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Coupling mode-destination accessibility with a quantitative seismic-risk assessment to identify at-risk communities

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Abstract

In this paper, we develop a framework for coupling mode-destination accessibility with a quantitative seismic-risk assessment to identify communities at a high risk for travel disruptions after an earthquake. For a case study of the San Francisco Bay Area, we find that accessibility varies more strongly from location to location than between income classes, and we identify particularly at-risk communities. We also observe that communities more conducive to local trips by foot or bike are predicted to be less impacted by losses in accessibility.

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1. Introduction

Seismic risk assessment in earthquake engineering tends to focus on buildings, bridges, and the performance of infrastructure systems. For example, for measuring the performance of transportation systems, researchers typically use engineering-based metrics such as the post-earthquake connectivity loss, which quantifies the decrease in the number of origins or generators connected to a destination node [e.g., 1, 2], or the post-earthquake travel distance between two locations of interest [e.g., 3], as described in Chapter ???. These frameworks have provided insight into seismic vulnerability and possible risk mitigation. However, the link to the human ramifications can be limited.

In the field of vulnerability sciences, researchers have long stressed the importance of the impact on human welfare from earthquakes. For example, Bolin and Stanford write that, “‘Natural’ disasters have more to do with the social, political, and economic aspects than they do with the environmental hazards that trigger them. Disasters occur at the interface of vulnerable people and hazardous environments” [4]. A recent World Bank and United Nations report echoed this idea that the effects on human welfare turn natural hazards into disasters [5]. Historical events emphasize the complex social effects of earthquakes. For example, on one hand the 1994 Northridge earthquake caused major damage to nine bridges, which, while significant, represented only 0.5% of the bridges estimated by Caltrans to have experienced significant shaking [6]. On the other hand, over half of businesses reported closing after the earthquake with 56% citing the “inability of employees to get to work” as a reason [7]. Furthermore, the total economic cost of transport-related interruptions (“commuting, inhibited customer access, and shipping and supply disruptions”) from this earthquake is estimated at 2.16 billion USD (2014) [8], using the consumer price index to account for inflation [9].

An emergent trend in earthquake engineering related to the social impacts is measuring the cumulative extra time needed for travel after an earthquake, sometimes called travel time delay [e.g., 10, 11]. This performance measure captures basic re-routing due to road closures and enables identifying roads more likely to be very congested. Travel time approximately measures one aspect of impact on people, but does not capture the fact that some destinations

and trips have higher value than others. Furthermore, this approach measures the impacts by focusing on aggregate regional effects rather than individual communities and demographic groups. Some recent work has looked at other metrics, such as the qualitative criteria-based metric “disruption index” [12]. However, this does not provide a quantitative link between the technical impact and the human ramifications. Other work has looked at resiliency, but defined it in pure engineering terms, such as percentage of a simplified road network that is functional [13]. Outside of transportation systems, some researchers have investigated the interplay between earthquake damage, such as damage to water networks, and the usability of houses and other buildings; this represents an important first step [14, 15, 16].

In contrast to the work on transportation-related seismic risk, urban planning has a long tradition of studying the impact on people of events and policy [17, 18]. Accessibility is one metric popular in urban planning to measure the impact of different transportation network scenarios, and it measures how easily people can get to desirable destinations [19]. This ability to travel easily is considered a measure of social impact [e.g., 20]. Furthermore, accessibility, by definition, quantifies one key aspect of human welfare [e.g., 19]. Within urban planning, accessibility has been measured in many ways, including individual accessibility, economic benefits of accessibility, and mode-destination accessibility [21]. The mode-destination accessibility is computed by taking the log value of the sum of a function of the utilities of each destination over all possible destinations and travel modes, where the utility decreases if getting to that destination is more costly or time-intensive (Equation ??) [22]. This choice of accessibility definition is particularly applicable to quantifying the impacts of catastrophes, such as earthquakes, because certain destinations might be more critical for people in certain locations or from different socio-economic groups (such as low income or high income).

While recent work has investigated the interdependencies between different infrastructure networks, such as electric power and water distribution [23, 24, 1], a less well-understood topic is the interdependencies within the transportation system itself. For example, the collapse of a highway bridge may close a transit line if the bridge crosses the transit line. Furthermore, the majority of work to date assumes that travel demand and mode choice will remain unchanged after a future earthquake, which historical data suggests is not the case [8]. A first step towards considering variable demand is work in the literature that varies demand by applying a constant multiplicative factor on all pre-earthquake travel demand [10]. Thus, the prior work suggests three areas of further investigation: 1) the risk of post-earthquake accessibility losses for different people and communities in a region, 2) the impact to the risk assessment results of modeling interdependent transit systems, and 3) the consequences of capturing varying travel demand and different travel modes in the analysis.

In this chapter, we develop a framework for coupling mode-destination accessibility with a quantitative seismic-risk assessment to identify at-risk populations and measure the accompanying impacts on human welfare. We illustrate our approach with a case study of the San Francisco Bay Area transportation network described in Chapter ???. We simulate earthquake scenarios, ground-motion intensity maps, and damage maps. We then compute basic network performance (travel time delay) with an efficient travel model, as described in Chapter ???. Using the optimization procedure of Chapter ???, we select a subset of these maps for modeling in a high-fidelity transportation model used by the local transportation authorities. Our high-fidelity model includes damage to bridges, roads, and transit lines, and varies demand using an agent-based model. While these more comprehensive models are already used in practice for general transportation planning, we extend the models to seismic risk assessment by creating an automated method for damaging and analyzing networks, in order to estimate risk in an event-based probabilistic risk framework. Finally, we analyze the predicted losses in accessibility according to 12 socio-economic groups used by local planners for the case study region, based on income class, and ratio of personal vehicles to workers in a household.

64 **2. Case study: San Francisco Bay Area**

65 We focus on the San Francisco Bay Area, a seismically-active region with a complex web of roads and transit
66 networks, to illustrate our approach (Figure 1). The area follows a polycentric metropolitan form, with San Francisco
67 as the primary center and other jobs concentrated in suburban centers, such as Silicon Valley [25]. The region has a
68 wide array of trip patterns for mandatory and non-mandatory trips. Furthermore, trip times and routes vary greatly
69 depending on travel preferences and workplace locations [25]. Thus, we might expect noticeable disparities between
70 households in the risk of travel time delays due to earthquakes.

71 As described in Section ??, we consider the road network and the relevant transit systems. We model damage
72 to bridges and other structures from a probabilistic set of earthquake events in order to predict the loss in mode-
73 destination accessibility (as introduced in Section ??). From a large set of ground-motion intensity maps and damage
74 maps, we choose a set of forty maps, using the optimization procedure presented in Chapter ??; we chose the fixed-
75 demand travel time delay as the proxy metric, because it is related to travel time delays expected in the high-fidelity
76 model. We then use the high-fidelity model to predict the transportation network impacts of the forty pairs of ground-
77 motion intensity and damage maps. Readers are referred to Appendix ?? for a step-by-step procedure for aggregating
78 the requisite data sources, modeling interdependencies, and adapting an activity-based transportation model for catas-
79 trophe risk assessment. The outcome is forty sets of results for the target performance metric, mode-destination
80 accessibility (Section ??). Each accessibility value has a corresponding annual rate of occurrence. In the follow-
81 ing sections, we first compare region-wide results, and then focus on particular characteristics of three communities
82 (Figure 1 shows the study area and three communities). Finally, we discuss generalizable trends.



Figure 1. Study area: San Francisco Bay Area, CA with specific travel analysis zones (TAZs) used in the case study marked in blue.

83 **3. Results and Discussion**

84 *3.1. Overview of results region-wide*

85 In this section, we analyze region-wide trends in accessibility losses for the case study area. As mentioned in
 86 Section 1, we first analyze each of the 12 socio-economic groups used in practice for the case study region [26], which
 87 are characterized based on households. The socio-economic groups correspond to all combinations of four different
 88 income classes (Table ??), and three different classes of automobile availability in the household (zero automobiles,
 89 fewer automobiles than household members that work, a greater or equal number of automobiles as compared to the
 90 number of household members that work).

91 We first assess the data availability for each of the segments. Each data point represents a trip by a person of a
 92 household, who is modeled as an agent in the high-fidelity transportation model. The results suggest comparing house-
 93 holds with at least one car, because for households without cars (no cars), only the low income class has reasonably
 94 many trips (Figure 2).

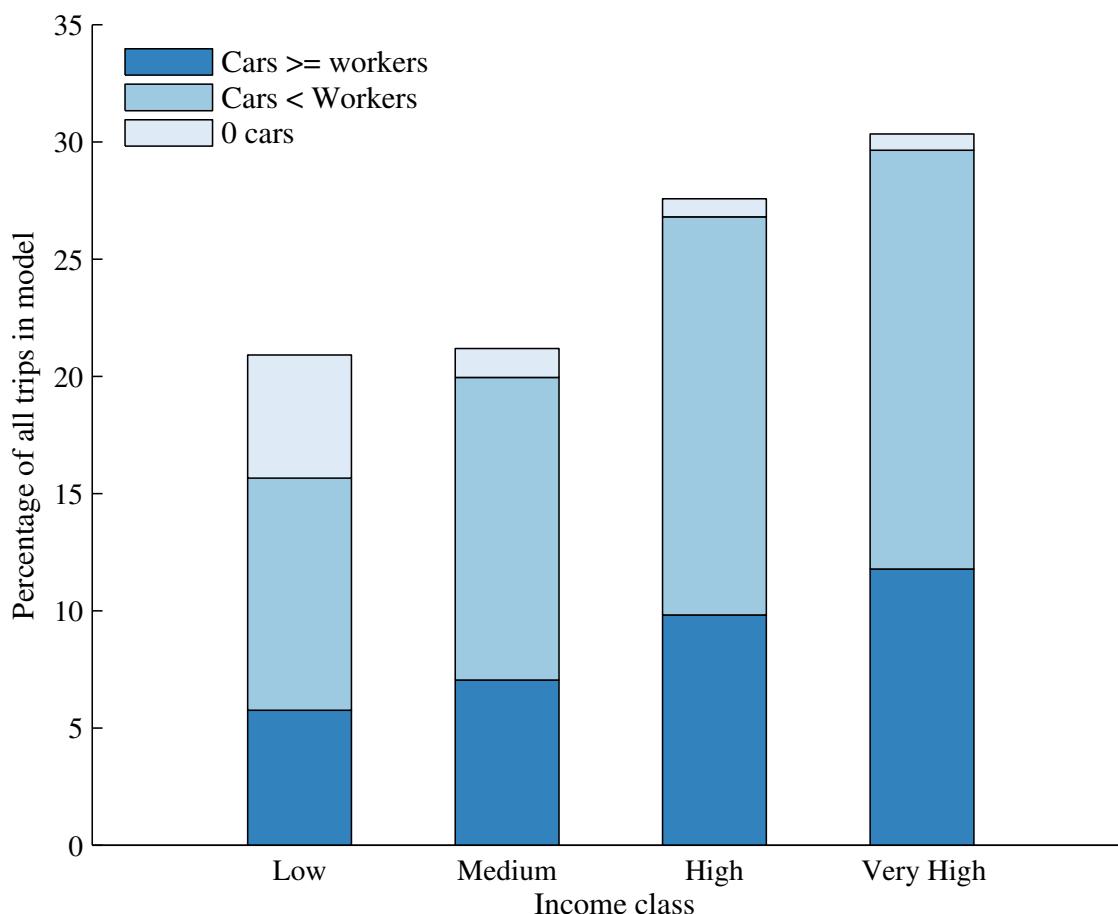


Figure 2. Percentage of total number of trips considered in the high-fidelity model by socio-economic group (determined by income class and household car ownership category) for the baseline (pre-earthquake) case.

95 General patterns emerge in the expected losses in accessibility. The expected losses are computed by taking
 96 an average of the accessibility results for each of the 1454 travel analysis zones (TAZ) for each earthquake event,
 97 weighted by the adjusted annual likelihood of occurrence from the optimization results.

98 First, we notice that the ratio of cars to the number of people who work in a household is correlated with accessi-
 99 bility risk; a higher ratio corresponds to higher expected decreases in accessibility. This corresponds to going across a

100 column in Figure 3. For example, for the first row representing low income households, we notice a marked change in
 101 accessibility across the columns, as indicated by an expanded area of darkened TAZs from left to right (Figure 3(a-c)).
 102 Note that 1 *util* corresponds to a consumer value of compensating variation of approximately \$20 per person per day,
 103 which assumes low (conservative) estimates of the value of time for travel delays and value of getting to destinations
 104 (Section ??).

105 We might expect these households with more cars to take longer trips because there might be a relationship
 106 between needing to travel longer distances and needing an extra car or two in a household. This is indeed the case
 107 (Figure 4(b)), but it is not fully predictive. In fact, there is only a weak trend between average trip length for a TAZ
 108 before any earthquake and the predicted impact on accessibility (Figure 5). Instead, we hypothesize that there are
 109 other latent variables correlated with car ownership. For example, the geographic distribution of people without cars
 110 varies. Additionally, in Section 3.5, we will further explore the correlation between the percentage of car-based trips
 111 and accessibility risk. We will show that TAZs with fewer car-based trips, tend to have lower risk of accessibility
 112 losses.

113 Second, controlling for car ownership, we see a fairly equitable distribution of risk across income class segments.
 114 For example, by looking at households with fewer workers than cars (middle column of Figure 3), the variation from
 115 TAZ to TAZ is significantly more striking than the difference across income segments (Figure 3(b,e,h,k)). Similarly,
 116 while trip lengths are slightly longer for higher income households, the differences are subtle (Figure 4(a)).

117 Thus, for a given TAZ, the differences across incomes are not that great. At the same time though, there is
 118 an unequal geographic distribution of wealth in the San Francisco Bay Area. Because of this, when we aggregate
 119 accessibility risk across TAZs, we see that accessibility risk rises with increasing household income (Figure 7(b)).
 120 Therefore, even though the poor are generally the most vulnerable to climatological and geophysical hazards and
 121 disasters including hurricanes, floods and earthquakes [27], wealthier households in the San Francisco Bay area are
 122 more vulnerable than the other income groups to earthquake-related accessibility risk.

123 Next, we consider which geographic parts of the San Francisco Bay Area are at an elevated risk. The results show
 124 regions of high risk: in the East Bay due East of San Francisco, in the suburbs of San Jose, along the coastal and
 125 Bay-side regions South of San Francisco (Millbrae and Pacifica, e.g.), and in parts of San Francisco (South-Central
 126 neighborhoods including Westland Highlands and Glen Park neighborhoods) (see labeled map in Figure ??). One
 127 may have expected more high risk areas on the San Francisco Peninsula, because of the San Andreas fault, which can
 128 generate large magnitude events. In contrast, the East Bay has higher shaking levels at more moderate return periods,
 129 due to the higher relative annual frequency of events on the Hayward Fault; this is correlated to bridge damage and thus
 130 road closures. Furthermore, the data suggests that both the more common moderate-magnitude East Bay events and
 131 the rare higher-magnitude San Andreas events can cause accessibility problems for the East Bay. Figure 6 shows one
 132 sample realization of a M6.85 Hayward event and one sample realization of a M7.45 San Andreas event—both follow
 133 the general trend of high predicted accessibility losses in the East Bay. In contrast, while any events could contribute
 134 to the risk in San Francisco, our model results show the main accessibility losses in San Francisco corresponding
 135 to the San Andreas events. Figures 6(c,d) provide one such example. Figures 6(e,f) show an example of a lower
 136 magnitude event farther away from the main population centers, a M6.35 event in the Great Valley Pittsburg-Kirby
 137 Hills Fault. This shows how the range of more minor faults in the East Bay can contribute to that area's risk. Also,
 138 we have shown the results for one socio-economic group in Figure 6, but the other socio-economic groups follow the
 139 same general patterns, albeit with different specific values.

140 Finally, we can examine the rates of loss exceedance (Section ??). Figure 7 shows a similar shape to the loss
 141 exceedance curves for other performance metrics (Section ??). Note that the results are primarily valid in the 100 to
 142 2475 year return periods, since this is the range chosen for the map selection optimization problem. As a sense of
 143 scale, if we use the average value over all TAZs for this

144 Recognizing that the impact varies significantly by TAZ, as indicated by Figure 3, we also examine the accessibility
 145 loss exceedance curve for three communities: part of the San Francisco financial district, Danville, and Pacifica
 146 (Figure 1). These correspond to TAZ IDs 2, 1161, and 224 respectively. This part of the San Francisco financial
 147 district represents an area with relatively low expected changes in accessibility (Figure 3), whereas Danville and Paci-
 148 fica are at an elevated risk in almost all socio-economic groups (Figure 3). The general trends are corroborated by
 149 the loss exceedance curves for these three communities (Figure 7(a) shows an example for the socio-economic group
 150 with medium income households with fewer cars than workers). In other words, the average middle-class person from
 151 Danville in a household with fewer cars than people who work is expected to experience travel-related losses up to 1

152 *utils* per day after a rare earthquake, which he or she values at approximately \$20 per day considering a conservative
153 estimate of travel time and destination value (Section ??). In contrast, his or her fellow Bay Area resident in San
154 Francisco has expected losses of only a tenth as much as experienced by a Danville resident. At return periods greater
155 than 100 years, we notice that Danville and Pacifica follow a similar general pattern, which differs dramatically from
156 that of San Francisco.

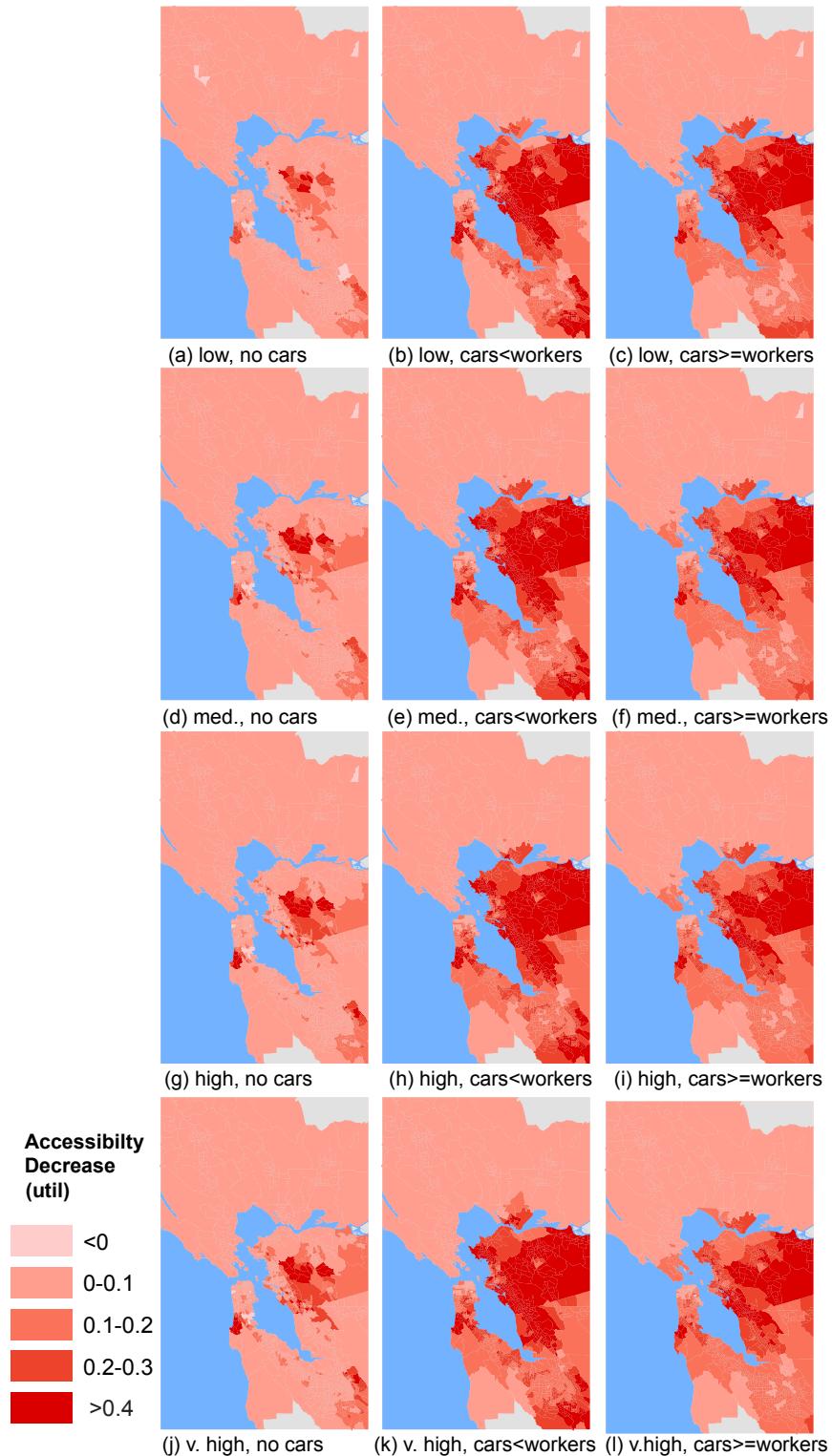


Figure 3. Expected changes in accessibility per person per day for each combination of income class and car ownership group. The darker the color, the greater the losses in accessibility.

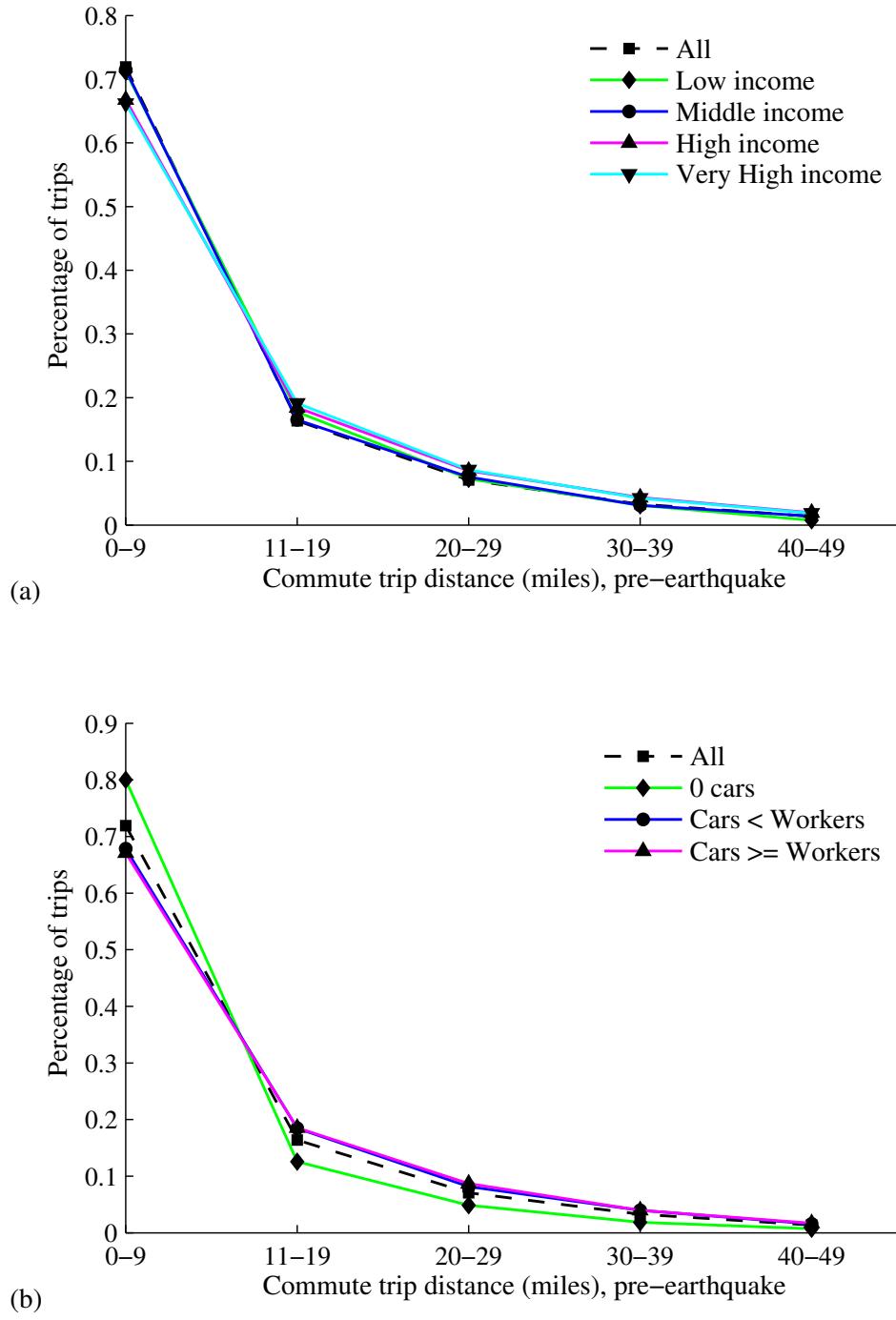


Figure 4. Distributions of commute trip length in 10-mile intervals by a) income class segment, and b) car ownership segment, (pre-earthquake)

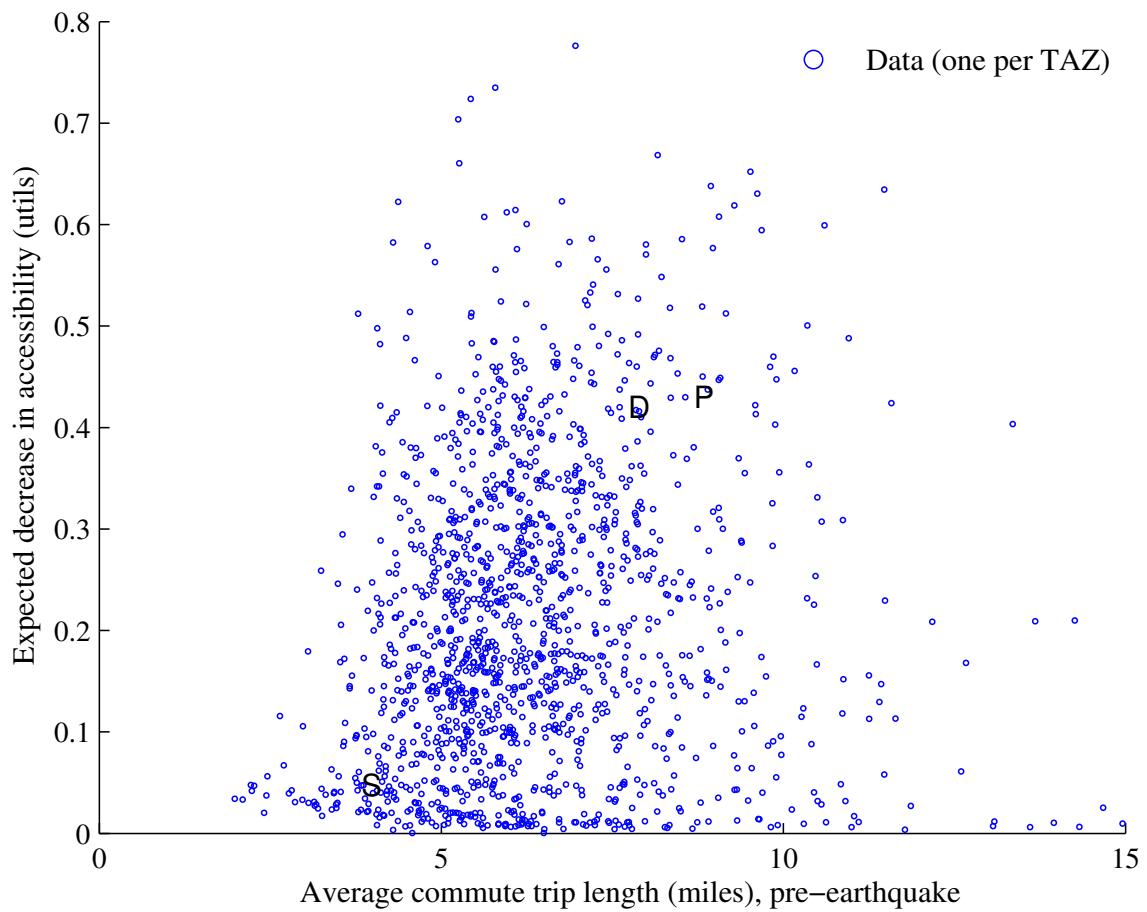


Figure 5. Trip length (pre-earthquake) versus change in total accessibility per person per day. Each dot represents one TAZ and the three case study communities, San Francisco financial district, Danville, and Pacifica are marked by S, D, and P respectively.

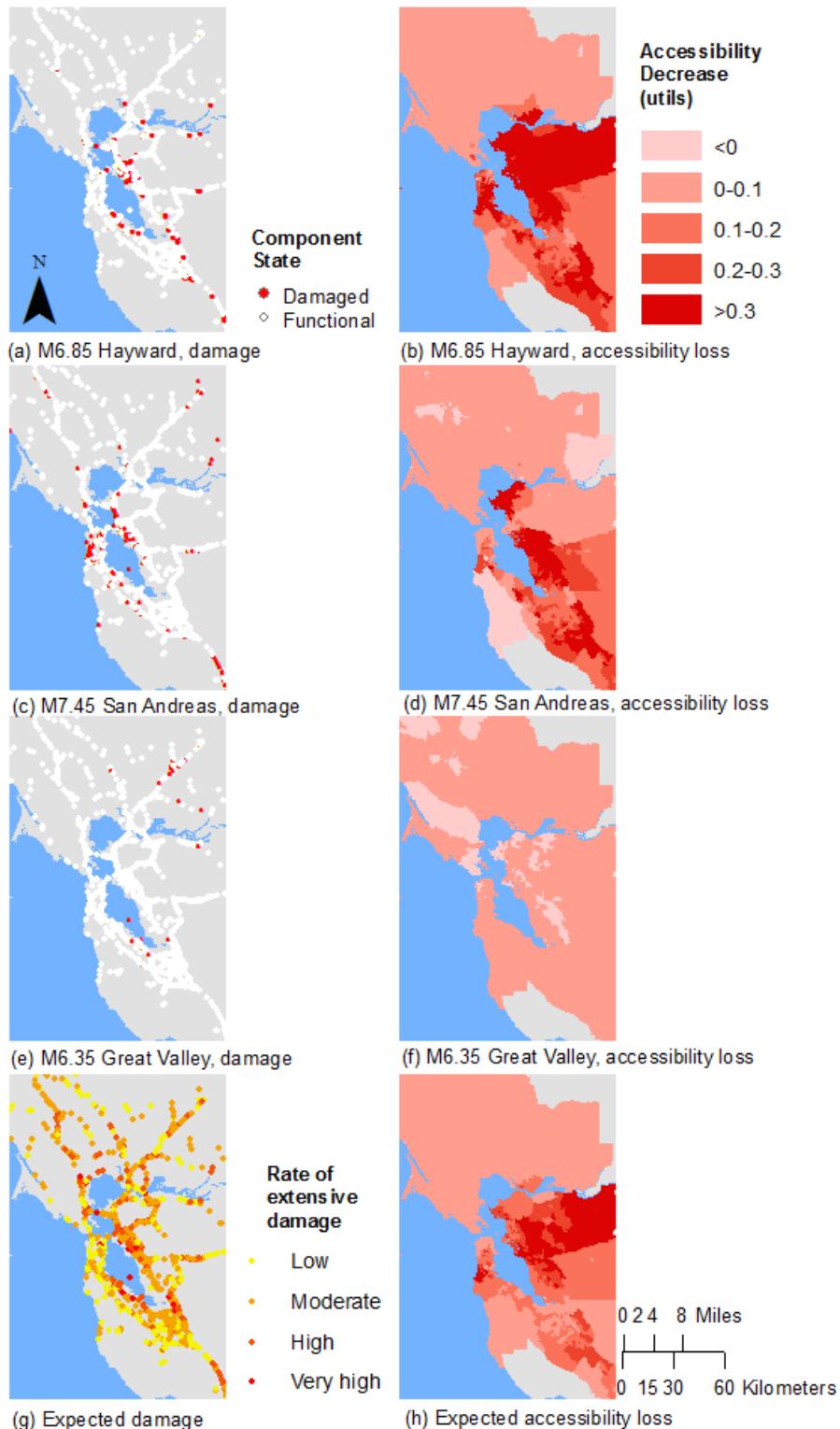


Figure 6. Bridge damage (red = damaged) and corresponding accessibility losses per person per day by TAZ for medium income households with fewer cars than workers. The bottom row has expected values calculated as a weighted average over all events.

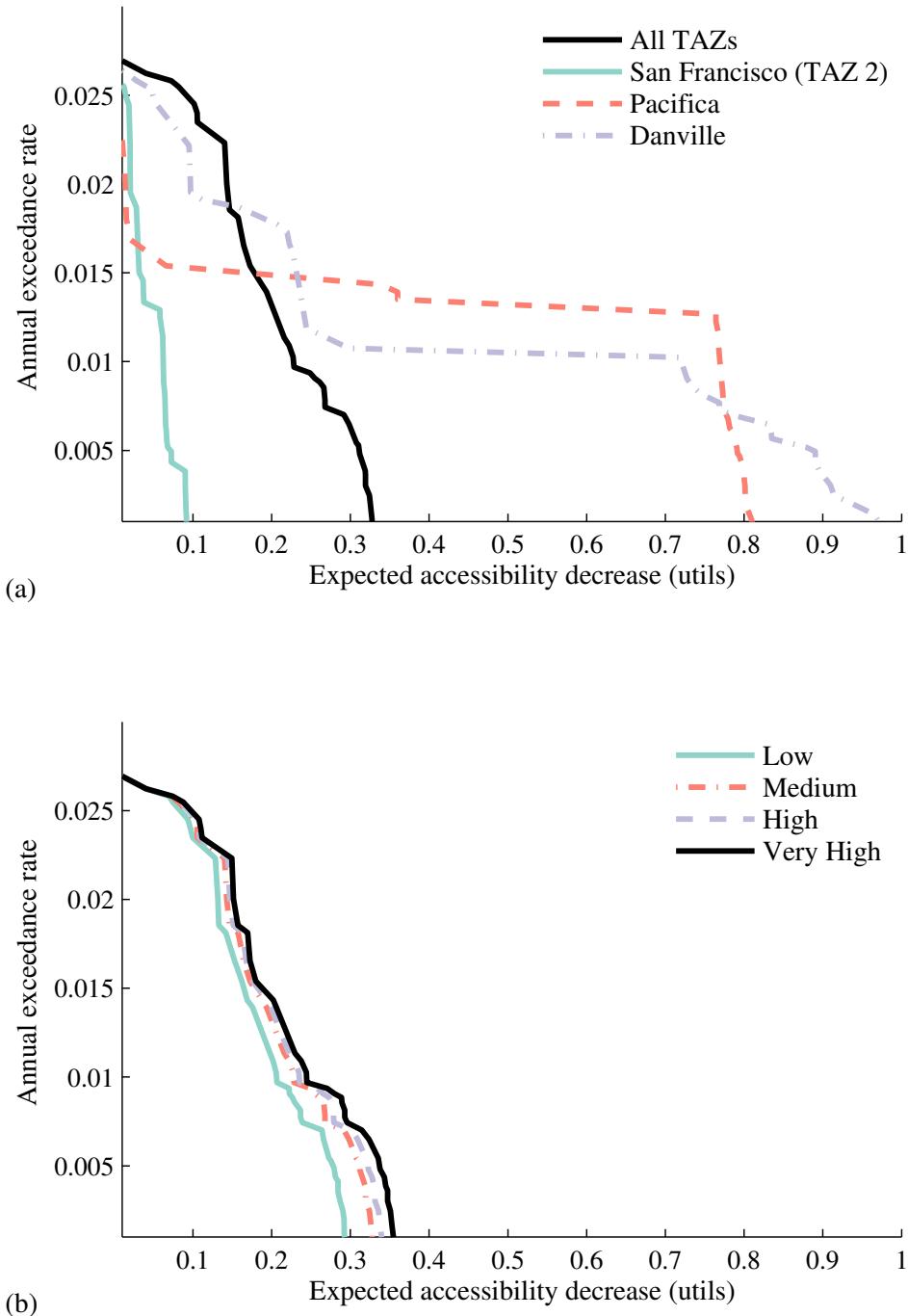


Figure 7. Accessibility annual loss exceedance curve with a comparison by (a) case study TAZs and average over all TAZs and (b) income class; all curves are in *utils* per person per day for medium income households with fewer cars than workers .

157 *3.2. Analysis for San Francisco, CA financial district*

158 In this section, we will explore some possible explanations for why this San Francisco TAZ (Figure 1) has lower
159 expected accessibility losses than most other communities. First, the financial district of San Francisco differs dramat-
160 ically from many other TAZs in that the percentage of trips made by car is relatively small (38% versus an average of
161 85% across all TAZs). Households traveling by foot or bike will be less influenced by network damage, because the
162 model considers only damage to the road network and transit systems; thus, foot travel routes and travel times will not
163 be affected in this model. We also observe that more trips by foot and bike correspond to destinations that are closer
164 geographically. The impact of travel mode shift post-earthquake will be further explored in Section 3.5.

165 Second, Figure 8(a) shows that the average time for a trip to and from work is about average for a TAZ in this
166 region and also follows a similar distribution to that of the other TAZs. Figure 8(b) suggests a slight trend towards
167 shorter trips, but the average trip distance for trips is only 7% lower than the average for all trips region-wide. Since
168 the trip time and length are relatively typical, but the accessibility is much lower than average, the trip time and length
169 do not explain the differences in accessibility losses.

170 In summary, the data suggests that a major cause for the low expected accessibility impact for the financial
171 district of San Francisco is the lower relative dependence on cars for mobility. In the next section, we will contrast
172 the San Francisco example with results from Pacifica, another Peninsula community that, nonetheless, is expected to
173 be at high risk of losses in accessibility.

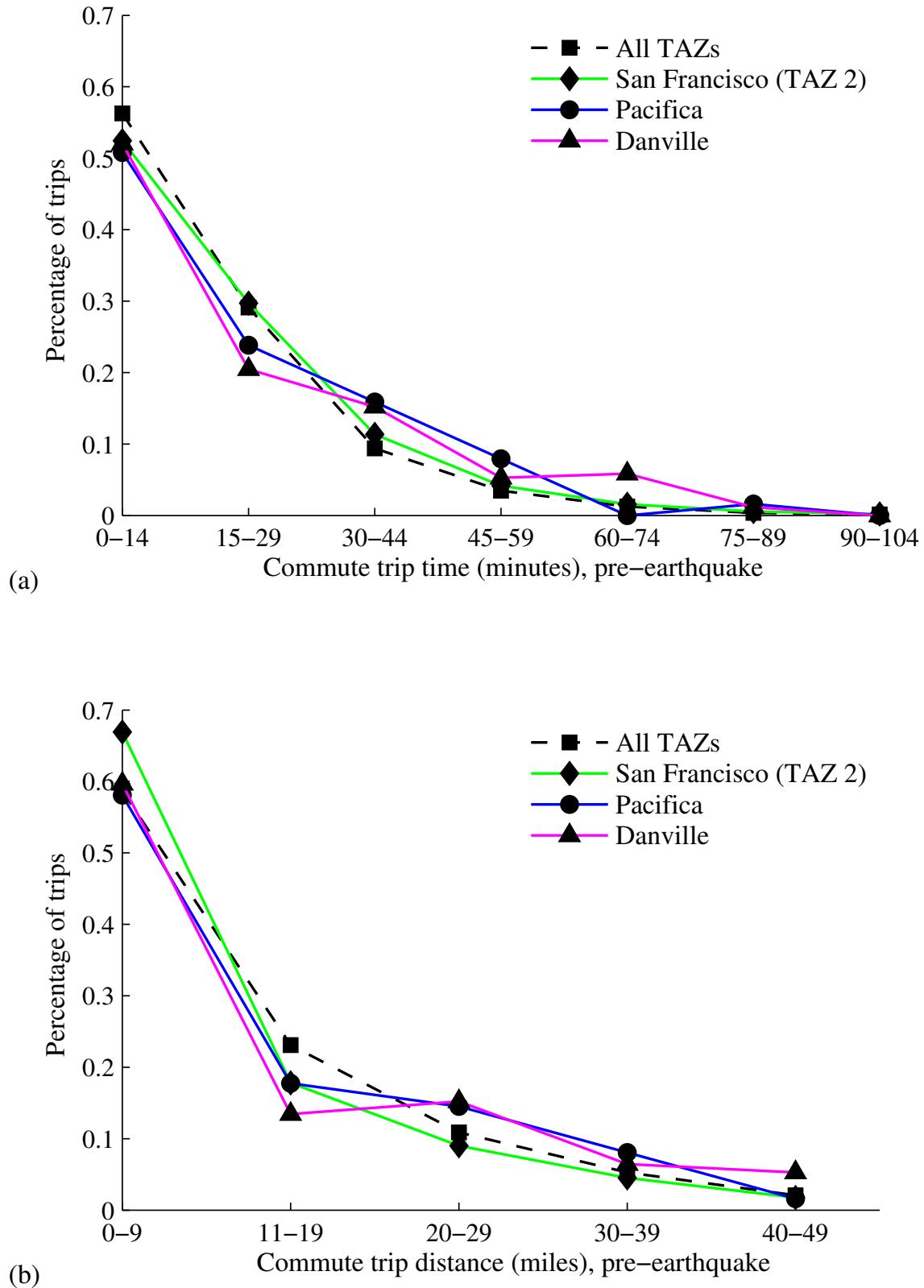


Figure 8. One-way commute trip information by (a) 15-minute time interval, and (b) 10-mile distance interval for 3 case study TAZs and the average over all TAZs.

174 3.3. Analysis for Pacifica, CA

175 Based on the fault locations (Figure ??), we might not suspect that Pacifica, CA would be at an extremely elevated
176 risk of accessibility losses across most market segments, as compared to other communities. In addition, the percent-
177 age of pre-earthquake car-based trips is around average for the case study area (88% versus an average of 85%). In
178 contrast to most other regions, however, Pacifica is wedged between the Pacific Ocean to the West and the coastal
179 mountains to the East. Indeed, the main access road is California Highway 1, which has various vulnerable bridges
180 included in the case study dataset. There are no viable alternative routes on local roads. Since almost all trips are by
181 car from Pacifica and the average trip length is much longer than the region-wide average (108% longer), the road
182 issue is particularly serious.

183 As a comparison, consider the next main town along the Pacific coast, Half Moon Bay, about 13 miles South.
184 Half Moon Bay has significantly lower expected accessibility losses compared to Pacifica, as illustrated in Figure 6
185 with cities labeled for reference in Figure 9. This corresponds to an expected accessibility loss of 0.43 *utils* per day
186 for a person in Pacifica in middle income household with fewer cars than workers, given an event in the dataset. In
187 comparison, a similar person in Half Moon Bay is expected only a 0.11 *utils* loss. While the seismic hazard is similar,
188 the population is about one third the size, so there is less demand for the limited road capacity [28]. Furthermore,
189 and likely most significantly, Half Moon Bay has a key alternative to California Highway 1, California Highway 92,
190 which links to Silicon Valley and the main highways of that region (US-101 and I-280). The differences in the road
191 topology are illustrated in Figure 9. Since Pacifica, CA is unusually reliant on one road with key vulnerabilities for
192 access, it has an elevated risk for losses in accessibility.

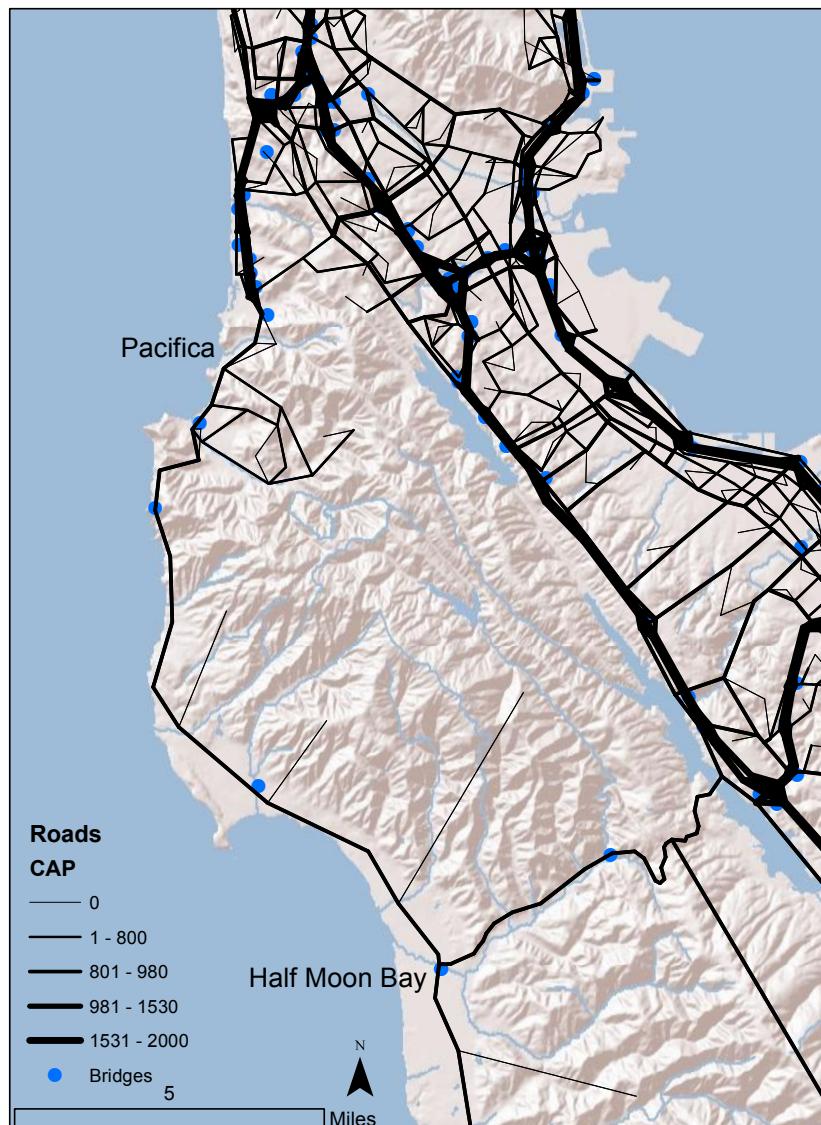


Figure 9. Differences in road access: limited roads in and out of Pacifica, CA, but an extra access highway for Half Moon Bay, CA.

193 *3.4. Analysis for Danville, CA*

194 We will first examine the trip length characteristics for Danville, CA. As illustrated in Figure 8, the distribution
 195 of pre-earthquake commute trips from Danville, CA is shifted towards both longer distance and longer time than the
 196 communities we have studied so far with a relatively higher proportion of trips taking 60–74 minutes and traveling
 197 over 40 miles than in the other communities. The same trend holds for other trip purposes. On average, the trip lengths
 198 are longer than many other TAZs (85% longer than the average over all trips originating from any of the TAZs). The
 199 consequence of these longer trips is more opportunities to be impacted by a road closure, simply because more roads
 200 and bridges will be used. Moreover, the road layout near Danville, CA mandates many highway trips, which increase
 201 the likelihood of crossing bridges; bridges are the part of the network for which we model the vulnerability.

202 Next, we look at patterns of expected bridge damage. Bridge damage is important for many regions, including
 203 Danville, because the percentage of car-based trips is high (85% of all trips on average, and also 85% of Danville-
 204 origin trips). For damage map realizations for the three earthquake events we introduced—M6.85 Hayward Fault,
 205 M7.45 San Andreas Fault, M6.35 Great Valley Fault—some bridges in the Oakland area are in the extensive or
 206 greater damage state (Figure 6(a,c,e)). These correspond to bridge closures in the model. In addition, in the first two
 207 cases, there are closures to the north of Danville, which represents one of the two main travel routes from Danville.
 208 There are also scattered closed bridges to the west of Danville, likely a top travel corridor because of the workplace
 209 centers in San Francisco, Oakland, and Silicon Valley (all to the west). As for transit, in the first two events, all BART
 210 lines are closed, so there are limited alternatives to the popular road routes. The result is that the residents of Danville,
 211 CA have reduced access to their normal destinations after all these events.

212 We can also look at bridge damage in a probabilistic event-set-based manner. The expected damage over all events
 213 represents the annual rate of a bridge being in the extensive or complete damage state for the set of 113,940 damage
 214 maps (Figure 6(g)), as discussed as the first baseline method in Chapter ???. This figure indicates that bridges in
 215 the Oakland-Berkeley area are particularly likely to be damaged. We also see a few high likelihood bridges to the
 216 North of Danville. Thus, the data suggests that the relative position of high-risk bridges to Danville contributes to this
 217 community's accessibility risk.

218 3.5. Impact of travel mode shifts and regional variations in travel mode patterns

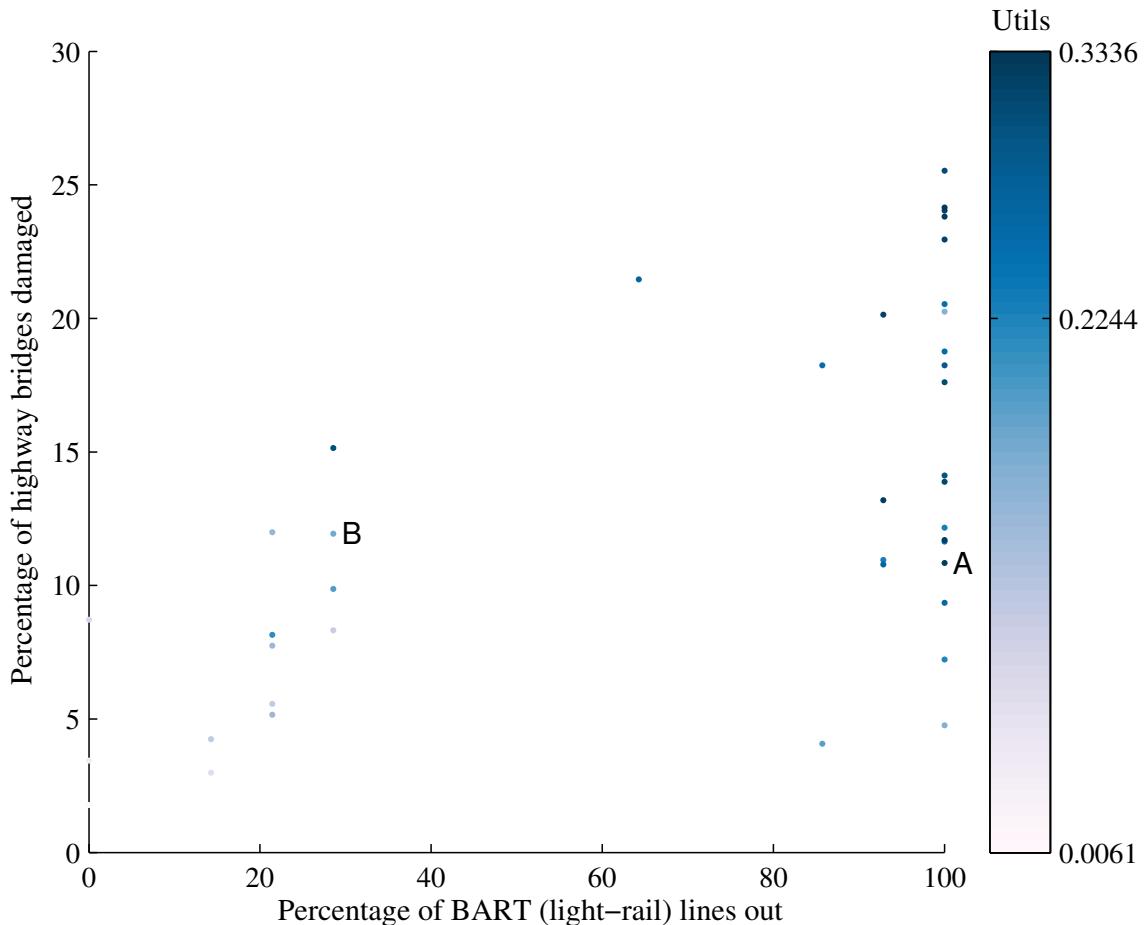


Figure 10. Percentage of BART (heavy-rail) lines not operational versus percentage of highway bridges damaged, where each data point corresponds to one earthquake damage map. The values are color-coded by the average loss in accessibility per day per person over all TAZs for households with the fewer cars than people who work. Two events discussed in this section are marked by the letters A and B.

219 First, we compare patterns of transit system damage with patterns of travel mode shifts after earthquake events.
220 Over all the simulated events, taking a weighted average by the annual likelihood of each event, we see a reduction in
221 transit ridership (25% weighted average decrease from the base case). This is not surprising. The heavy rail systems
222 (BART and Caltrain) are not fully operational in most of the forty simulated events (Table 1), and these have heavy
223 ridership. The light rail systems (VTA and Muni light rail) also suffered losses in many events (Table 1). As discussed
224 in Section ??, with regards to the other transit systems, trans-bay and cross-county bus lines were suspended in the
225 forty events and the baseline case; main local buses are modeled as operational, although with possible delays; and
226 ferries are modeled as operational. The result is an average increase in the percentage of trips by the other modes
227 (foot, car, and bike).

228 A notable exception is the M6.35 Great Valley, Pittsburg-Kirby Hills Fault earthquake event, as illustrated in
229 Figure 6(e,f). In this event, there were no line closures on the major transit systems (BART, Caltrain, Muni, and
230 VTA Light Rail). There were, however, some bridge closures on the highways (Figure 6(e)). The result was a slight
231 increase in transit ridership and also in trips by foot.

232 In general, accessibility impact grows with increasing number of damaged transit lines, particularly in combina-
233 tion with high numbers of damaged bridges (Figure 10). The results do not conclusively show that transit is a key
234 contributor to accessibility risk, but based on individual examples, the data suggests this conclusion. For example,

Functionality	BART	Caltrain	Muni Light Rail	VTA Light Rail
Full	3	13	25	9
50-99%	10	0	15	0
1-49%	8	0	0	0
None	19	27	0	31

Table 1. Transit network functionality as a count out of the forty simulated events for BART, Caltrain, Muni Light Rail, and VTA Light Rail. Functionality is measured by the percentage of lines that are operational given a damage map (based on a ground-motion intensity map).

in the set of forty events analyzed with the high-fidelity model, the M6.85 Hayward Rogers-Creek and the M7.45 Northern San Andreas Fault event both have a similar number of damaged bridges (around 11%); these are noted by points A and B respectively in Figure 10. These correspond to the bridge damage and accessibility maps in Figures 6(a,b) and 6(c,d) respectively. However, this Hayward Rogers-Creek event has significantly higher accessibility impact. Similarly, the transit impact was different. This Northern San Andreas event had only 4 of the 14 BART lines, all Caltrain, and all VTA Light Rail lines not operational, whereas this Hayward Rogers-Creek event had all 14 of the 14 BART lines, all Caltrain, all VTA Light Rail and 3 of the 8 Muni light rail lines not operational. Thus, the transit lines were impacted significantly differently. Moreover, the differences in accessibility results could not have been predicted from the efficient transportation model introduced in Section ??, because the percent of damaged bridges was about the same, and the San Andreas event actually corresponded to a greater increase in travel time.

Second, we examine the correlation between a community's walkability, as measured by the percentage of total trips made by that travel mode, and the expected decrease in accessibility by community. We see that an increased percentage of pre-earthquake trips on foot corresponds to a lower average decrease in accessibility (Figure 11). This result corroborates the specific example of the San Francisco Financial District we saw in Section 3.2. Furthermore, on average, the number of by-foot trips slightly increases after the earthquake events where road congestion worsens. This model result is consistent with the observations after the 1995 Kobe earthquake, in which many commuters switched to walking and biking ("non-mechanized modes") in the weeks after the earthquake [8]. In conclusion, the data suggests that TAZs, i.e. communities, which have a greater walkability are also more resilient to earthquake-related accessibility risk.

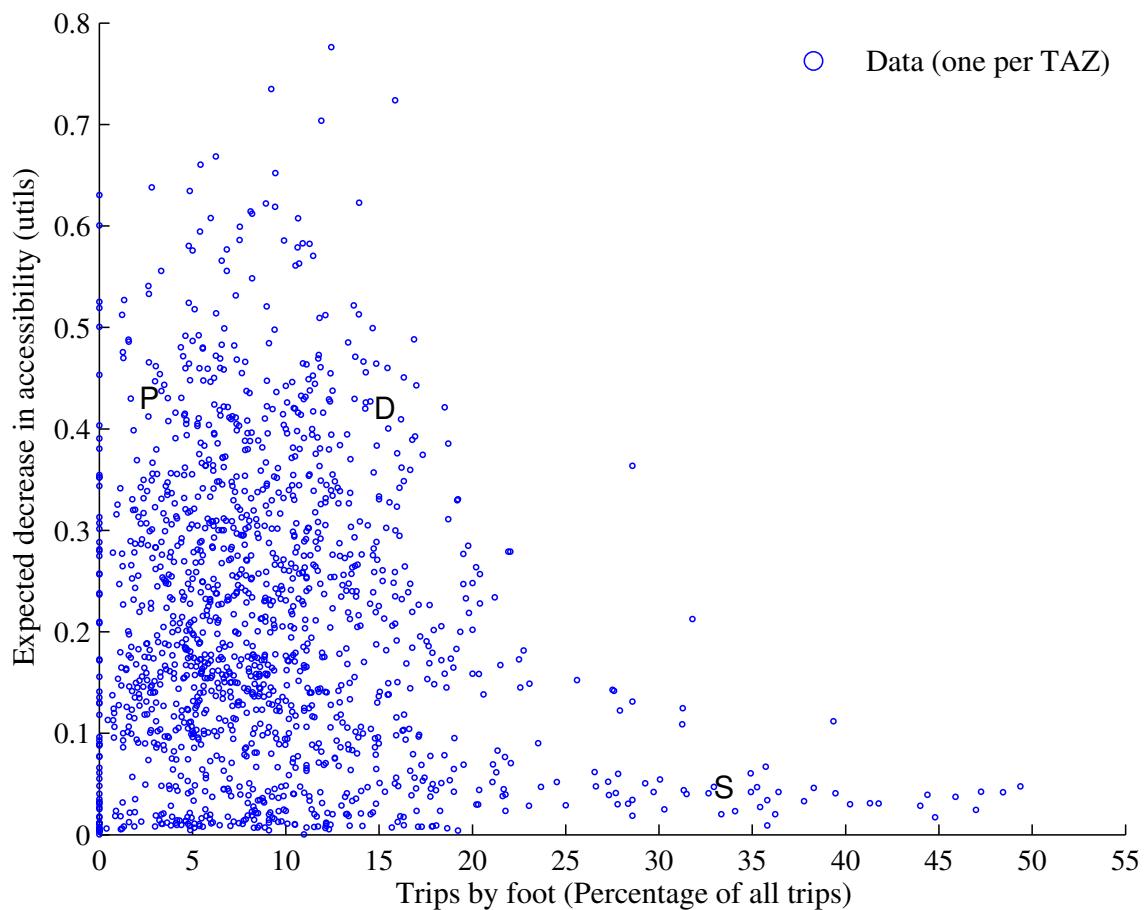


Figure 11. Percentage of total trips by foot (pre-earthquake) versus decrease in total accessibility, measured in *utils* per day (for households with the number of cars less than the number of workers). Each dot represents one TAZ and the three case study communities, San Francisco financial district, Danville, and Pacifica are marked by S, D, and P respectively.

254 **4. Conclusions**

255 Here we have shown how mode-destination accessibility links post-earthquake infrastructure damage to the impact
 256 on human welfare and enables identifying at-risk geographic and demographic groups in a region. Adopting this
 257 performance metric from the urban planning community, we have illustrated its use for seismic risk assessment and
 258 mitigation through a case study of the San Francisco Bay Area. Furthermore, we have proposed a model that captures
 259 transport mode choice and the interdependencies of the roads and transit systems. We have nested this network
 260 performance model within an event-based probabilistic seismic risk framework. In the case study, we first simulated
 261 a large set of earthquake scenarios, ground-motion intensity maps, and damage maps. Then, we used optimization
 262 to select a subset of the maps. After that, for each of the selected maps, we processed the data for analysis in a
 263 high-fidelity, activity-based travel model that includes the road network, transit networks, walking and biking options,
 264 variable travel demand, and mode choice. From this, we computed the mode-destination accessibility, a state-of-
 265 the-art performance measure for each community and each socio-economic group (defined by income class and car
 266 ownership).

267 We saw stark differences in accessibility from location to location. Specifically, we found that areas in the suburbs,
 268 such as the far East Bay, South San Jose and select communities just south of San Francisco, were particularly at risk.
 269 We found that these geographic trends persisted across income classes and car ownership groups. Nonetheless, on
 270 average, higher income households with more cars than workers had the highest risk across the studied socio-economic
 271 groups. One key reason is the geographic clustering of these households in higher-risk areas. Another factor is that
 272 these households tend to take longer daily trips, thus crossing more roads and bridges and possibly increasing the
 273 likelihood of disruption.

274 The third finding from this study is that travel modes shift after an earthquake, and communities who can more
 275 easily make these adjustments are generally predicted to experience lower post-earthquake losses in accessibility. The
 276 results suggest that the walkability of a community, as measured by the percentage of pre-earthquake trips by foot, is
 277 closely linked to reduced accessibility risk. We also found that one adaptation measure after major earthquakes is an
 278 increased likelihood to walk or bike. We also found that in almost all of the simulated earthquake events, the transit
 279 system, particularly the heavy rail (BART and Caltrain) lines, is predicted by this model to be severely impacted. The
 280 result is a reduced mode share for transit and increased trips by the other modes (car, walk, bike). Thus, this study
 281 suggests that not including transit can lead to an unconservative estimate of seismic risk of transportation systems. The
 282 model shows, however, that when transit is not damaged—which is very rare for this case study—ridership increases.

283 In conclusion, mode-destination accessibility offers important applications for further investigation into the impact
 284 to human welfare of engineering losses and mitigation efforts. In addition, we have provided researchers a method
 285 for including the interdependencies of the transportation system into an event-based probabilistic risk framework.
 286 This work lays the foundation for future work in risk mitigation and policy to reduce the vulnerability of at-risk
 287 communities. It also suggests that initiatives making communities more conducive for cycling and walking to work
 288 can increase resiliency.

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