics of specific road segments and their immediate surroundings) collection systems focused on very small geographical areas, such as mobile mapping and LiDAR technologies, to gather precise, real-time information on road conditions and hazards. These advanced data collection methods ensure that decision-makers have access to high-resolution, accurate data, leading to more informed assessments of road networks. The hyperlocal data collection system helps uncover previously undocumented road features, such as hidden damage or emerging hazards, providing a more detailed understanding of the network’s vulnerabilities. This section supports the multi-dimensional tool from Section 1 by enhancing data accuracy for better decision-making.

Section 4: Framework for Optimal Capital Investment Decisions

Section 4 presents an integrated framework based on the condition, importance, and hazard risk ratings from Sections 1 and 2 and the hyperlocal data from Section 3. This framework provides guidance on capital improvement budget allocations, ensuring that resources are directed to the most critical roads—those essential to the network and most vulnerable to hazards. An equity perspective is embedded in the decision-making process ensuring that investments address the needs of underserved communities, thus promoting fair and balanced resource allocation. By combining these metrics, the framework provides guidance on how limited financial resources can be used effectively, prioritizing roads that need urgent improvements to enhance resilience and equity.

Conclusion

This report proposes a comprehensive, data-driven approach to improving road network resilience through strategic capital investment decisions, emphasizing the need to incorporate equity in such decisions. Along with multiple attributes, this equity-seeking framework allows critical roads to be identified and prioritized for investment. The proposed framework aims to not only strengthen urban infrastructure but also promotes fairer resource distribution, leading to safer and more resilient road networks capable of withstanding future challenges.

Multidimensional Prioritization Framework

Introduction

The Los Angeles Hillside Ordinance [3] classifies certain areas in the city as "Hillside," highlighting the need for resilient infrastructure to support both daily commutes and emergency response (**Figure 1a**). These Hillside areas present significant challenges for infrastructure management due to complex terrain and aging road networks, making them prone to hazards like mudslides, wildfires, and earthquakes. Narrow roads, poor pavement, and inconsistent maintenance further increase these risks.

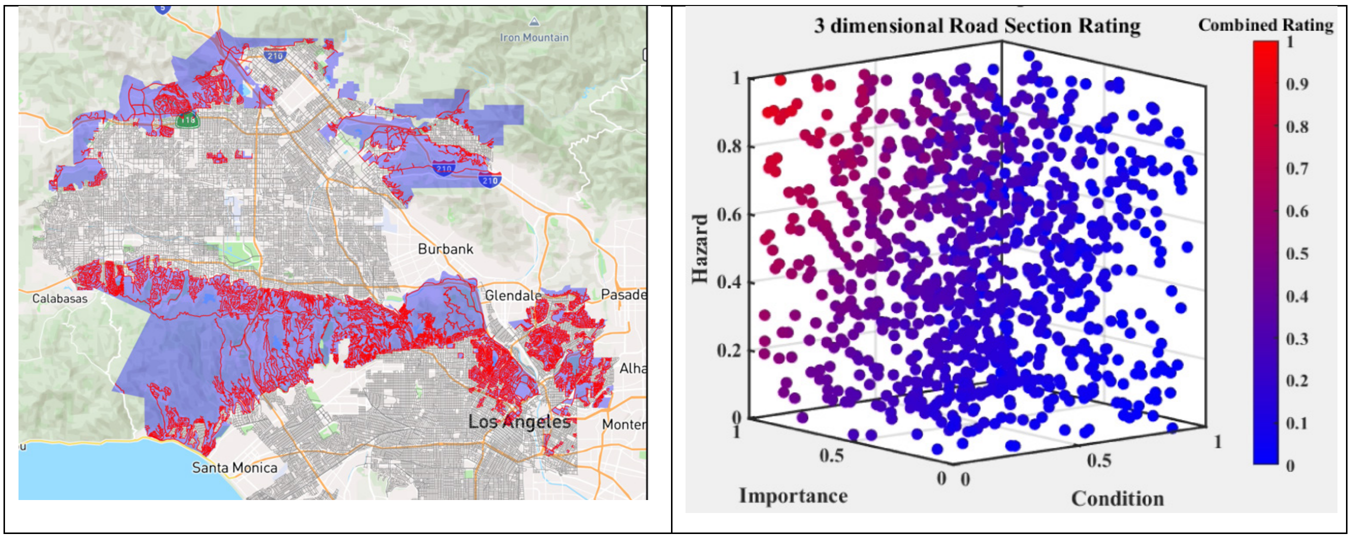

Figure 1. (a) Los Angeles Street Inventory (grey), with the Hillside Ordinance Layer (blue), and Hillside Roads (red); (b) Three-Dimensional Perspective of Road Rating

The deteriorating condition of these roads poses serious safety risks, especially during emergencies when reliable infrastructure is critical. Poor conditions also hinder daily access and affect residents' quality of life. Enhancing the resilience of these roads is essential to ensure they can handle routine and emergency demands.

The decision-support framework presented in this report aims to improve the resilience of Los Angeles' hillside roads by prioritizing improvements where they will have the greatest impact. Using a data-driven approach that combines on-site data collection with advanced technologies like LiDAR, cameras, the Global Navigation Satellite System (a satellite network that provides global positioning, navigation, and timing services) , and data from GeohubLA [4] and Google Maps API (application programming interface), the framework evaluates roads based on condition, importance, and hazard levels (**Figure 1b**). This helps city planners efficiently allocate resources to the most critical areas.

These three key axes are defined as follows:

1. **Condition:** The physical state of the road, with lower scores indicating higher need for maintenance.
2. **Importance:** The road's role in the network (e.g., usage, connectivity), with higher scores indicating roads that are more significant in facilitating travel throughout the region.
3. **Hazard Risk:** The risk or safety concerns associated with the road, with higher scores denoting roads more susceptible to failure.

In the scatter plot in Figure 1(b), color coding from blue to red indicates the combined rating of these factors. Roads in red are the highest priority for improvements due to their poor condition, regional importance, and high hazard risk. Focusing on these high-priority areas can significantly improve safety, performance, and resilience. This 3D visualization tool can aid planners in effectively allocating resources for maximum impact.

Three-dimensional Framework

The following sections explain each analytical axis—condition, importance, and hazard—along with additional factors like evacuation routes, equity, and maintenance. Lastly, we introduce the Hillside Street Prioritization Application (HSPA), a web tool that allows users to visualize, manipulate, and export the data for further analysis. The equity aspects described in the Section 2 are embedded in this tool.

Road Condition Rating

Definition and Significance

The road condition rating compares a street's current state to standards outlined in the *City of Los Angeles Complete Street Design Guide* [5]. Key elements crucial for safety and maintenance like road width, pavement, curbs, and sidewalks are assessed to determine the need for improvements.

Sub-Condition Rating

The road sub-condition rating considers four factors:

1. **Road width**: Essential for traffic flow and evacuation.
2. **Pavement Condition Index (PCI)**: Ensures a safe driving experience.
3. **Curbs**: Critical for flood control.
4. **Sidewalks**: Important for pedestrian safety.

Each factor is scored from 0 to 1, and a final condition rating is calculated by weighting these sub-ratings based on their importance.

Street Width Rating

Street width is rated by comparing the actual width to the designated standard. A street receives a full score of 1.0 if its width meets or exceeds the required standard. A formula adjusts the rating for streets that fall short, prioritizing those with significant deficiencies.

Curbs and Sidewalks Rating

Curbs and sidewalks are rated based on their presence along street sections. Streets with full coverage receive a score of 1.0, while partial or missing curbs and sidewalks lower the score.

Pavement Condition Index (PCI) Rating

The PCI rating, obtained from the NavigateLA database [6], reflects the road surface's condition. Poor pavement is penalized more heavily to prioritize maintenance for deteriorated sections.

Combined Rating

The combined condition rating is a weighted sum of the sub-ratings for width, PCI, curbs, and sidewalks. Weights can be adjusted to reflect the importance of each factor, resulting in an overall condition score between 0 and 1.

Road Importance Rating

Critical streets are identified using two approaches:

1. **Edge Betweenness Centrality (EBC):** This method identifies critical infrastructure by calculating how frequently a specific street serves as a connecting segment within the optimal routes (shortest paths) between key regional destinations. These optimal routes are determined by weighting travel distance, time, street width, and population served. Streets that constantly appear within these routes act as vital arteries for overall network efficiency. [7].
2. **Demographic-Based Approach using Travel Patterns:** This approach incorporates social factors, such as the utility of streets for different demographic groups, to ensure resources are allocated equitably. It prioritizes streets serving vulnerable or underserved communities.

Together, these methods provide a comprehensive view of road importance, balancing structural significance with social equity considerations.

The transportation system is converted into a graph, where roads are represented as edges and intersections as nodes. This allows the use of graph theory to assess the importance of streets based on their role in network connectivity.

Importance by Edge Betweenness Centrality

EBC identifies important connections within the network by measuring how often an edge is part of the shortest paths between two nodes [8]. Roads frequently used in shortest paths receive higher centrality scores, indicating their significance. The formula for EBC is:

$$c_B(e) = \sum_{s,t \in \mathcal{V}} \frac{\sigma(s,t|e)}{\sigma(s,t)} \quad (1)$$

Where $\sigma(s,t)$ is the total number of shortest paths between two nodes, and $\sigma(s,t|e)$ is the number of paths passing through edge e.

To calculate EBC, the following road characteristics are considered:

- **Distance:** Shorter roads contribute less to travel cost.
- **Travel Time:** Takes into account speed limits, traffic, and road capacity. Proportional to cost.
- **Street Width:** Wider streets are given lower costs, reflecting their ability to support more traffic.
- **Population:** Roads serving larger populations are prioritized.

Data for distance, travel time, and population is collected from the Google Distance Matrix API and U.S. Census block-level GIS datasets [9].

Importance by Travel Patterns and Demographics

This approach uses the Longitudinal Employer-Household Dynamics (LODES) dataset [10] to account for real travel patterns and demographic factors. The travel patterns of different workforce segments (age, earnings, industry) are used to calculate the importance of roads based on their utility to different demographic groups. This approach is described in detail in Section 2.

Combined Importance

The combined importance measure integrates the EBC scores and demographic-based metrics. Users can assign weights to each factor to calculate a final importance score using the following formula:

$$\boldsymbol{Importance} = \sum_{\text{attributes}} \boldsymbol{C}_{\text{attribute}} \times \boldsymbol{w}_{\text{attribute}} + \sum_{\text{demographics}} \boldsymbol{L}_{\text{segment, tier}} \times \boldsymbol{w}_{\text{segment}} \quad (2)$$

Here, $C_{\text{attribute}}$ denotes the importance, based on EBC for different edge attributes and $L_{\text{segment. tier}}$ denotes the importance based on the equity and demographic-based approach for different workforce segments.

Results for Road Importance

Applying both EBC and travel pattern-based metrics to the Los Angeles road network highlighted key hillside streets like Cahuenga Boulevard and Beverly Glen Boulevard as critical by both methods. EBC prioritized roads that connect northern and southern parts of the city, while the demographic-based approach highlighted areas with higher population density (**Figure 2**).

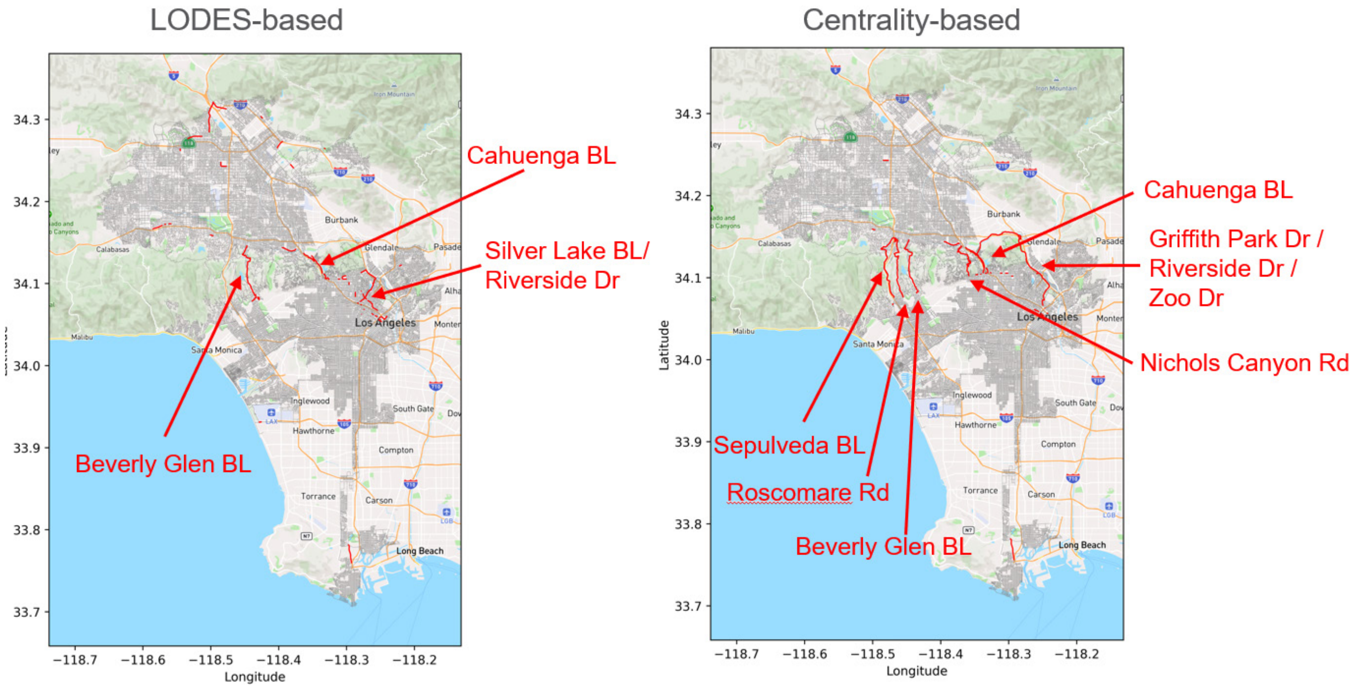

Figure 2. High Importance Roads in Los Angeles Based on Travel Patterns (left) and EBC (right)

Hazard Risk Rating

In this study, road hazards are determined by the slope profile adjacent to each road section. Steep slopes increase risks such as landslides, rockfalls, and erosion, which can block roads and damage infrastructure. They also pose dangers to vehicles, with a higher likelihood of accidents, reduced visibility, and drainage issues that can lead to hydroplaning. These slopes make maintenance and emergency response more difficult, requiring engineering solutions like barriers, retaining walls, and improved drainage systems.

Slope data was collected using the Google Elevation API, measuring elevation along the road centerline and 50 feet on both sides. For each road, the mean uphill and downhill slopes were calculated, and a hazard metric was defined as a weighted sum of these slopes, as shown in Equation 3. The weights can be adjusted to reflect the relative importance of uphill and downhill slopes. Both slopes are normalized on a scale from 0 to 1.

$$\boldsymbol{Hazard = H_{uphill} \times w_{uphill} + H_{downhill} \times w_{downhill}} \tag{3}$$

Figure 3 highlights 200 roads identified as the most hazardous based on adjacent slope profiles. The steepest slopes are concentrated in the Santa Monica Mountains, particularly within City Council Districts 1, 4, 5, 13, and 14.

Hillside Street Prioritization Application

The Hillside Streets Prioritization Application (HSPA) is a web-based tool that integrates the prioritization framework outlined in this report. It allows users to visualize and analyze hillside road data, combining metrics like road condition, importance, and hazard risk in an interactive platform. The tool leverages data from sources like LiDAR remote sensing technology, GIS (geographic information systems), and APIs to help decision-makers prioritize infrastructure improvements efficiently. With features for filtering, customization, and data export, HSPA provides a streamlined, accessible way for city planners to make data-driven decisions and target critical areas for upgrades.

Software Architecture and Development

The HSPA interface, developed using React.js and hosted on Vercel, provides dynamic visualizations through interactive maps, graphs, and dashboards, allowing users to explore road conditions, importance and hazard risks with seamless navigation via React-Router-Dom. The back end, built in Express.js, handles user requests and core logic, with multiple API endpoints for different applications. Containerized with Docker, the back end is stored in AWS Elastic Container Registry (ECR) and deployed on AWS EC2, ensuring scalability and consistent updates. All data is securely stored in AWS S3, accessible for real-time analysis.

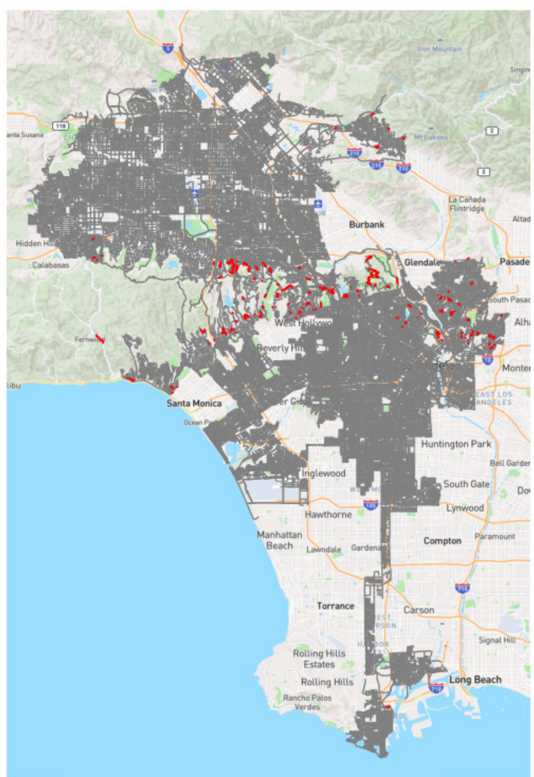

Figure 3. 200 Roads (in red) with the Steepest Slopes Adjacent to the Roadway

Key Features and User Interface

Through the HSPA interactive dashboard (**Figure 4**), users can see each road section's performance across these axes using scatter plots and 3D views. These visualizations assist planners in determining which roads require immediate attention, making the tool highly effective for prioritizing maintenance and upgrades.

Users can adjust weights for road condition metrics such as width, pavement condition index (PCI), curbs, and sidewalks, tailoring the prioritization process to specific needs. Similarly, the tool allows users to customize importance factors like road width, travel time, and usage by how they affect different segments of the workforce. Hazard weights, including uphill and downhill slopes, can also be fine-tuned, reflecting the unique risks posed by the terrain in hillside regions.

In addition to customizable factors, the HSPA Prioritization Tool supports filtering by geographic location, city council district, and road characteristics, such as evacuation routes or maintenance status, as well as low-income communities (defined in Assembly Bill 1550) and disadvantaged communities (defined in Senate Bill 235). This makes it easy for users to focus on specific areas or roads that meet certain criteria. The ability to interact with both scatter plots, representing road sections in the three-dimensional framework, and maps enhances decision-making by providing a comprehensive view of the road network's condition, importance and risk. Complementing the prioritization tool, HSPA also includes features like an Evacuation Tool for route safety analysis, an Accessibility Tool for assessing emergency access, and a Data Collection Tool, which supports detailed inspections and data integration for better-informed planning.

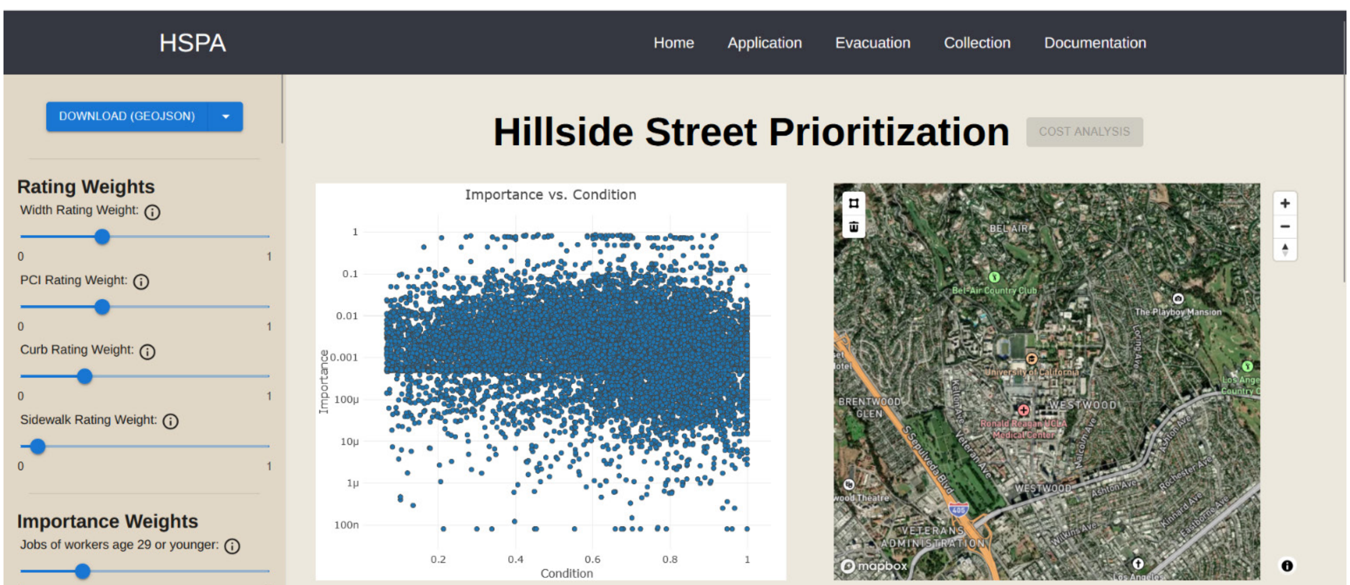

Figure 4. Dashboard of the HSPA Main Prioritization Application

Road Importance Rating by Demographic Travel Patterns

To complement the analysis of roads' functional importance provided by Edge Betweenness Centrality (EBC) method described in Section 1, the analysis presented in this section incorporates travel patterns by different demographic groups using the Longitudinal Employer-Household Dynamics (LODES) [10] dataset. This dataset provides demographic and employment data, allowing for a more equitable prioritization of infrastructure upgrades by focusing on roads that serve critical commuter routes and vulnerable communities.

In this analysis, the LODES dataset is used to complement the EBC results by considering:

- **Age Groups (SA):** Prioritizes roads crucial to various age demographics, such as younger or older workers.
- **Income Levels (SE)**: Emphasizes roads serving lower-income communities to address equity gaps.
- **Employment by Industry (SI)**: Differentiates roads serving workers in different sectors like trade, transportation, and utilities.

This approach ensures that infrastructure improvements are more equitable, directing resources to the roads that benefit diverse demographic groups.

LODES Dataset

The LODES dataset, provided by the U.S. Census Bureau, offers data on commuting patterns, employment distribution, and population movement at the census block level.

The dataset classifies workers into three main segments of the workforce, each divided into three tiers:

- **SA (Age Segments):**
  - SA01: Workers aged 29 or younger.
  - SA02: Workers aged 30 to 54.
  - SA03: Workers aged 55 or older.
- **SE (Earnings Segments):**
  - SE01: Workers earning $1,250 per month or less.
  - SE02: Workers earning $1,251 to $3,333 per month.
  - SE03: Workers earning more than $3,333 per month.

- **SI (Industry Segments):**
  - SI01: Jobs in goods-producing sectors.
  - SI02: Jobs in trade, transportation, and utilities.
  - SI03: Jobs in all other service sectors.

Procedure for Assigning Road Importance:

1. **Data Collection**: The LODES dataset is used to gather data on commuting trips between census blocks, segmented by workforce groups and tiers.
2. **Trip Distribution**: The total number of trips for each demographic group is identified and evenly distributed across pairs of nodes within census blocks.
3. **Shortest Path Calculation:** The shortest travel paths between node pairs are calculated, and roads used in these paths are assigned a portion of the corresponding trips.
4. **Accumulation of Importance Scores:** As multiple node pairs may use the same roads on their shortest paths, trip counts are accumulated to provide an overall importance score for each road segment.
5. **Normalization:** The total importance scores are normalized across each workforce segment to ensure comparability.

This methodology enables a comprehensive and equitable assessment of road infrastructure based on both structural significance and demographic travel patterns.

Proposed Generalized Algorithm for Node-to-Node Trip Assignment and Edge Importance

Input Variables:

B: The set of all blocks, where each block $b \in B$ contains a set of nodes N_b.

$$B = \{b_1, b_2, \dots, b_k\}, \quad N_b = \{n_1, n_2, \dots, n_m\}$$

P_{b_i,b_j}: The set of node pairs between block b_i and block b_j, where $i \neq j$.

$$P_{b_i,b_j} = \{(n_a, n_b) \mid n_a \in N_{b_i}, n_b \in N_{b_j}\}$$

T_{b_i,b_j}: The total number of trips between block b_i and block b_j, derived from a dataset like LODES.

G: The network graph where nodes represent locations, and edges represent travel paths with associated travel times t_e, where e is an edge.

Output Variables:

E: The set of edges in the network graph G.

Trips_e: The number of trips assigned to each edge $e \in E$.

Steps:

1. Block and Node Setup:

Define the set of blocks and the nodes within each block. For each block pair (b_i, b_j), identify the corresponding set of node pairs P_{b_i,b_j}.

2. Trip Assignment to Node Pairs:

Distribute the total trips T_{b_i,b_j} between the node pairs P_{b_i,b_j}. If trips are distributed evenly:

$$\text{Trips Per Node Pair} = \frac{T_{b_i,b_j}}{\left|P_{b_i,b_j}\right|}$$

3. Shortest Path Calculation:

For each node pair $(n_a, n_b) \in P_{b_i,b_j}$, compute the shortest path $\text{SP}(n_a, n_b)$ based on travel time. This can be done using Dijkstra's or any other shortest-path algorithm on the graph G:

$$\text{SP}(n_a, n_b) = \{e_1, e_2, \dots, e_k\}, \quad \text{where each } e \text{ is an edge in the shortest path}$$

4. Assign Trips to Edges:

For each edge $e \in \text{SP}(n_a, n_b)$, assign the number of trips corresponding to the node pair (n_a, n_b):

$$\text{Trips}_e = \text{Trips Per Node Pair}$$

Sum the trips for each edge by accumulating trips from all node pairs:

$$\text{Trips}_e \leftarrow \text{Trips}_e + \text{Trips Per Node Pair}$$

5. Accumulate Edge Importance:

Finally, for each edge $e \in E$, sum the total number of trips assigned from all node pairs to compute the final importance score:

$$\text{Total Trips}_e = \sum_{\text{All Node Pairs}} \text{Trips}_e$$

This calculation is performed for every workforce segment and tier independently. Following this procedure, every road will receive importance ratings $\boldsymbol{L}_{\text{segment, tier}}$ for all segment and tier pairs. The importance ratings are normalized to scores between 0 and 1.

Correlation between Road Ratings

Analyzing correlations between road ratings across demographic groups is crucial since transportation infrastructure serves a wide range of socio-economic groups. Understanding how different groups—segmented by age, income, or industry—use the road network is vital for making informed investment decisions. While improvements may benefit one group, they can affect others differently, potentially promoting equity or increasing disparities if certain needs are prioritized. Examining these correlations helps identify both synergies and conflicts in infrastructure changes across communities.

Table 1 shows the correlations between road ratings for different workforce segments and tiers. Correlations are calculated by first determining road importance scores for each group, such as workers under 29 (SA01), then comparing these scores with another group, like mid-level income workers (SE02), yielding a correlation coefficient (e.g., 0.996 for SA01 and SE02). This process is repeated for all segment pairs, offering insights into how different groups use the road network.

Table 1. Correlations in Road Ratings between all Groups and Tiers

	Age [Years]			Earnings [USD/month]			Industry [Type]		
	<29	30-54	>54	<1250	1250-3333	>3333	Goods	Trades	Others
Segments	**SA01**	**SA02**	**SA03**	**SE01**	**SE02**	**SE03**	**SI01**	**SI02**	**SI03**
SA01	1	0.999	0.998	0.994	0.996	0.994	0.978	0.997	0.998
SA02	0.999	1	0.999	0.991	0.997	0.997	0.974	0.994	1
SA03	0.998	0.999	1	0.992	0.996	0.996	0.973	0.992	1
SE01	0.994	0.991	0.992	1	0.988	0.98	0.968	0.992	0.991
SE02	0.996	0.997	0.996	0.988	1	0.991	0.982	0.994	0.996
SE03	0.994	0.997	0.996	0.98	0.991	1	0.966	0.987	0.997
SI01	0.978	0.974	0.973	0.968	0.982	0.966	1	0.983	0.97
SI02	0.997	0.994	0.992	0.992	0.994	0.987	0.983	1	0.992
SI03	0.998	1	1	0.991	0.996	0.997	0.97	0.992	1

Key insights include the highest correlation in the age group (SA) segments, with an average of 0.9987, suggesting similar road usage patterns across age groups. This may be due to major roads being equally accessible regardless of age. In contrast, industry sectors (SI) show the lowest correlation, with an average of 0.982, likely due to spatial clustering of specific industries, such as goods-producing sectors in industrial hubs and service jobs near residential areas.

Correlations among income groups (SE) fall between those of age and industry, with an average of 0.986. Higher-income workers (SE03) have more flexibility in housing and job location, leading to diverse travel patterns, while lower-income groups may show more uniformity.

Age-income correlations reveal that roads that are significant for those under 29 (SA01) are also very important for middle-income drivers (SE02), while those that are important to older drivers (SA02 and SA03) are also important to those with higher incomes (SE02 and SE03). Age factors are more significant with respect to trade, transportation, utilities (SI02), and service (SI03) sectors, but less significant in regard to goods-producing sectors (SI01).

Income-industry correlations show that those roads that are significant for lower income drivers (SE01) are also highly important to those employed in manufacturing (SI01), while roads that are important to high income drivers (SE03) are likewise important to those in service jobs (SI02 and SI03) compared to goods production.

Finally, industry-age correlations reveal that roads that are significant to drivers employed in goods-producing and trade/transport sectors (SI01 and SI02) are also important to younger drivers (SA01), while those with jobs in other services (SI03) are more important to older age groups (SA02 and SA03)).

Differences in Road Rankings based on age, industry and earnings

Differences Between Age Groups

Figure 5 (a) shows the top 20 percent of roads ranked by importance for workers under 29 (SA01) and workers 55 and above (SA03). Black lines represent roads that are important for both groups, revealing an 88 percent overlap, indicating that most critical roads benefit both younger and older workers equally.

Red lines highlight roads important for younger (SA01) but not older (SA03) drivers, mainly clustered in central Los Angeles, Glendale, and Pasadena. These areas are likely to attract younger workers due to their proximity to universities, such as USC, and industries like tech that employ younger persons.

Blue lines represent roads important for older (SA03) but not younger (SA01) drivers, concentrated in suburban areas like Bel Air, Beverly Hills, and Laurel Canyon. These roads suggest older workers may reside or commute in these regions, possibly due to long-term residential stability or different employment and lifestyle patterns.

Overall, the plot shows substantial overlap in road importance between younger and older workers, but also highlights distinct areas of divergence: red clusters near urban centers for younger workers, and blue clusters in suburban areas for older workers.

Figure 5 (b) illustrates ranking differences between younger (SA01) and older (SA03) drivers by subtracting SA03 rankings from SA01. Red areas indicate roads more important for younger drivers and blue areas show those prioritized by older drivers. The patterns align with Figure 5 (a), reinforcing the trend of younger workers prioritizing urban roads, while older workers rely more on suburban routes.

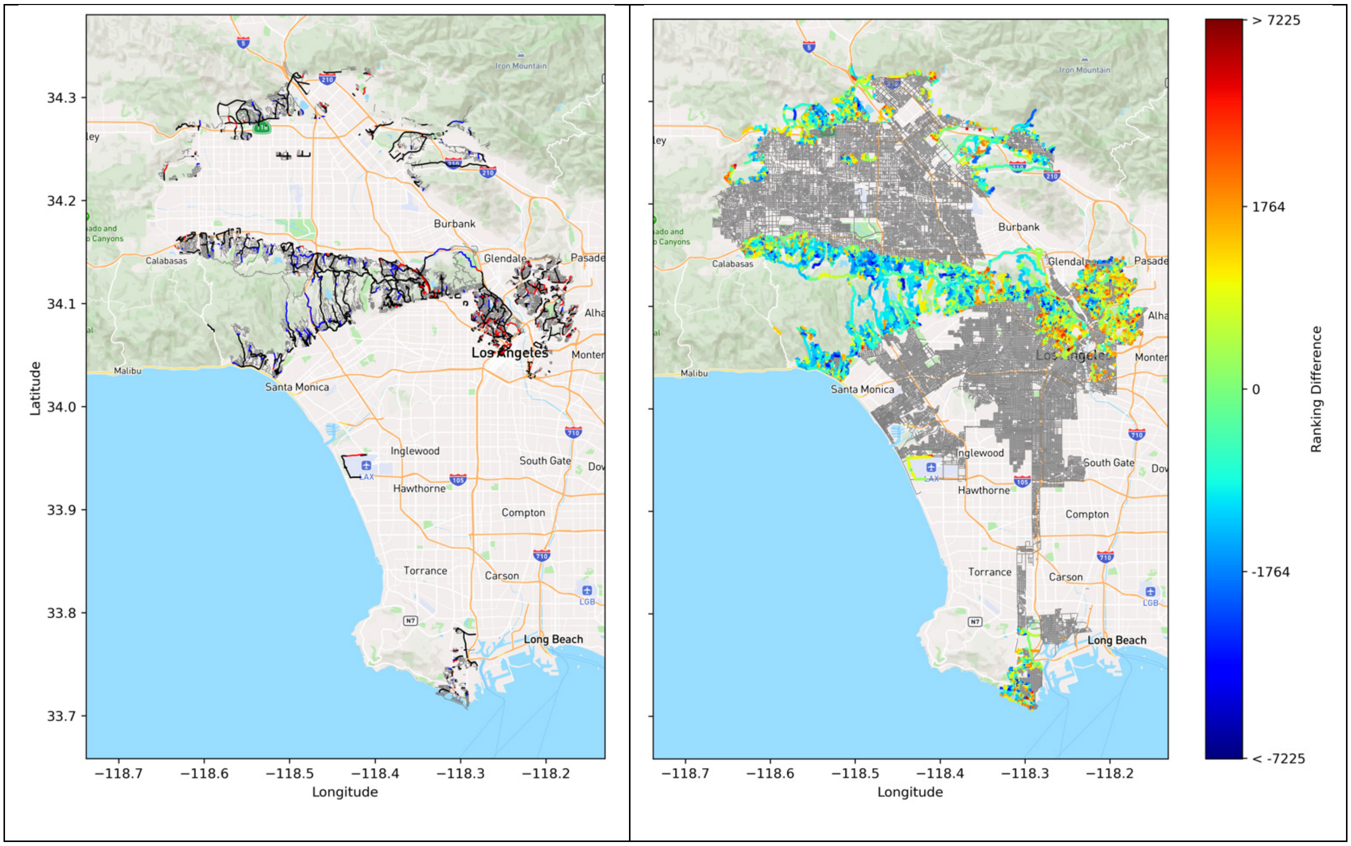

Figure 5. (a) Top 20% of Roads Ranked Based on SA01 and SA03, (b) SA Ranking Difference

Differences between Earning Groups

Figure 6 (a) shows the top 20 percent of roads ranked by importance for workers earning less than $1,250 (USD) per month (SE01) and workers earning more than $3,333 (USD) per month (SE03). Black lines indicate roads that are important for both groups, with a 90.4 percent overlap, suggesting that many critical roads serve both lower- and higher-income workers, like major arteries central to commuting patterns across income levels.

However, differences emerge between the groups. Red lines highlight roads important for lower income workers (SE01) but not higher income workers (SE03), clustering in densely populated urban areas, such as downtown, where lower-income workers rely more on public transit. These areas reflect a need for shorter commutes and proximity to service-oriented jobs. In contrast, blue lines show roads important for higher (SE03) but not lower income workers (SE01), concentrated in suburban, higher-income regions like Bel Air and

Beverly Hills. These roads indicate longer commutes and a reliance on private transportation among higher-income workers.

In summary, while there is a significant overlap in critical road infrastructure for both income groups, urban roads more important for lower-income workers, while suburban routes are vital for higher-income workers.

Figure 6 (b) illustrates ranking differences between lower income (SE01) and higher income workers (SE03), with red areas showing where roads are most critical for those with lower incomes (SE01), primarily located in central, urban areas where public transit is more accessible and proximity to workplaces is crucial for lower-income workers.

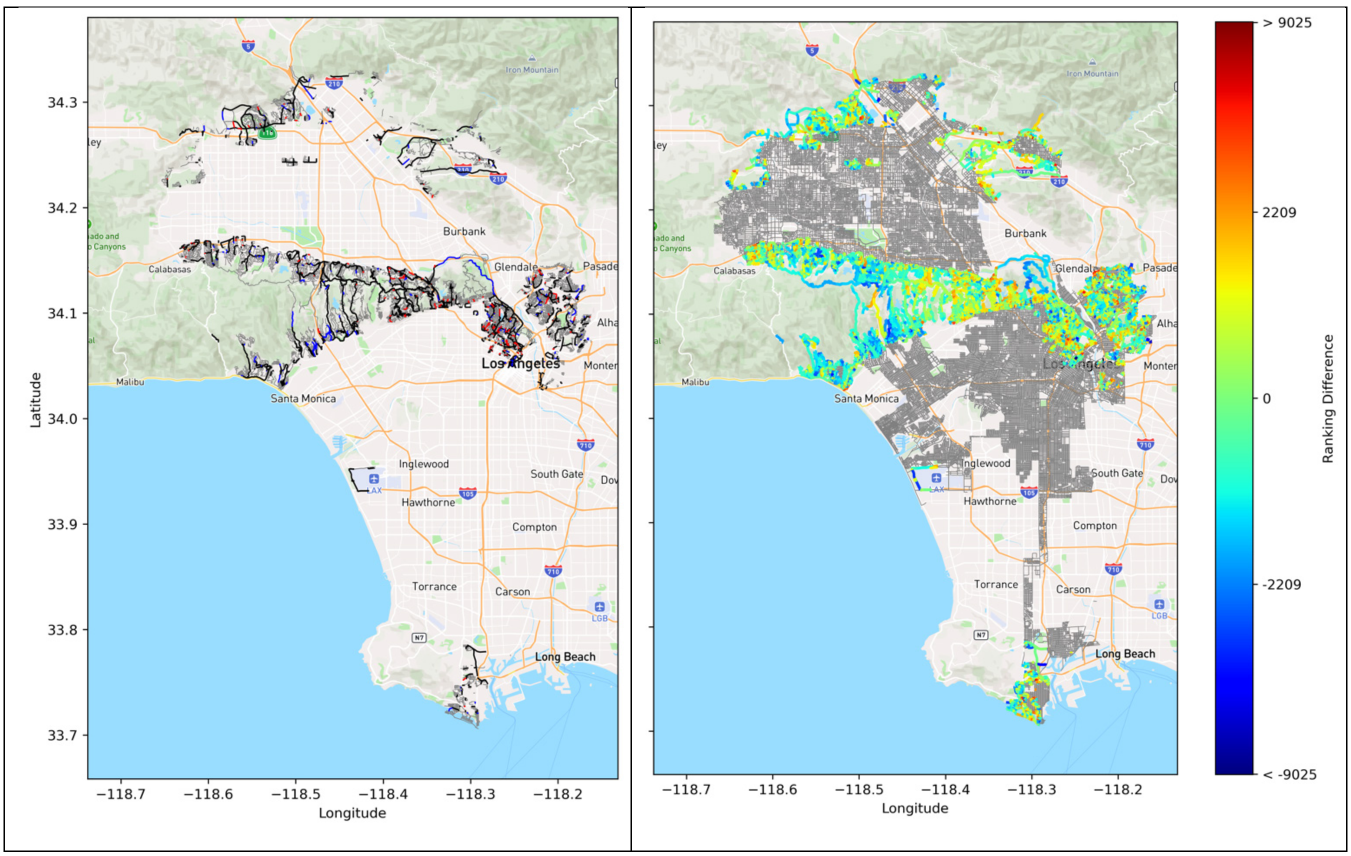

Figure 6. (a) Top 20% of Roads Ranked Based on Income (SE01 and SE03), (b) SE Ranking Difference

Differences between Industry Worker Groups

Figure 7 (a) shows the top 20 percent of roads ranked by importance for manufacturing industry sectors (SI01) and "other" service sectors (SI03). The black lines indicate an 81.2 percent overlap, suggesting that both industrial and service sector workers rely on key transportation routes, particularly major commuting corridors connecting industrial zones and service-related job centers.

The red lines highlight roads important for manufacturing sectors only (SI01) but not “other” service sectors (SI03), with clusters in the north, around Santa Clarita Valley, a hub for advanced manufacturing, and in the south near the Los Angeles Harbor, which supports shipping, logistics, and transportation industries. These areas are crucial for accessing industrial sites, port facilities, and distribution centers.

The blue lines represent roads important for “other” service sectors (SI03) but not manufacturing sectors (SI01), primarily spread across central hillside suburban areas, reflecting the broader distribution of service-based jobs. Downtown Los Angeles shows a mix of black, red, and blue roads, indicating shared infrastructure for both type of sectors.

In summary, while there is substantial overlap in road importance, manufacturing workers rely more on northern roads serving industrial hubs, while “other” service workers depend on suburban roads.

Figure 7 (b) shows ranking differences between manufacturing and “other” service sector jobs. Red areas indicate roads ranked higher for manufacturing (SI01), particularly in northern industrial hubs like Santa Clarita. Blue areas, ranked higher for “other” service employment (SI03), are spread across suburban and hillside regions, reflecting service job distribution. Downtown Los Angeles has a mix of red and blue, reflecting shared but differentially important roads for each group.

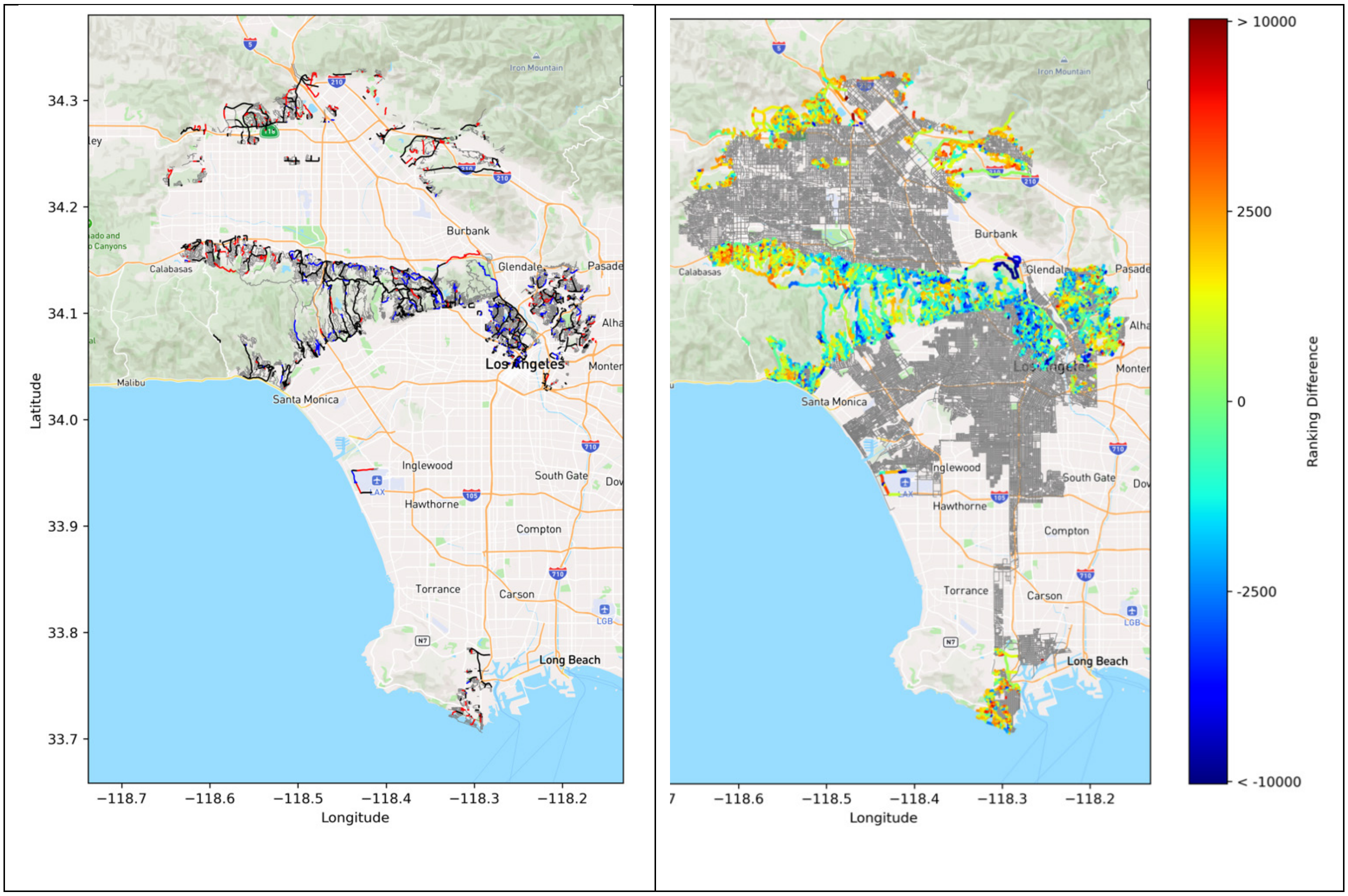

Figure 7. (a) Top 20% of Roads Ranked Based on SI01 and SI03, (b) SI Ranking Difference

Hyperlocal Data Collection

Accurate assessment of road and roadside features in Los Angeles' hillside regions is essential for urban planning, safety, and infrastructure maintenance. Existing municipal records, such as the StreetsLA GeoHub Street Inventory [4], often contain inaccuracies in road widths and features, and may lack details on sidewalks, curbs, slopes, and guardrails. These gaps hinder effective planning and emergency response, particularly in challenging hillside areas.

Updating road network data is critical for better decision-making in infrastructure development and emergency response. Incomplete or inaccurate data, such as underestimated road widths or missing safety features, can impede the effectiveness of emergency services. Capturing previously unmapped features helps prioritize infrastructure projects, improving safety and resilience in urban environments. This section examines how LiDAR and advanced surveying techniques can enhance the accuracy of road documentation and support infrastructure improvements [11].

Data Collection Device Description

Kaarta Stencil Pro, used for this project, is a mobile mapping system designed for high-precision data collection in diverse environments (**Figure 8**). It is equipped with a Velodyne VLP-32C LiDAR unit, which captures a high-density 3D point cloud at 600,000 points per second over up to 120 meters. Additionally, the system features four 8-megapixel 4K panoramic color cameras, which capture 360-degree imagery to enhance the LiDAR point clouds with color, aiding in visual documentation and geospatial analysis (**Figure 9**).

Figure 8. (a) Sensor Kit Mounted on the Car, (b) Perception Kit Showing GPS, LiDAR, and a Panoramic Camera

Figure 9. Sample Panorama Image Captured During Data Collection

Sample Point Cloud

Kaarta Stencil Pro combines LiDAR, camera, and GPS data using a modified LiDAR Odometry and Mapping (LOAM) algorithm [12], creating a dense, colorized, geo-referenced point cloud. The LOAM algorithm uses two processes: a high-frequency odometry algorithm to estimate LiDAR velocity and a lower-frequency algorithm for accurate point cloud alignment. The result is a precise, real-time map that reduces drift and enhances accuracy. **Figure 10** shows a 200-ft sample point cloud from a 2.6-mile scan in Council District 1, which generated about 300 million colorized points.

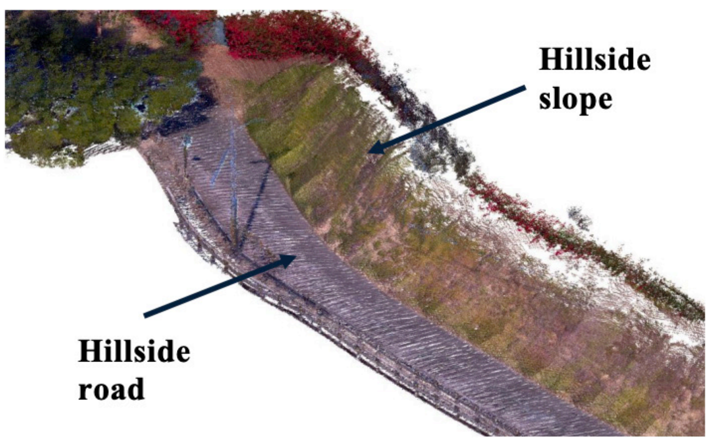

Figure 10. Sample Point Cloud from a Larger Scan Using the Kaarta Stencil Pro

Data Collection Locations

We conducted on-site data collection over approximately 76 miles of hillside roads across city council districts 1, 2, 3, 4, 7, 12, 13, and 14 as shown in **Table 2**. Data collection focused on streets in poor condition, particularly in council districts with the highest concentration of such roads. Streets with a condition rating below 0.3 were prioritized for data collection, covering approximately 76 miles across the targeted districts. Table 2 presents the detailed metrics for each district's data collection, which was undertaken concurrently for the ongoing project with the City of Los Angeles.

Table 2. Hyperlocal Data Collected in Different Council Districts

Council District	Date	Neighborhood	Miles
1	13th November 2022	Mount Washington	11.6
3	22nd June 2022	Woodland Hills	11
4	1st October 2022	Laurel Canyon, Mount Olympus, Hollywood Dell	17.3
7	16th June 2022	Sunland-Tujunga (near Verdugo Mountains)	8.9
13	28th January 2023	Silverlake, Echo Park and Elysian Heights	8.9
14	11th February 2023	El Sereno, Rose Hill, Highland Park, Eagle Rock	10.7
2	6th April 2024	Lakeside Park	2.3
12	6th April 2024	Studio City	4.8

Evaluating Road Condition and Features

The selected roads were prioritized based on ratings derived from online data sources, focusing on road condition, importance, and hazard exposure. The collected data, which are summarized below, provides key insights into road conditions and features:

- **Road width**: Critical for safety and traffic flow, particularly in narrow hillside areas.
- **Sidewalk and curb dimensions**: Important for pedestrian safety and flood control.
- **Slope profiles**: Essential for assessing road stability and the need for erosion control.
- **Road surface**: Differentiating between paved and unpaved roads is crucial for maintenance planning.
- **Presence of parked cars**: Provides insight into road capacity and emergency access.
- **Presence of street trees and guardrails**: Street trees may obstruct visibility, while guardrails are critical for safety on steep roads.
- **Presence of trash bins:** Offers information on street service routes.

The LiDAR data provided three-dimensional point clouds, allowing for the analysis and quantification of various roadside features, such as road width and slope profiles. This data complements, updates, and verifies the data obtained from online sources, helping to improve planning and decision-making for infrastructure projects. **Figure 11** presents four sample roads in different council districts. that were inspected. These roads were identified as candidates solely based on the ratings derived in Section 1, using only online data. All the selected roads are narrow, have steep slopes, poor pavement conditions, little to no protection such as guardrails, and lack curbs and sidewalks.

Figure 11. Sample Roads That Were Inspected During On-Site Data Collections a) Yucca Trail in Council District 4, b) Abargo Street in Council District 3, c) Verdugo Crestline Drive in Council District 7, d) West Rose Hill Drive in Council District 14

Improving Road Network Resilience for Earthquake-Induced Landslide Hazards

Introduction

The 6.7 magnitude Northridge earthquake in 1994 highlighted the vulnerability of urban infrastructure to seismic events. Centered in the San Fernando Valley, Los Angeles, the earthquake caused extensive damage, resulting in 57 fatalities, 9,000 injuries, and over $20 billion (USD) in direct damage, with broader economic losses exceeding $40 billion (USD) [13]. Major freeways, including Interstates 5, 10, and State Routes 14 and 118, were significantly impacted, disrupting critical connections, particularly between the Santa Clarita Valley and Los Angeles. The earthquake also affected local roads, especially in hillside areas like Santa Monica and Malibu, where landslides and rockfalls led to road closures and further impeded recovery efforts [14].

This event underscores the necessity for risk assessments to identify vulnerable road segments, enabling targeted retrofitting to improve infrastructure resilience. However, focusing solely on network performance without considering the diverse socioeconomic needs of commuters carries the risk of inequitable resource allocation. Incorporating equity metrics in capital improvement policies ensures that underprivileged neighborhoods, which have historically been underfunded, receive appropriate attention.

This section has three key parts. First, we present the overall framework for optimal road retrofitting. Second, we present the probabilistic risk assessment in hillside road networks involving multiple potential damage scenarios from earthquake events. Third, we integrate the concept of welfare loss into the optimization process, to guide equitable retrofitting decisions compared to traditional travel-delay-based policies[15]. To speed up the computational aspect of estimating optimal solutions, a Siamese Graph Convolution Network (GCN) is developed. The framework is applied to the Los Angeles Hillside Road Network to prioritize roads for retrofitting as a case study.

Proposed Framework for Pre-event Optimal Road Retrofitting

The problem can be framed as follows: Consider a network modeled as a graph with edges (road segments) and nodes (road junctions), denoted by $G = (V, E)$. This network can exist in either its original or retrofitted states, represented as $NETWORK_{(orig/retro)-(pre/post)}$, as shown in **Figure 12**. The subscripts indicate whether the network is in its original or retrofitted state and whether this is before or after an event.

In **Figure 12** (a), the original road network before any event is depicted as $NETWORK_{(orig-pre)}$. In a hypothetical event, three roads—e_1, e_2, and e_3—are damaged, rendering them unusable and causing congestion that degrades the network's performance. This impaired network is shown in **Figure 12** (b) and is labeled $NETWORK_{(orig-post)}$.

This project proposes an optimal pre-event retrofitting strategy, under a constrained budget, to minimize network performance degradation in potential disaster scenarios. In this example, roads e_1 and e_2 are retrofitted, as shown in **Figure 12** (c) and labeled as $NETWORK_{(retro-pre)}$. After the event, the retrofitted roads, e_1 and e_2, show a significantly reduced likelihood of damage, while road e_3, which was not retrofitted due to budget limitations, remains damaged. This is illustrated in **Figure 12** (d), labeled as $NETWORK_{(retro-post)}$.

The proposed framework helps determine which roads, from a set of vulnerable roads, should be retrofitted to minimize network performance loss in future events. The optimization problem thus involves selecting a subset of edges, $S \subseteq E$, for retrofitting under a given budget constraint, considering all potential earthquake scenarios.

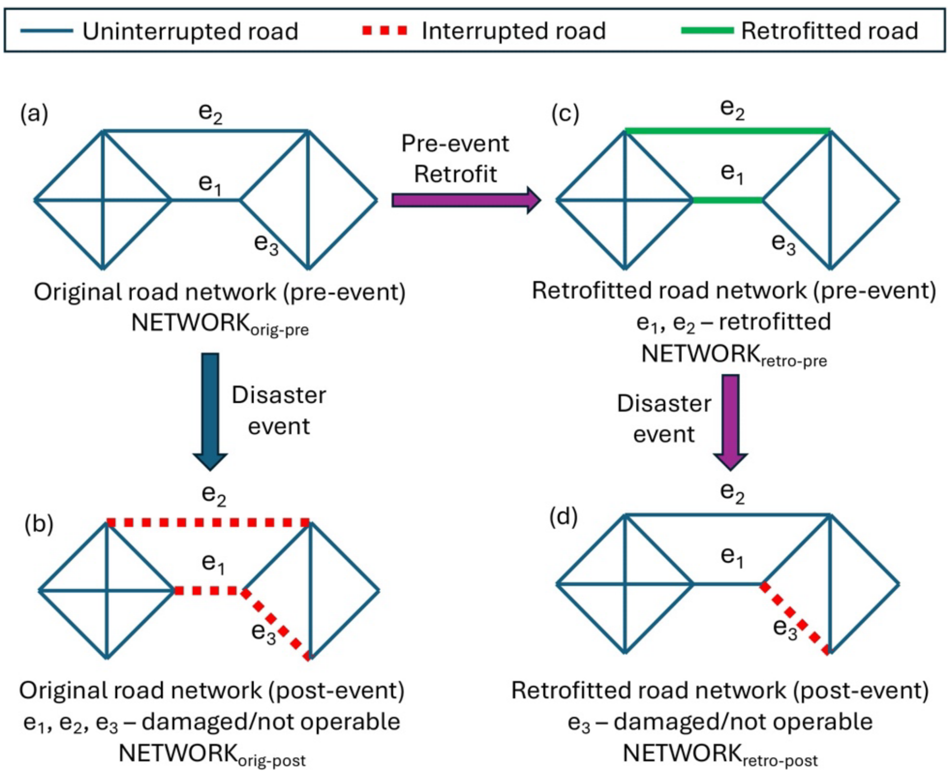

Figure 12. (a) Original Network Before Event, (b) Original Network After Event, (c) Retrofitted Network Before Event, (d) Retrofitted Network After Event

The problem is framed by conducting a probabilistic risk assessment of the current hillside road network to identify vulnerable road segments and assess the risk curve (**Figure 13**). The process starts by generating earthquake scenarios for the area of interest and deriving ground motion intensity maps for each scenario, accounting for uncertainties. The likelihood of road failure from earthquake-induced landslides is estimated using fragility parameters based on soil and slope properties, which help simulate damage maps. The impact on network performance, specifically Total System Travel Time (TSTT), is evaluated to create a delay-based risk curve. By incorporating demographic income data, welfare loss is assessed, forming the welfare loss-based risk curve. Both travel time and welfare loss serve as indicators of network performance loss. The goal is to develop an optimal road retrofitting strategy that minimizes these losses in future disaster events within a set budget.

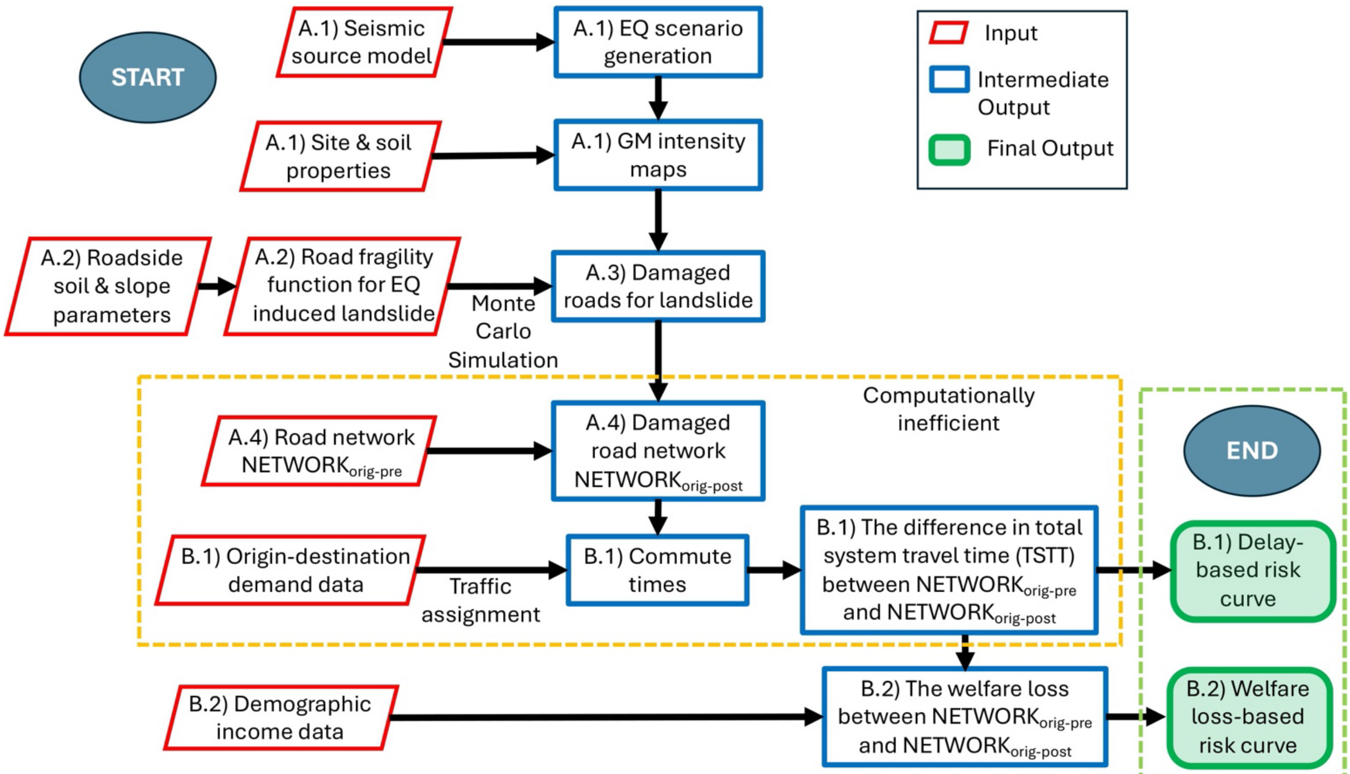

Figure 13. Probabilistic Risk Assessment for Earthquake-Induced Landslide Hazard, Which Considers Failure Scenarios of the Network for Potential Future Events and Generates Risk Curves

Developing an optimal road retrofit strategy requires large-scale optimization and functions for both delay-based and welfare loss-based retrofitting, involving tens of thousands of potential scenarios. A key challenge is the computational inefficiency of the "traffic assignment" step in the risk assessment process (**Figure 14**). To address this, we created a GCN (Graph Convolution Network)-based surrogate model to efficiently calculate changes in traffic performance (Figure 15).

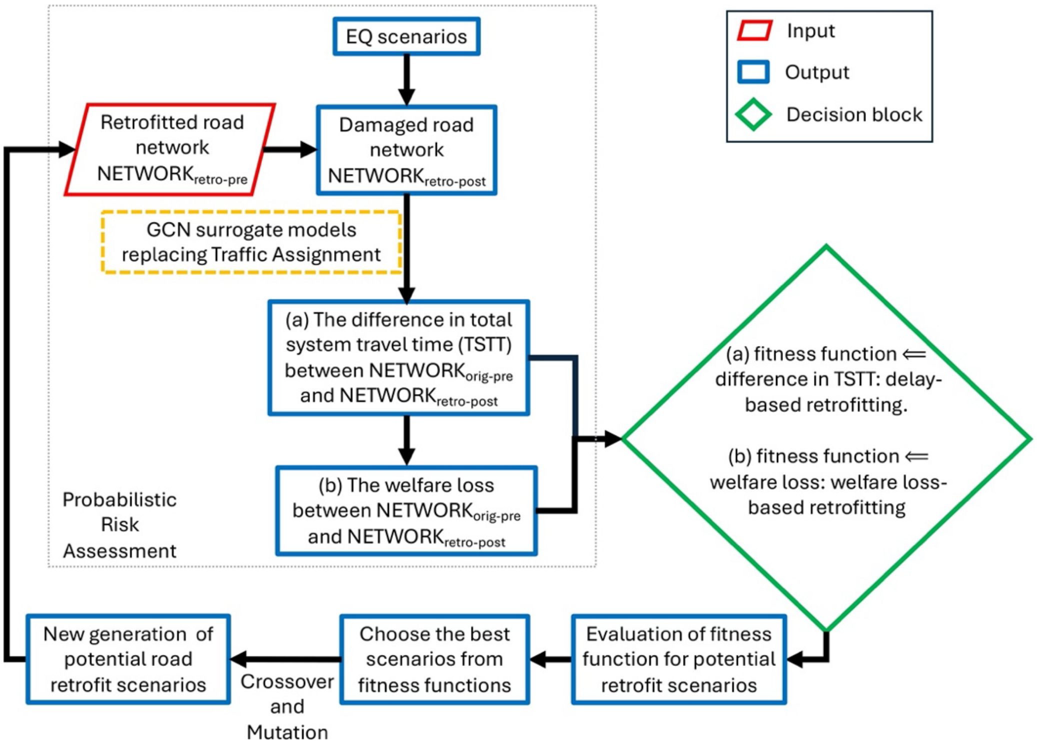

Figure 14. One Typical Cycle of the Optimization Framework

We performed a probabilistic risk assessment on the potential road retrofit scenarios. The best solutions progressed into the next generation. The cycle was continued until the results converged on the optimal solution.

Probabilistic Risk Assessment for Earthquake-Induced Landslide Hazards

Potential Future Earthquake Scenario Generation and Ground Motion Intensity Simulation

The first step was to explore potential earthquake scenarios in the region of interest and their impacts on the road network, integrated into a probabilistic risk assessment. A seismic source model, such as the region-specific Uniform California Earthquake Rupture Forecast (UCERF) [16] [17], is used to identify possible future earthquake events based on magnitude, location, and fault type. An earthquake catalog with Q scenarios is generated, followed by sampling b realizations of spatially correlated ground motion intensity residuals.

For each scenario, the ground motion intensity at each site is calculated using an empirical Ground Motion Prediction Equation (GMPE) [18]. The log ground motion intensity Y_{ij}, represented by Peak Ground Acceleration (PGA), is calculated as:

$$\ln Y_{ij} = \ln(\overline{Y}_{ij}) + \sigma_{ij}\epsilon_{ij} + \tau_j\eta_j \tag{4}$$

Here, $\overline{Y}_{ij}$ is the predicted median ground motion value, influenced by factors such as earthquake magnitude M_j, distance R_{ij}, and local site conditions (e.g., shear wave velocity $V_{s30,i}$). The terms $\sigma_{ij}\epsilon_{ij}$ and $\tau_j\eta_j$ account for intra-event and inter-event residuals, representing location-to-location and event-to-event variability, respectively.

Road Fragility Model for Earthquake induced Landslide Hazard

Evaluating road network risk involves estimating the physical damage caused by ground motion, typically represented by fragility functions. A fragility function expresses the probability of a road on a slope, indexed by i, reaching or exceeding a specific damage state ds_ζ due to ground motion intensity $PGA_{ij} = y$, where PGA_{ij} is the peak ground acceleration for the i-th road and j-th intensity map. The fragility function is given by:

$$\boldsymbol{P\left(DS_i \geq ds_\zeta \middle| PGA_{ij} = y\right) = \Phi\left(\frac{\ln(y/\mu_{\zeta,ij})}{\beta_{\zeta,ij}}\right)} \tag{5}$$

Where Φ is the standard normal cumulative distribution, $\mu_{\zeta,ij}$ is the median of PGA_{ij} causing damage state ds_ζ, and $\beta_{\zeta,ij}$ is the standard deviation.

To estimate road failure risk from earthquake-induced landslides, both ground motion intensity and a fragility model are needed [19]. The fragility model depends on soil properties like cohesion c, friction angle ϕ, and slope parameters such as angle and height, captured by the yield acceleration coefficient k_y, which is calculated as

$$\boldsymbol{k_y = h(\phi, c, \gamma, H, \beta)} \tag{6}$$

Where h is a nonlinear function of soil properties and slope geometry. The fragility curve for landslides can be derived as a function of k_y and PGA at the road location. Minor damage doubles travel time due to congestion, while moderate and extensive damage blocks the road completely, stopping all traffic flow.

Exhaustive Damage Maps Simulation and Representative Subset Selection

Damage maps are generated using κ Monte Carlo simulations based on fragility curves for each of the $Q \times b$ ground motion intensity maps. These maps show road damage levels—none, minor, moderate, or extensive—caused by landslides, reflecting road blockage. The total number of damage maps is $Q \times b \times \kappa$, and the annual probability of each damage map, w_k, is the annual probability of the corresponding ground motion intensity map, w_j, divided by the number of simulations: $w_k = \frac{w_j}{\kappa}$.

Since network performance calculations are computationally intensive, especially for large networks, importance sampling is used to prioritize significant events, such as larger earthquakes. To reduce computational complexity, a subset of damage maps is selected using a proxy performance metric—chosen as the ratio of damaged roads to the total number of roads—which correlates with total system travel time [20]. This approach, based on optimization techniques, allows for an accurate estimation of network performance while minimizing errors in the distribution of ground motion intensity exceedance.

Network Performance Loss and Risk Curve generation

Delay in Total System Travel Time as Network Performance Metric

After obtaining sampled damage maps showing the damage state of each road, the network's performance under damage is evaluated by solving the Traffic Assignment Problem [21]. This study uses a stochastic incremental traffic assignment model to assess how road damage affects trip disruption [22]. Traffic demand between origin-destination pairs is incrementally assigned by determining the shortest path and updating travel times as traffic is allocated. This process continues until all demand is assigned, resulting in final traffic flows and travel times for each road segment [23]:

$$\boldsymbol{t_a = t_f \left[1 + 0.15\left(\frac{q_a}{c_f}\right)^4\right]} \tag{7}$$

Where t_a is the travel time, t_f is free-flow travel time, q_a is current traffic flow, and c_f is the road capacity. The total system travel time (TSTT) is calculated as:

$$\text{TSTT} = \sum_{\boldsymbol{e \in E}} \boldsymbol{q_e t_e} \tag{8}$$

Where e represents each road in the network, q_e is its flow, and t_e is its travel time. In cases where damage isolates communities, a penalty for lost trips is added to the TSTT, resulting in an aggregated metric:

$$\text{AggTSTT}_{\boldsymbol{k}} = \text{TSTT}_{\boldsymbol{k}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}_{\text{lost},\boldsymbol{k}}} \boldsymbol{\gamma_{i,k}(t)} \cdot \boldsymbol{q}_{\text{lost}(\boldsymbol{i,k})} \tag{9}$$

Where AggTSTT_k includes a penalty $\gamma_{i,k}(t)$ for lost trips, assumed to be four hours. The change in TSTT for damage map k, ΔTSTT_k, is:

$$\boldsymbol{\Delta}\text{TSTT}_{\boldsymbol{k}} = \frac{\text{AggTSTT}_{\boldsymbol{k}} - \text{TSTT}_{\text{orig}}}{\text{TSTT}_{\text{orig}}} \tag{10}$$

The risk is assessed by combining changes in performance, ΔTSTT_k, with annual occurrence rates for each damage map, and determining the annual rate of exceedance (of the welfare loss threshold *x*):

$$\boldsymbol{\lambda_{X \geq x} = \sum_{k=1}^{K} w_k \cdot I(X_k \geq x)} \tag{11}$$

Where X_k is the performance change for map k, w_k is its occurrence rate, and I is 1 if $X_k \geq x$, 0 otherwise. The risk curve is generated by evaluating λ for various ΔTSTT thresholds.

Welfare Loss as a Network Performance Metric

The change in total system travel time ΔTSTT is a useful metric for assessing road network performance, but it doesn't consider how disruptions affect different user groups. To address this, we incorporate welfare loss to account for the impact on different populations.

Travel time delay assumes an equal value of time (VoT) for all travelers, but VoT varies based on factors like trip purpose, mode, and individual characteristics such as income. The welfare model calculates the change in welfare for income group i as [24]:

$$\boldsymbol{\Delta W_i} = \boldsymbol{\Omega_i} \cdot \boldsymbol{\lambda_{u,i}} \cdot \mathrm{SVTT}_{\boldsymbol{i}} \cdot \boldsymbol{\Delta}\mathrm{TSTT}_{\boldsymbol{i}} \tag{12}$$

Where Ω_i is the weight for group i, $\lambda_{u,i}$ is the marginal utility of income, $\mathrm{SVTT}_i = \frac{y}{2}$ is the subjective value of travel time based on income y, and $\Delta\mathrm{TSTT}_i$ is the change in travel time for group i. The marginal utility of income is given by:

$$\boldsymbol{\lambda_u} = \frac{\boldsymbol{1}}{\boldsymbol{y^{\rho}}} \tag{13}$$

Where $\rho = 1.26$ represents the elasticity. The simplified welfare loss formula becomes:

$$\boldsymbol{\Delta W_i} = \frac{\boldsymbol{1}}{\boldsymbol{2 \cdot y_i^{0.26}}} \cdot \boldsymbol{\Delta}\mathrm{TSTT}_{\boldsymbol{i}} \tag{14}$$

The mean annual rate of exceedance for welfare loss is:

$$\boldsymbol{\lambda_{\Delta W \geq x}} = \boldsymbol{\sum_{k=1}^{K} w_k \cdot I(\Delta W_k \geq x)} \tag{15}$$

Where K is the number of damage maps, w_k is the occurrence rate of damage map k, and $I(\Delta W_k \geq x)$ is 1 if true, 0 otherwise. The welfare loss-based risk curve is generated by assessing λ at different welfare loss thresholds. This equation calculates the annual rate of exceedance for welfare loss, which serves as a metric to evaluate risk. Simply put, it measures the likelihood that a community will experience a certain level of socio-economic hardship in any given year. Rather than just measuring raw travel time delays, welfare loss translates those delays into an economic impact metric that accounts for a commuter's income level, ensuring equity is captured in the assessment. The equation calculates this by establishing a specific threshold of welfare loss (*x*) and summing together the annual probabilities of *every* potential damage scenario that would cause damages exceeding that threshold. By comparing this exceedance rate for the network before and after proposed upgrades, decision-makers can precisely quantify how much a retrofitting strategy reduces the overall risk of severe disruptions for different income groups.

Developing an Optimal Road Retrofitting Policy

Earthquake-induced landslide retrofitting strategies focus on stabilizing slopes and infrastructure to reduce seismic risk. Techniques include retaining walls, soil nailing, rock bolts, geosynthetics, drainage systems, and vegetation planting to reinforce soil and control water infiltration. Regrading slopes can also help mitigate landslides. This report assumes retaining walls as the retrofit option, though the framework is flexible enough to include other strategies.

Two retrofitting policies are outlined: (a) delay-based, aimed at reducing travel time delays (ΔTSTT); and (b) welfare-loss based, which not only minimizes delays but also reduces the welfare loss for commuters, ensuring more equitable benefits for the community.

After evaluating damage scenarios and generating a risk curve, we compiled a list of candidate roads for retrofitting. The goal was to identify the optimal subset of roads for repair, minimizing performance losses across all return periods while adhering to budget constraints.

For large networks, finding the optimal retrofit set often requires heuristic optimization algorithms, which can be computationally intensive. To address this, we introduced a GCN-based surrogate model to accelerate computations without sacrificing accuracy.

Delay-Based Optimal Road Retrofitting Policy

To evaluate the impact of a retrofitting strategy, the expected annual change in total system travel time ($E[\Delta \text{TSTT}]$) is calculated by summing event-specific impacts, weighted by their annual occurrence rates:

$$\boldsymbol{E}[\boldsymbol{\Delta}\text{TSTT}] = \sum_{\boldsymbol{k}=\mathbf{1}}^{\boldsymbol{n}} \boldsymbol{w_k} \cdot \boldsymbol{\Delta}\text{TSTT}_{\boldsymbol{k}} \tag{16}$$

Where w_k is the annual occurrence rate of each damage scenario. The goal is to minimize $E[\Delta \text{TSTT}]$, constrained by a budget, resulting in an optimal retrofitting strategy. This strategy could involve techniques like retaining walls or slope adjustments. The optimization problem is posed as follows:

$$\min \boldsymbol{E}[\boldsymbol{\Delta}\text{TSTT}(\boldsymbol{R}_{\text{retrofitted}})] \quad \text{subject to } \sum_{\boldsymbol{i}} \boldsymbol{g_i}(\boldsymbol{R}_{\text{retrofitted},\boldsymbol{i}}) \leq \boldsymbol{B} \tag{17}$$

Where g_i is the retrofitting cost for road i, and B is the budget. Genetic algorithms (GA) [25] are used to solve the optimization problem.

The GA begins with a population of solutions representing road retrofitting options. Each solution is evaluated using a fitness function, $E[\Delta \text{TSTT}]$, and the best solutions are selected to create the next generation through crossover and mutation. This process repeats until an optimal solution is found.

The most computationally intensive part is estimating ΔTSTT for thousands of scenarios. To speed the process, we introduced a Siamese GCN-based surrogate model, shown in **Figure 15,** to predict changes in network performance, significantly reducing computational costs. This model leverages the effectiveness of graph neural networks (GNNs) [26] in transportation network problems.

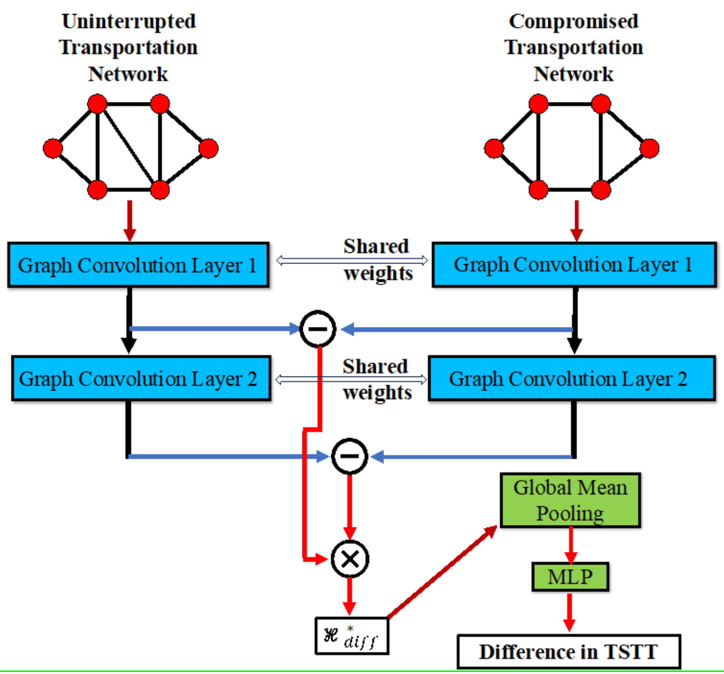

Figure 15. Architecture of the Proposed Siamese Graph Convolutional Network for Predicting ΔTSTT Welfare Loss-based Optimal Road Retrofitting Policy

The delay-based optimal road retrofitting policy focuses on minimizing total system travel time across hazard scenarios but may unintentionally increase the welfare loss gap between low and high-income commuters compared to the original network. To address this, the retrofitting strategy is adjusted to consider welfare loss, prioritizing low-income commuters to reduce the disparity between income groups.

Welfare-based Optimal Road Retrofitting Policy

Since welfare loss depends on total system travel time variation among demographic groups, separate Siamese-GCN models predict travel time changes for each income group. The genetic algorithm's fitness function, based on the welfare model of Mackie et al. [24], is modified as follows:

$$\boldsymbol{\mathcal{F}} = -\sum_i \sum_{k=1}^{n} \boldsymbol{w_k} \cdot \boldsymbol{\Omega_i} \cdot \boldsymbol{\lambda_{u,i}} \cdot \boldsymbol{SVTT_i} \cdot \boldsymbol{\Delta TSTT_{i,k}} \tag{18}$$

Where w_k is the damage map's occurrence rate, i represents the income group, Ω_i is the group's weight, $SVTT_i$ is their subjective travel time value, and $\lambda_{u,i}$ is the marginal utility of income for group i.

Application to the Los Angeles Hillside Road Network

This section applies the proposed framework to the Los Angeles hillsides road network, shown in **Figure 16**, covering 120 square miles with a population of about 306,000. The road data, sourced from OpenStreetMap, includes 16,517 road sections spanning 1,233 miles. The length of the network underscores the scale of infrastructure vulnerable to geological hazards in the region. Initially, the network was modeled as a directed graph with 8,698 nodes (road junctions) and 30,479 edges (roads).

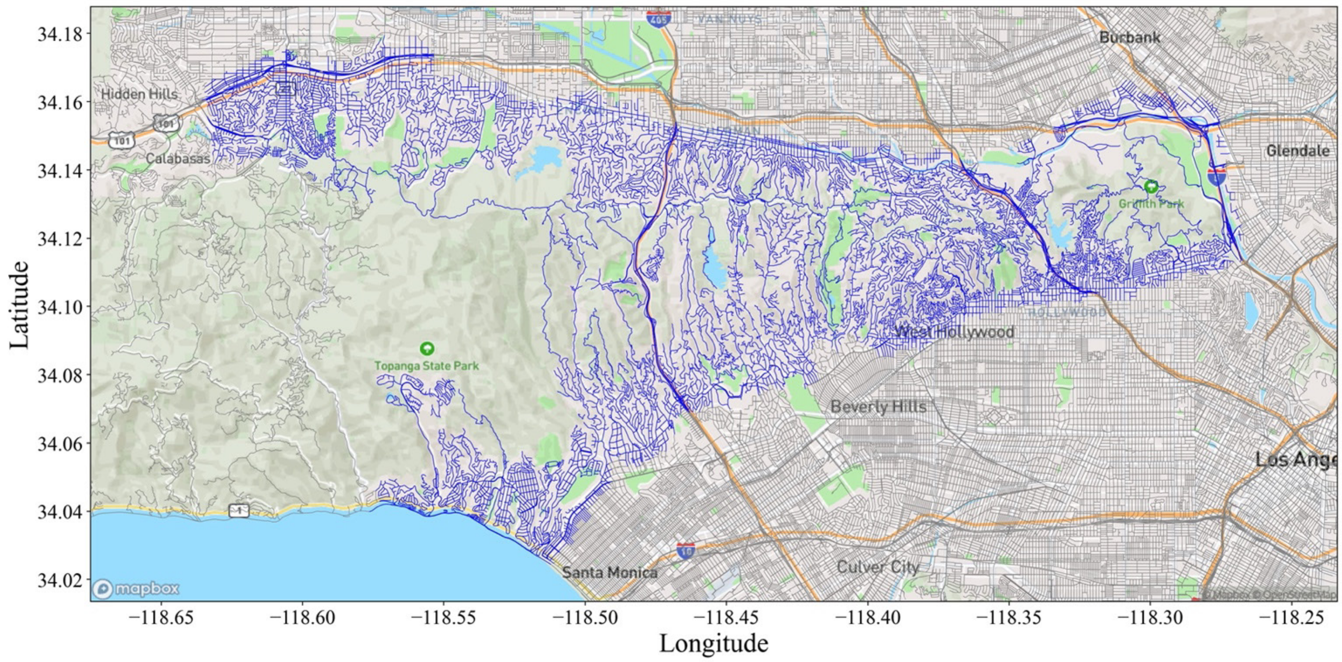

Figure 16. Map of Road Sections (in blue) within the Los Angeles Hillside Network

Earthquake-Induced Landslide Risk Curve Generation for the Hillside Road Network

Plausible Earthquake Scenarios from Seismic Source Model

The study area is located near several active earthquake faults, presented in **Figure 17**, including the Hollywood, Santa Monica, North Salt Lake, San Vicente, and Verdugo Faults. Nearby faults, like the Sierra Madre, Northridge Hills, San Gabriel, and San Andreas Faults, pose a high risk of generating earthquakes exceeding magnitude 8.

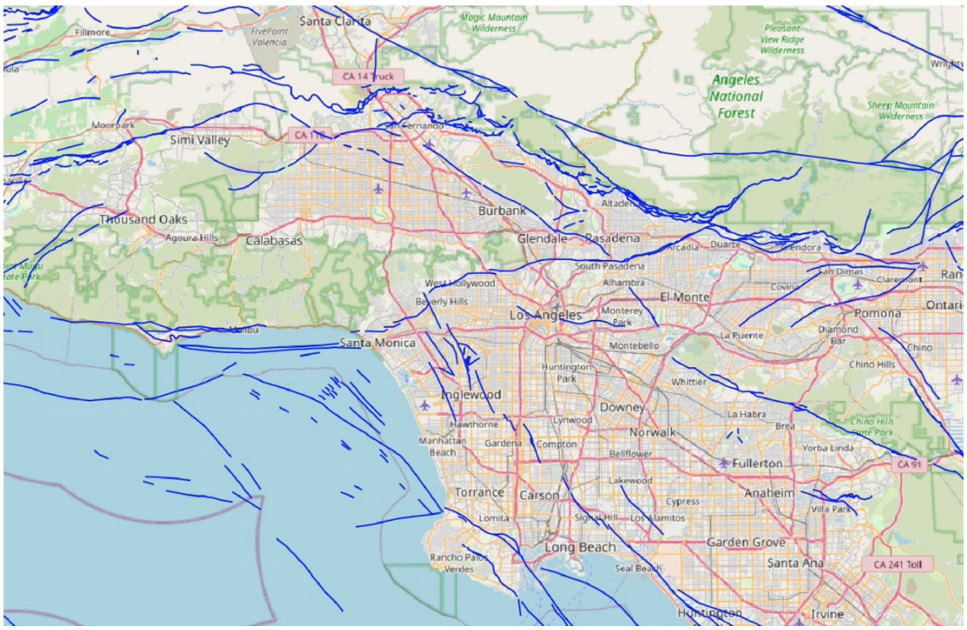

Figure 17. Comprehensive View of 941 Faults in the Greater Los Angeles Area, Showing Potential Seismic Sources That Could Affect the Los Angeles Hillsides

Obtaining Earthquake-Induced Landslide Fragility Model Parameters

To assess seismic risk, we used earthquake simulations to predict ground motion intensities, influenced by factors like earthquake magnitude, distance from the source, and local soil conditions (measured by V_{s30}). Peak Ground Acceleration (PGA) was selected as the intensity measure, serving as input for landslide fragility analysis. Ground motion maps were generated for potential earthquakes using the Campbell and Bozorgnia ground motion prediction equation [18].

Using the OpenSHA Event Set Calculator [27], we created a stochastic catalog of 35,280 ground motion intensity maps for 7,056 earthquake events, with magnitudes ranging from 5.95 to 8.45. Each event has five realizations to account for variability, producing both mean and standard deviation of PGA. **Figure 18** shows an example earthquake from the Hollywood Fault with a magnitude of 6.45, where some areas experience PGA over 1.2g, indicating significant risk to the road network.

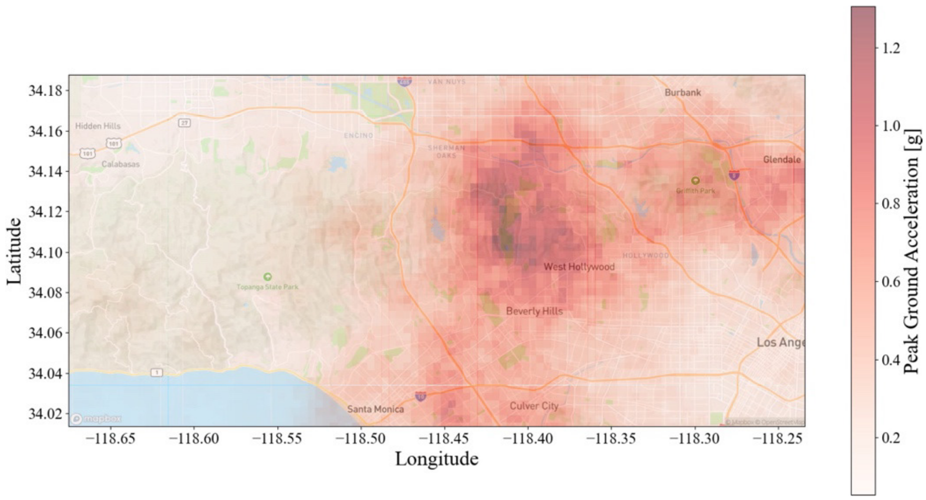

Figure 18. Spatial Distribution of Ground Motion Intensity (PGA) Realization for a Sample Earthquake Originating at the Hollywood Fault

Obtaining Earthquake-Induced Landslide Fragility Model Parameters

Soil properties for this analysis were sourced from geotechnical reports and manuals. Near-surface soil cohesion is set at 50 kPa, with a friction angle of 35° for the alluvium and soft rock typical of Southern California hillsides. The unit weight of the soil is 19.2 kN/m³. Elevation data along and around the roads were obtained using the Google Elevation API, and the maximum slope height and angle for each road section were calculated.

These soil and slope characteristics were used to determine the yield acceleration coefficient (k_y), which indicates landslide vulnerability. Lower k_y values reflect higher risk. The k_y values were then applied to derive fragility curves that estimate road failure probability under various damage states, extending the analysis for k_y values above 0.3. **Figure 19** displays the estimated k_y values for each road segment in the road network, with low values of k_y reflecting higher vulnerability.

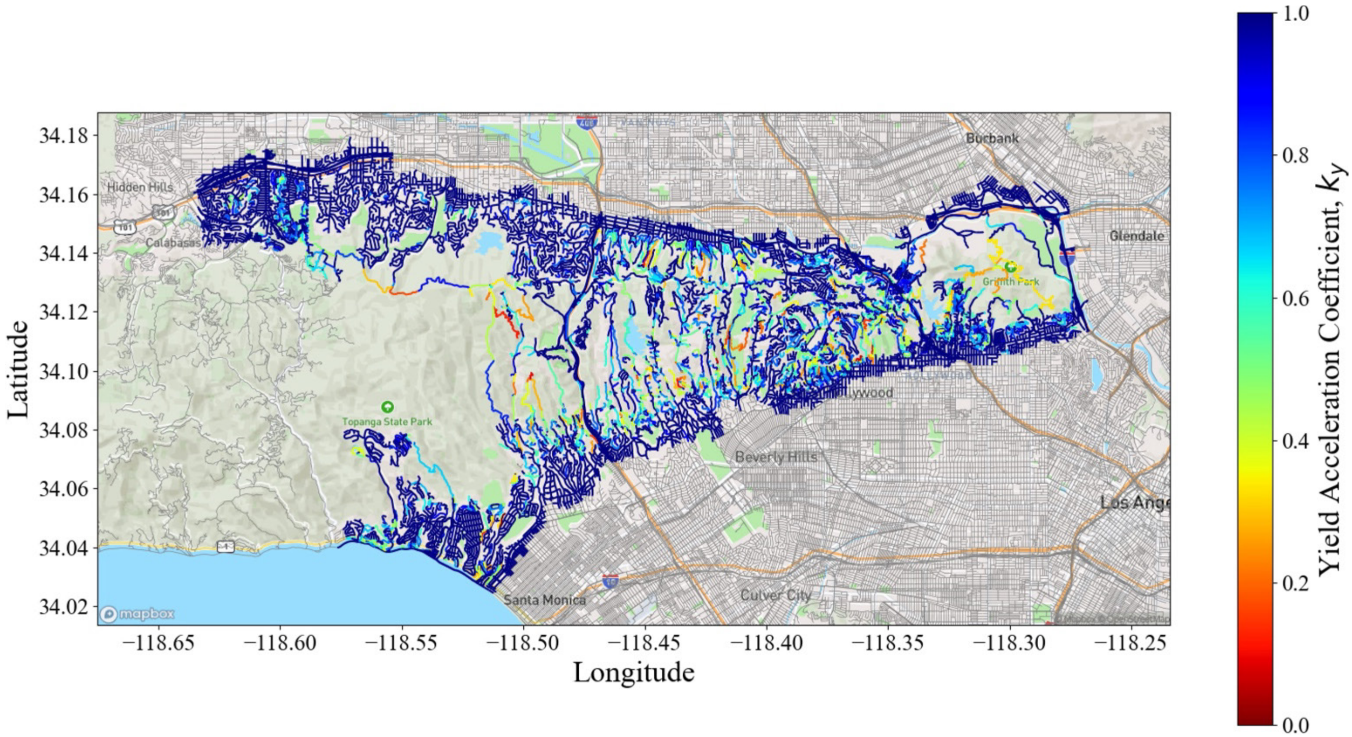

Figure 19. Map of the Los Angeles Hillside Road Network Indicating the Yield Acceleration Coefficient k_y for Each Roadway

Note: Lower k_y values suggest a higher susceptibility of roads to failure during seismic events.

Generating a Damage Map Catalog

After generating 35,280 ground motion intensity maps and fragility curves for various damage states, 100 Monte Carlo simulations were performed for each map, resulting in 3.528 million damage maps. Minor damage corresponds to reduced speed, while moderate and extensive damage lead to partial or full road closures. Roads with minor damage are assumed to double travel time, while fully damaged roads are impassable. A sample damage map is shown in **Figure 20**.

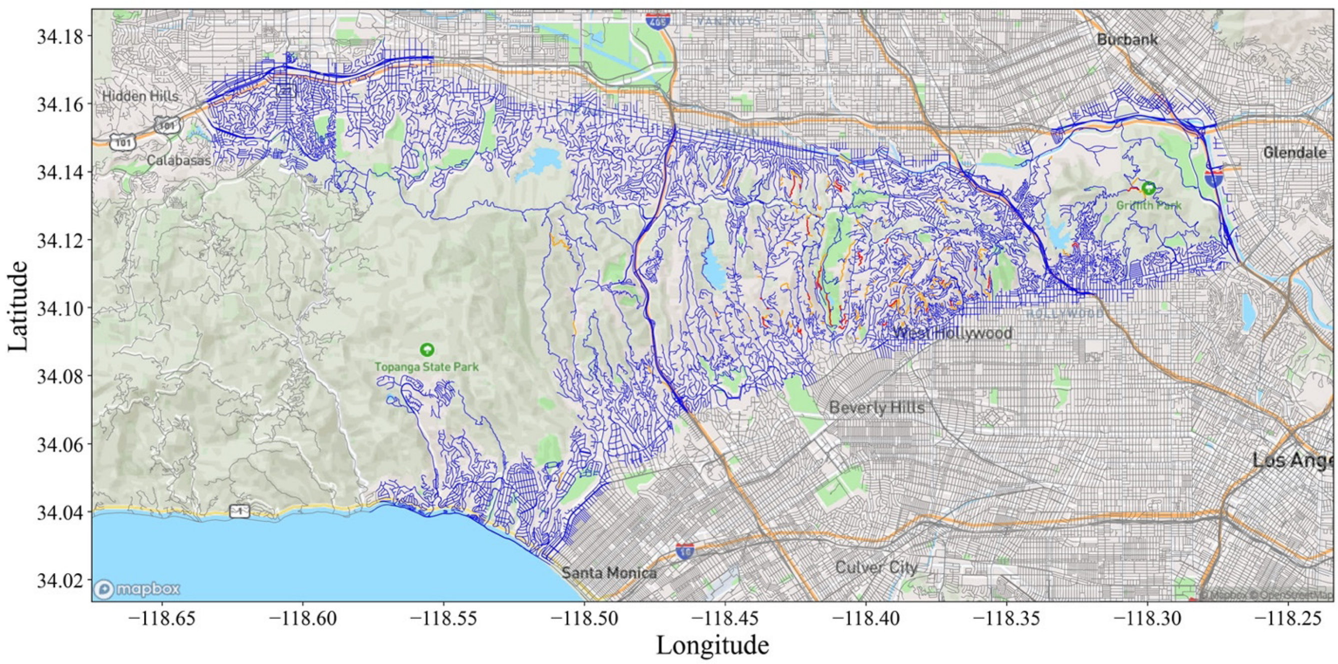

Figure 20. A Sample Road Damage/Blockage Map

Note: Roads in blue are the hillside roads, roads in orange are partially damaged due to landslide—hence roads are partially blocked. Roads in red are fully damaged due to landslide—hence roads are fully blocked.

To reduce the computational load of calculating total system travel time for all 3.528 million damage maps, an optimization process selected a subset of 89 representative maps, capturing the risk curve. This subset provides a close approximation to the full set of damage maps, covering an occurrence rate from 250 to 5,000 years. Among these, 6,494 roads experience damage, identifying potential candidates for retrofitting.

$\Delta TSTT$ Calculation and Risk Curve Generation

The risk curve is generated by calculating the increase in total system travel time for each damage map, using traffic demand data from the LODES 2020 dataset [10]. This data includes 338,750 daily trips in the Los Angeles area that either originate, end, or pass through the study area. Travel time is estimated by Incremental Traffic Assignment (ITA) [22], which divides the total travel demand into five increments.

The increase in travel time (ΔTSTT) is the difference between the damaged and undamaged network travel times. Lost trips due to network disconnection are penalized by adding four hours per trip. The risk curve, shown in **Figure 21**, was computed based on the annual occurrence rate of each damage map. It shows that small disruptions are frequent, while large increases in travel time are rare but have significant impacts, emphasizing the need for targeted risk management strategies to address both frequent minor and rare major events.

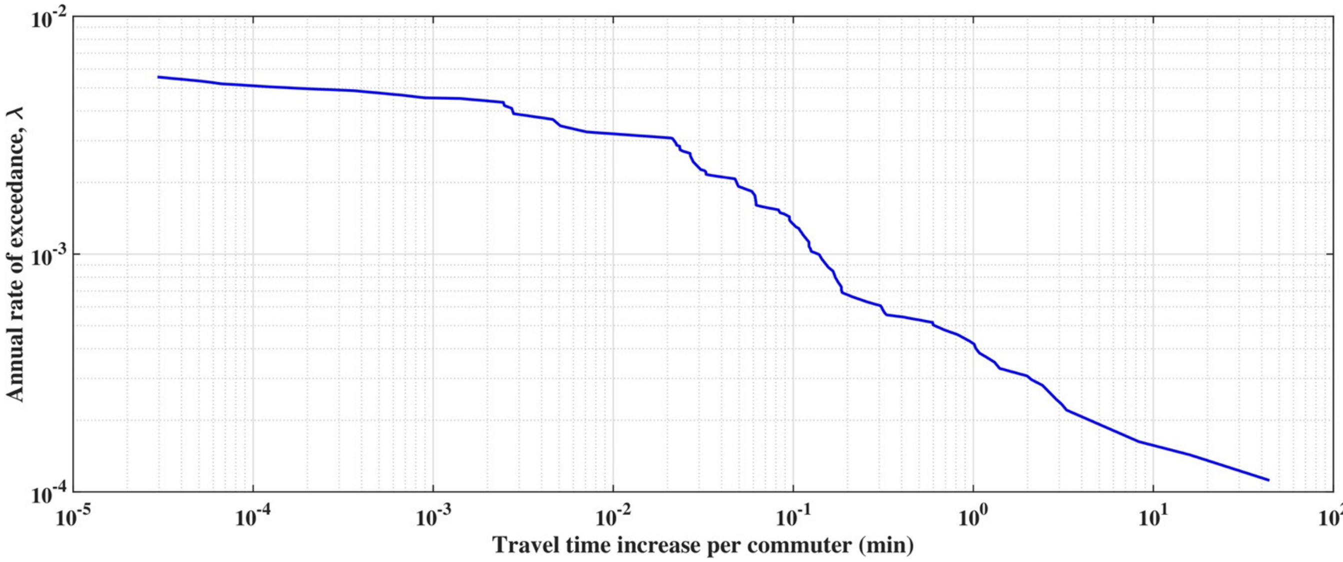

Figure 21. Annual Exceedance Curve for Travel Time Increase Per Commuter Due to Earthquake-Induced Landslide for the Los Angeles Hillside Road Network

Results from Implementing the Retrofitting Policy

The retrofitting policy aims to reduce traffic disruptions caused by landslides by shifting the risk curve downward compared to the original risk curve, such as shown in **Figure 22**. Given the area's complex terrain and high-density housing, gravity retaining walls are chosen as a practical retrofit, with costs estimated at $138 per foot for a 6-foot wall. The genetic algorithm explores retrofit options using a fitness function based on total system travel time, which is calculated using a Siamese GCN model for various damage scenarios. Detailed results of the GCN model are discussed below.

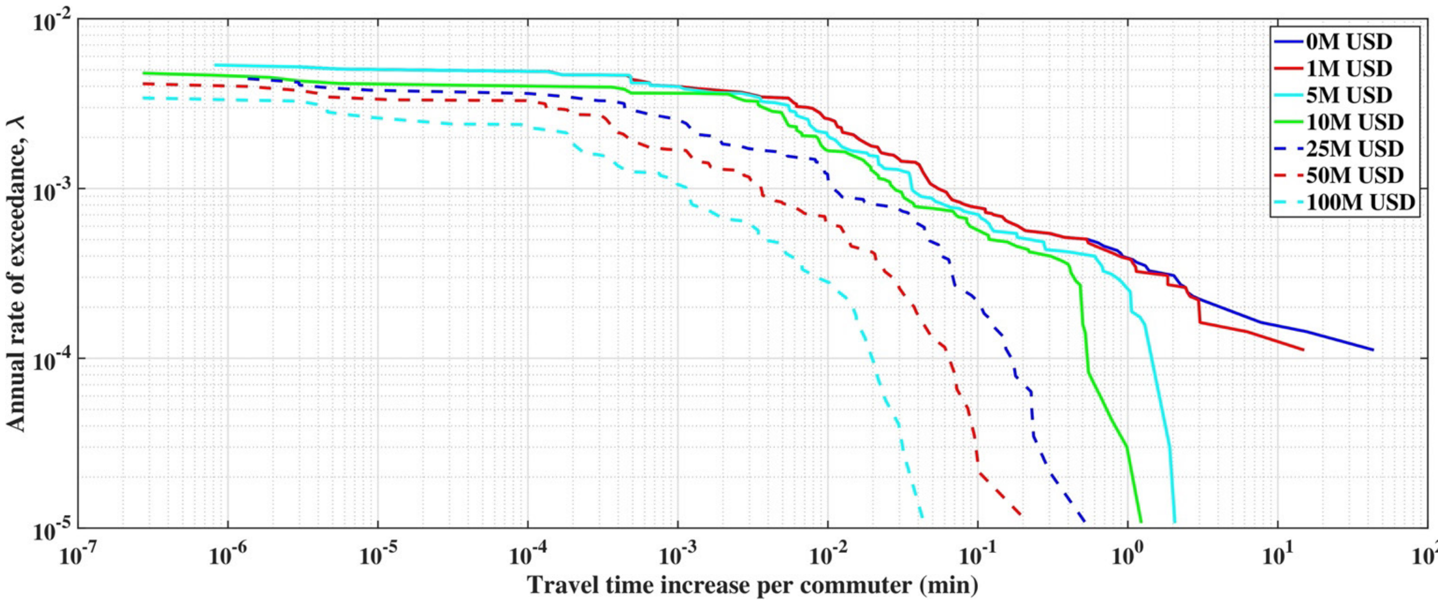

Figure 22. Annual Exceedance Curve for Travel Time Increase Per Commuter After Optimal Retrofitting of the Los Angeles Hillside Road Network for Various Budgets

Note: During extremely rare, worst-case hazard scenarios, higher retrofitting budgets result in travel time delays similar to those seen with lower budgets.

Performance of the Siamese GCN

The GCN model was trained to estimate changes in total system travel time (ΔTSTT) for retrofitted road networks affected by landslides. A dataset of 5,000 modified damage maps, simulating various retrofits, was used. The model was trained, validated, and tested on 80, 10, and 10 percent of the data, respectively.

The GCN input consisted of the original and damaged network structures, with the goal of minimizing mean squared error (MSE) during training. It used a LeakyReLU activation function, Adam optimizer, and dropout to prevent overfitting. Node embeddings were generated using PecanPy [28], and the model was trained for 1,000 epochs, with the best performance achieved at epoch 502 (R^2 values: 0.9971 for training, 0.9938 for validation, and 0.9676 for testing).

A comparison between the proposed GCN and an Artificial Neural Network (ANN) model used in a previous retrofitting study [29] reveals that the GCN significantly outperformed the ANN. The GCN achieved a testing R^2 of 0.9676, compared to the ANN's 0.9287, with 92 percent fewer trainable parameters. This made the GCN faster and simpler to train while maintaining high accuracy in estimating traffic flow disruptions. The results of this comparison are shown in **Table 3**.

Table 3. Performance Comparison Between the Proposed Siamese GCN and ANN, showing the Siamese GCN Improves Accuracy (higher R^2) and Computational Efficiency

Method	Trainable Parameters	Training R^2	Validation R^2	Testing R^2
ANN	3291751	0.9524	0.9626	0.9287
Proposed GCN	238593	0.9923	0.9874	0.9643

Optimally Retrofitted Roads Using Delay-based Retrofitting Policy

To develop retrofitting policies under various budgets, a binary genetic algorithm (GA) was used with the Siamese GCN-based ΔTSTT estimator. Each solution is a binary vector of 6,494 roads, where 1 represents a retrofitted road and 0 a non-retrofitted road. The GA evaluates solutions, selecting and mutating them until the budget is exhausted, with fitness determined by minimizing increases in total system travel time caused by the damage.

Over 2,000 generations, the GA optimizes retrofits for budgets ranging from $1 million to $100 million (USD), progressively shifting the risk curve to the lower left, indicating reduced disruption. The results are presented in **Table 4**. For example, a $1 million (USD) budget reduces expected delays $E[\Delta\mathrm{TSTT}]$, to 41.27 percent of the original expected delay, while a $25 million (USD) budget further reduces delay down to 1.25 percent. Beyond $25 million (USD), further improvements diminish, suggesting this is the optimal budget. **Figure 23** represents the optimized set of retrofitted roads for a budget of $25 million (USD).

The analysis reveals that roads near the Santa Monica and Hollywood faults are most critical for retrofitting, given their higher earthquake occurrence rates.

Table 4. Relative Expected Delays $E[\Delta TSTT]$ for Varying Retrofitting Budgets Ranging from $1 Million to $100 Million

Budget	0	1	5	10	25	50	100
Relative expected annual traffic performance metric (in %)	100	41.27	8.76	4.52	1.25	0.42	0.13

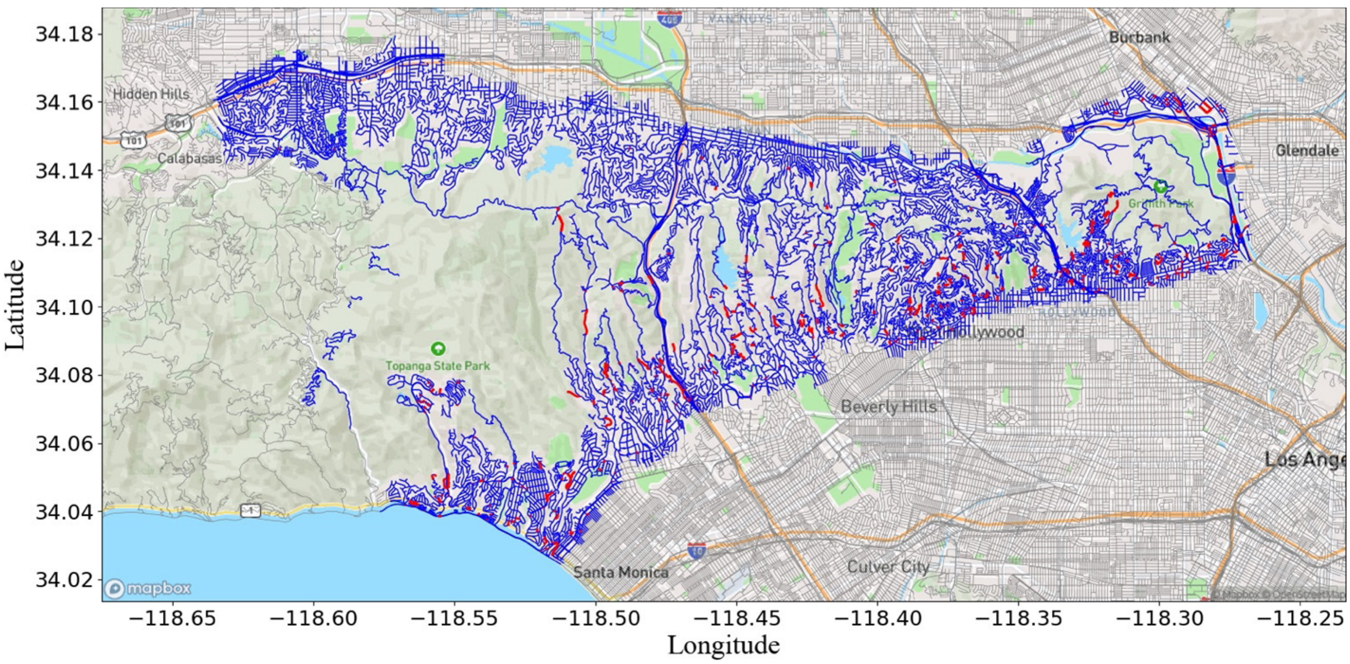

Figure 23. Optimal Set of Roads (in red) for Retrofitting with a Budget of $25 Million
Note: The roads in blue denote LA hillside roads. All these roads are located in proximity to both the Hollywood and the Santa Monica faults.

Results from the Welfare Loss-based Retrofitting Policy

This section presents the results from the welfare loss-based retrofitting policy. **Figure 24** illustrates the annual expected increase in travel time per commuter for all three income groups: under $1,250/month (SE01), $1,251-$3,333/month (SE02), and SE03 (above $3,333/month (SE03). The equity analysis in this study focuses primarily on income groups. Although the LEHD Origin-Destination Employment Statistics (LODES) dataset contains information on multiple worker characteristics—including income, age, and employment categories—we selected income as the primary demographic attribute for equity analysis because it directly reflects socioeconomic vulnerability and disparities in travel-time burdens. Extending the framework to incorporate additional demographic dimensions such as age and employment characteristics represents an important direction for future research. Additionally, **Figure 25** shows the welfare loss-based risk curve for all income groups, as per Equation 15. The welfare loss-based risk reveals that lower-income groups (SE01 and SE02) face greater welfare losses compared to the highest income groups (SE03), highlighting the need to integrate equity considerations into retrofit policies, as lower-income individuals are disproportionately impacted by travel time increases.

The GA optimizes welfare-based retrofitting for budgets from $1 million to $100 million. The retrofitted risk curves for each income group and each budget under the new strategy are depicted in **Figure 26**. The results show that as budgets increase, welfare losses decrease across all income groups. Additionally, the welfare gap (WLG) calculated as the difference between the welfare loss for low income (SE01) and high income (SE03) groups, and presented in **Figure 27** is significantly reduced under the welfare loss-based retrofitting strategy, especially for budgets up to $10 million. For higher budgets, the gap becomes negligible. Thus, the welfare loss-based approach proves more effective at reducing inequality compared to a delay-based strategy, as depicted in panels (a) and (b) in Figure 27. From a risk analysis perspective, the improvement achieved by the welfare-based retrofitting policy is reflected by a systematic shift of the welfare loss risk curves toward the bottom-left, indicating reductions in both the probability and magnitude of welfare loss. In practical terms, this implies that retrofit investments prioritized under the proposed framework more effectively reduce travel-time burdens for commuters from lower-income communities, thereby reducing the welfare loss gap between low- and high-income groups, particularly under limited retrofit budgets.

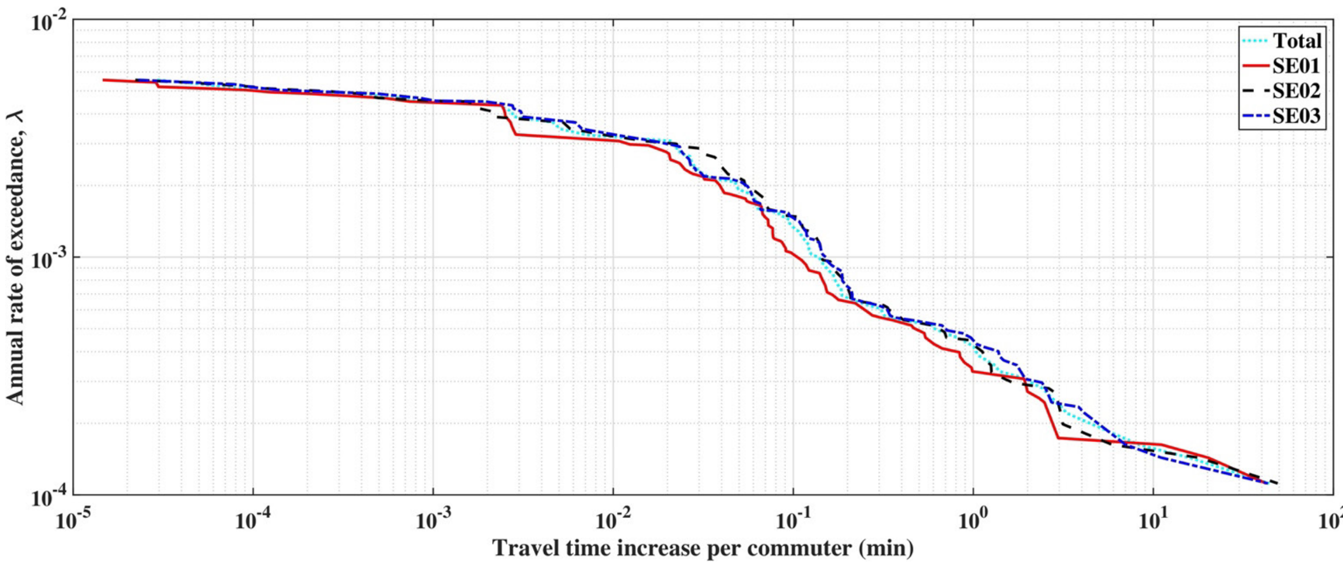

Figure 24. Annual Exceedance Curve for Travel Time Increase Per Commuter for Different Income Groups (SE01, SE02, SE03) Due to Earthquake-Induced Landslide for the Los Angeles Hillside Road Network

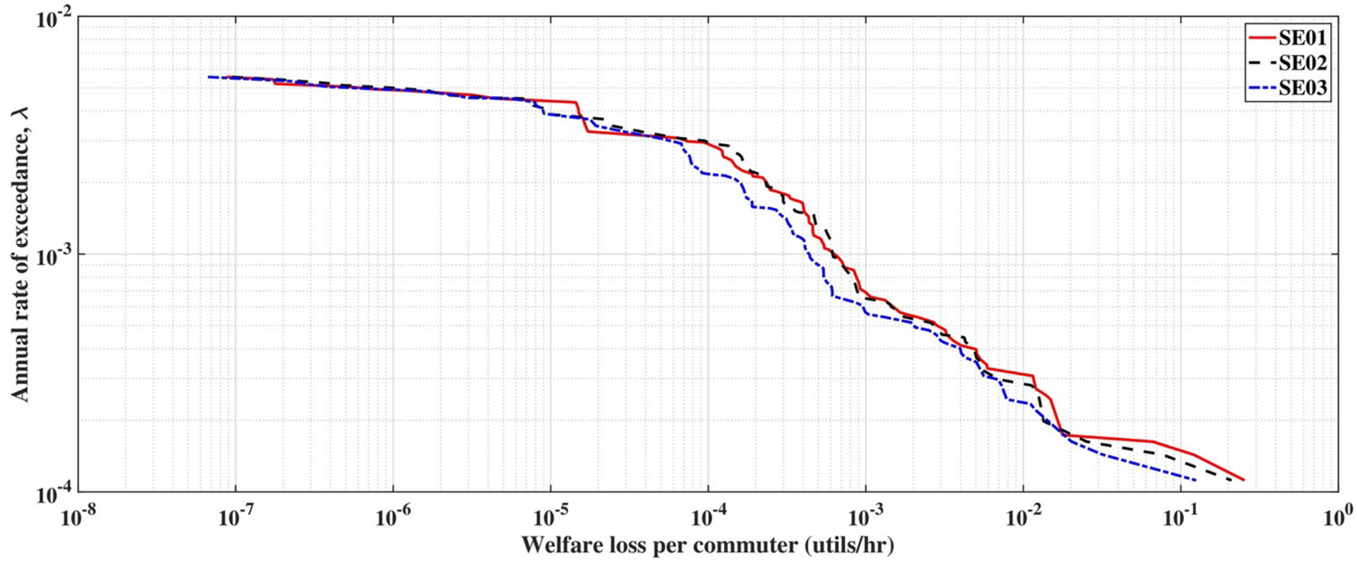

Figure 25. Annual Exceedance Curve for Welfare Loss Per Commuter After Welfare Loss-Based Optimal Retrofitting of the Los Angeles Hillside Road Network for Various Retrofit Budgets by Income Groups: (a) SE01, (b) SE02, (c) SE03

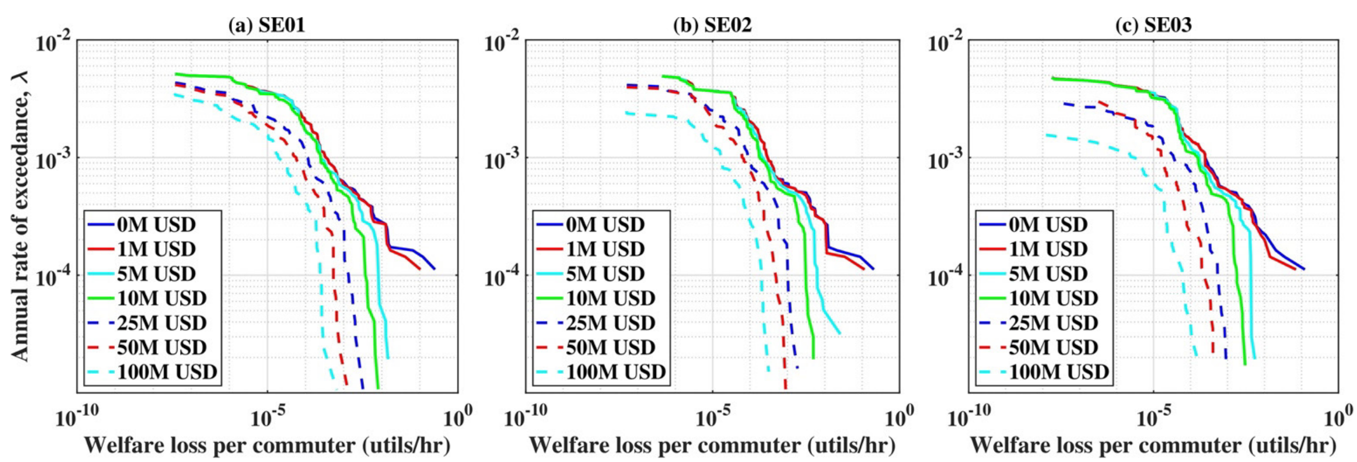

Figure 26. Annual Exceedance Curve for Welfare Loss Per Commuter After Welfare Loss-Based Optimal Retrofitting of the Los Angeles Hillside Road Network for Various Budgets by Income Groups: (a) SE01, (b) SE02, (c) SE03

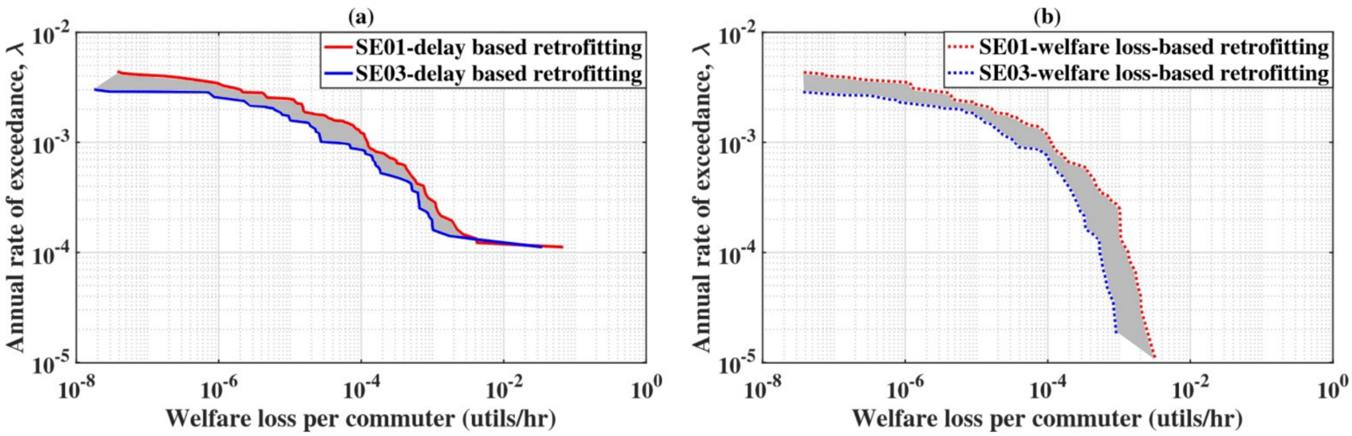

Figure 27. Disparity in Welfare Benefits (highlighted in gray) distributed among high- and low-income commuters after a 25 million USD investment, comparing the equity of benefits using (a) a delay-based retrofitting approach versus (b) a welfare loss-based retrofitting approach.

Summary and Conclusions

This report presents a comprehensive and data-driven approach for prioritizing capital investments in road networks, with a focus on enhancing resilience, safety, and equity in hazard-prone regions. By employing a multi-dimensional framework that integrates road condition, importance, hazard exposure, and an equity perspective, this methodology offers a robust solution for identifying critical road segments that require targeted investments. The holistic approach ensures that resource allocation not only addresses pressing infrastructure vulnerabilities but also equitably benefits underserved communities, promoting a more inclusive and fair transportation system.

Multidimensional Prioritization Tool

A key element of the framework is a multi-dimensional tool for evaluating road importance. This tool combines an evaluation of streets based on how they connect key destinations within the regional transportation network with analyses of demographic travel pattern to generate road “importance” scores that reflect both network-critical roles and social equity considerations. By leveraging data from the Longitudinal Employer-Household Dynamics (LODES) dataset, this approach provides a nuanced view of road usage across different population segments, ensuring that infrastructure improvements are equitably distributed to maximize social benefits and network efficiency.

The cornerstone of this approach lies in its use of advanced data collection and analytical techniques. Through the deployment of mobile mapping technologies, including LiDAR and panoramic imaging systems, hyperlocal data on road conditions and hazards was collected and integrated into decision-making processes. This data collection strategy allows for unprecedented precision in capturing road network characteristics, revealing hidden vulnerabilities and enabling a detailed understanding of road performance, structural integrity, and associated risks. Such high-resolution data supports informed decision-making and enhances the reliability of infrastructure assessments.

The proposed framework further incorporates hazard rating techniques, focusing on the risk posed by landslides and other geological hazards, particularly in Los Angeles' complex hillside regions. Slope data and terrain analysis were utilized to identify high-risk areas, informing hazard mitigation strategies and retrofitting plans that enhance resilience to natural disasters. Integrating hazard ratings with road condition and importance metrics allows city planners to prioritize roads that are both essential to the network and most vulnerable to external threats.

This project demonstrates the value of combining traditional engineering metrics with cutting-edge data science and machine learning techniques. The use of Graph Convolutional Networks (GCNs) and other advanced models exemplifies how computational efficiency can be significantly improved in large-scale infrastructure projects. These models enable efficient assessment and optimization of retrofitting strategies, ultimately leading to more effective and equitable infrastructure enhancements.

The application of this framework to the Los Angeles Hillside region illustrates its practical potential and scalability for broader urban areas. By integrating diverse data sources, employing sophisticated analytical methods, and prioritizing equity, this approach represents a step forward in capital investment decision-making for resilient urban infrastructure.

Recommendations

Prioritize Strategic Capital Investment. Policymakers should adopt this data-driven framework to prioritize critical road segments for infrastructure investment. This ensures that limited funds are used effectively to improve road resilience where they are most needed.

Center Equity in Infrastructure Decisions. Ensuring that vulnerable communities receive critical infrastructure improvements will promote transportation equity, fairness in transportation decision-making and transportation outcomes. Ignoring equity-focused considerations will lead to investment decisions that may not support the needs of vulnerable communities

Adopt Advanced Data Collection Technologies. Local governments should invest in advanced mapping and data collection technologies to gain accurate insights into road conditions and hazards. This will enable more informed decisions for future infrastructure projects.

Future Research

Future research can further refine this methodology by incorporating additional hazard types, such as wildfires and floods, and expanding the scope to include multimodal transportation systems. Enhancing predictive capabilities through machine learning and AI-driven models will continue to improve the accuracy and adaptability of infrastructure resilience strategies. Moreover, integrating welfare-based metrics into decision-making processes ensures that investments not only enhance technical resilience but also deliver equitable benefits across all population segments.

Conclusion

In conclusion, this project offers a transformative approach to urban infrastructure planning, setting the stage for resilient, safe, and equitable road networks capable of withstanding future challenges. By prioritizing data-driven methodologies, equitable resource distribution, and advanced technological integration, it provides a robust foundation for informed decision-making in urban infrastructure resilience and capital investment planning.

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Appendix: Integration of Equity into the Hillside Street Prioritization Application (HSPA)

The Hillside Street Prioritization Application (HSPA), introduced in Section 1, is a web-based tool designed to assist in infrastructure planning for the Los Angeles hillside regions. It integrates multidimensional metrics—such as road condition, importance, and hazard risk—into an interactive platform that facilitates data-driven decision-making. Key features of the application include customizable dashboards, data export capabilities, and the ability to adjust weighting factors to prioritize specific needs. These functionalities provide planners with a streamlined method to target critical infrastructure upgrades efficiently.

This appendix focuses specifically on the equity-related aspects of HSPA, highlighting how the tool ensures fair and inclusive resource allocation.

1. **Demographic integration and customizable weighting**: As described in Section 2, HSPA incorporates demographic data from the Longitudinal Employer-Household Dynamics (LODES) dataset to address equity in infrastructure prioritization. This dataset captures road usage patterns segmented by age, income, and employment sectors, allowing the tool to assess the importance of roads for different demographic groups, focusing on age, income, and industry sector. HSPA enables users to customize weighting factors for prioritization metrics. By adjusting these weights, planners can emphasize equity-focused parameters, such as road usage by low-income groups or specific workforce segments, ensuring that road improvements align with broader social equity goals. **Figure A-1** illustrates the HSPA dashboard. The red box on the left displays options for users to adjust sliders and emphasize different demographic groups in the overall importance metric, described in Section 1. In the example shown in the figure the user places full emphasis on low-income travelers and selects the top 100 most important road sections for this demographic group. The map on the right highlights these sections, primarily identifying Cahuenga Blvd East and Beverly Glen Boulevard.

2. **Filtering for disadvantaged- and low-income communities:** The application enables users to filter and analyze data for specific equity-focused regions, including low-income and disadvantaged communities identified under California's Assembly Bill (AB) 1550 and Senate Bill (SB) 235. This feature allows planners to prioritize infrastructure investments that directly benefit these communities, addressing historical underinvestment and promoting equitable development. In **Figure A-2** the red box on the left shows options for filtering roads based on their intersections with disadvantaged community areas defined by SB235 or low-income areas defined by AB1550. In the example, the user applies the low-income filter, displaying only roads intersecting with low-income areas. After selecting all points in the scatter plot, the map highlights the corresponding road sections, which are primarily clustered in City Council Districts 1, 7, 13, 14, and 15.

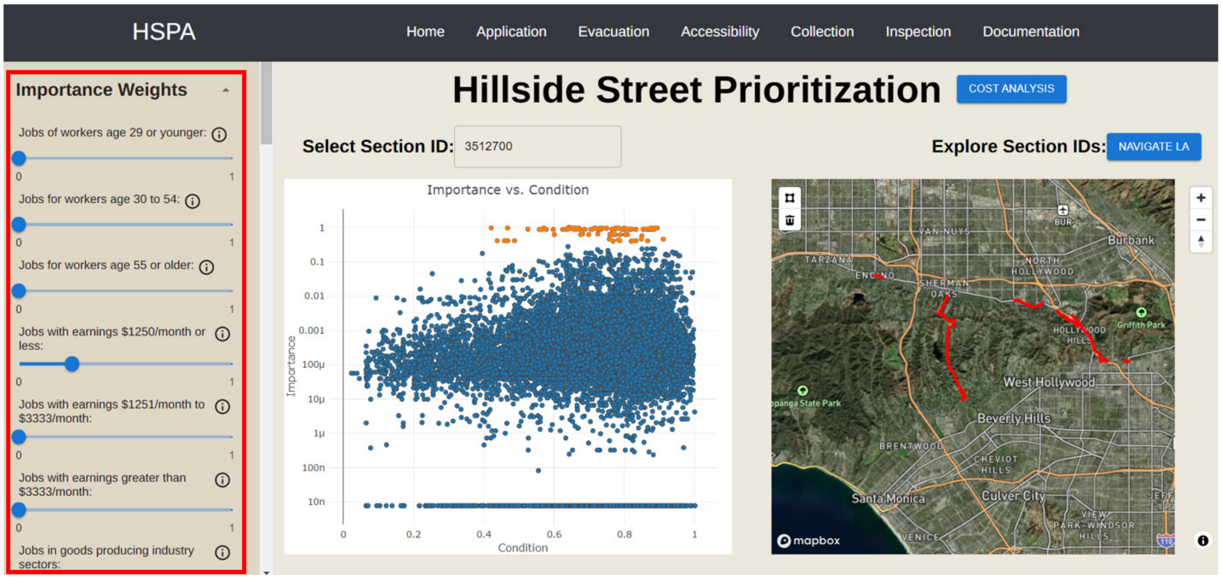

Figure A-1. HSPA Dashboard with Importance Sliders Based on the Analysis in Section 2

Note: Users can select which demographic group to emphasize in the overall importance metric.

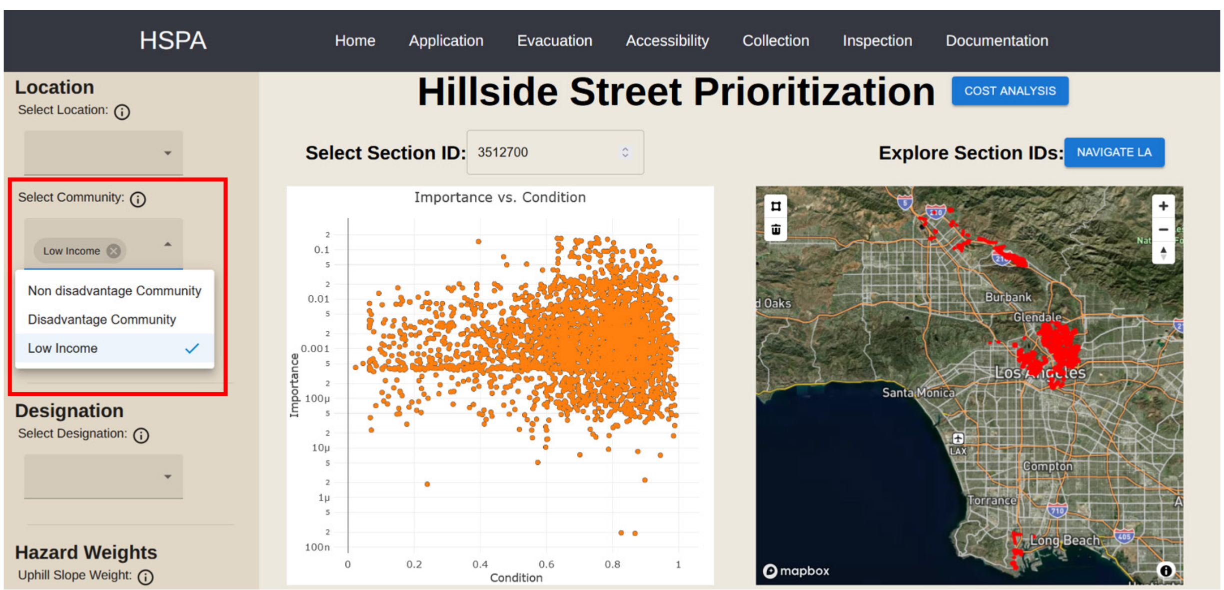

Figure A-2. HSPA Dashboard with Low-income and Disadvantaged Community Filters

Note: Users can choose to focus on roads intersecting with disadvantaged communities (SB235) or low-income communities (AB1550).