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

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todo

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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Keywords: Infrastructure, Risk, Earthquakes

- briefly summarize the risk assessment approach
- describe how you measure impact

1. Introduction

Seismic risk assessment in earthquake engineering tends to focus on buildings, bridges, and the performance of infrastructure systems. 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], or the post-earthquake travel distance between two locations of interest [e.g., 2]. 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" [3]. A recent World Bank and United Nations report echoed this idea that the effects on human welfare turn natural hazards into disasters [4].

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 [5]. 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 [6]. 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) [7], using the consumer price index to account for inflation.

An emergent trend in earthquake engineering is estimating the cumulative extra time needed for travel after a simulated future earthquake, sometimes called travel time delay [e.g., 8, 9]. 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 the 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" [10]. 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 [11]. Outside of transportation systems, some researchers have investigated the interplay between earthquake damage, such as damage to the electric power and wastewater networks, and the usability of houses and other buildings; this represents an important first step [12].

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 [13]. 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, which is one measure of social impact [14]. Within urban planning, accessibility has been measured in many ways, including individual accessibility, economic benefits of accessibility, and mode-destination accessibility [15]. 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 [16]. 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). However, this accessibility measure has not yet been linked to risk assessment. In addition, 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 [7]. 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 [8].

In this paper, we develop a framework for coupling mode-destination accessibility with a quantitative seismic-risk assessment to identify at-risk populations and measure the accompanyin[illegible]an welfare. We illustrate our approach with a case study of the San Francisco Bay Area transporta[illegible]ing highways, local roads, and public transportation lines. This study analyzes a set of forty [illegible] earthquake scenarios, ground-motion intensity maps, and damage maps, as ~~we~~ introduced in [17] using the optimization procedure ~~we~~ proposed in [18]. For each of these damage maps, we model damage with a practical, agent-based transportation model used by the local transportation authorities that includes damage to bridges, roads, and transit lines, and varies demand. Then, with this model, we estimate 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.

ok

2. Case study: San Francisco Bay Area

2.1. Case study overview

We focus on the San Francisco Bay Area, a seismically-active region, to illustrate our approach (Figure 1). The area follows a polycentric metropolitan form, with San Francisco as the primary center and other jobs concentrated in suburban centers, such as Silicon Valley [19]. The region has a wide array of trip patterns for mandatory and non-mandatory trips. Furthermore, trip times and routes vary greatly depending on travel preferences and workplace locations [19]. Thus, we might expect noticeable disparities between households in the risk of travel time delays due to earthquakes.

This analysis considers the complex web of roads and transit networks of the case study area. The roads are modeled by a directed graph $G = (V, E)$, where V is a finite set of vertices representing intersections, and the set E, whose elements are edges representing road links, is a binary relation on V. In this model, $(|V|, |E|) = (11{,}921, 32{,}858)$ including centroidal links and $(|V|, |E|) = (9{,}635, 24{,}404)$ without. Centroidal links do not correspond to particular physical roads but instead capture more subtle travel flows, such as from outside the study area or the flow of people to and from some minor local roads. We also in 43 transit networks, as detailed in [17].

We model damage f[illegible]
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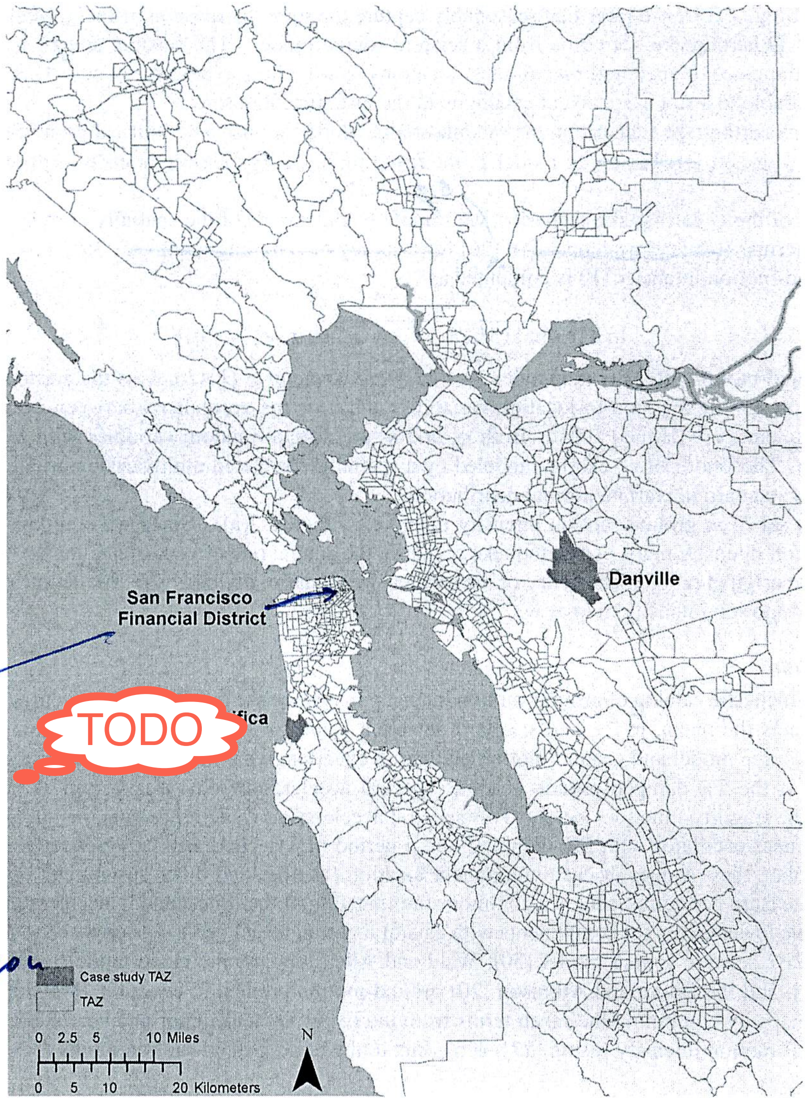

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Figure 1. Study area: San Francisco Bay Area, CA with specific travel analysis zones (TAZs) used in the case study marked in blue.

impacting the rapid transit network, BART, with data provided by that agency. We refer readers to [17] for more details about matching these structures, hereafter called components, to the relevant road and transit networks.

2.2. *Ground-motion intensity maps*

(ok)

2.2.1. *Theory*

We now describe how to produce a set of maps with ground-motion intensity realizations at each location of interest, and corresponding occurrence rates that reasonably capture the joint distribution of the ground-motion intensity. First, we generate Q earthquake scenarios from a seismic source model. The seismic source model specifies the rates at which earthquakes of specified magnitudes, locations, and faulting types wi[illegible]ur. This set of earthquake scenarios is comparable to a stochastic event catalogue in the insurance indu[illegible]

ok

(ok)

Second, for each earthquake scenario in the seismic source model, we use [illegible]d-motion prediction equation (GMPE) [e.g., 20, ~~21, 22, 23~~] to model Y, the resulting intensity measure at each location of interest [e.g., 25]. ?

Then, for each of the Q earthquake scenarios, e.g. we sample b realizati[illegible]ok[illegible]orrelated ground-motion intensity residual terms. ~~Readers are referred to~~ [26] ~~for a survey of sa~~[illegible]. Once residuals are sampled, the total log ground-motion intensity (Y) is computed as

$$\ln Y_{ij} = \overline{\ln Y(M_j, R_{ij}, V_{s30,i}, \ldots)} + \sigma_{ij}\epsilon_{ij} + \tau_j\eta_j \tag{1}$$

where j is the ground-motion intensity map index ($j = 1, \ldots, m$ where $m = Q \times b$), ϵ_{ij} is the normalized within-event residual in $\ln Y$ representing location-to-location variability and η_j is the normalized between-event residual in $\ln Y$ and the other parameters are defined above. Both ϵ_{ij} and η_j are normal random variables with zero mean and unit standard deviation. The vector of ϵ_{ij} can be modeled by a spatially-correlated multivariate normal distribution [e.g., 27] and the η_j by a standard univariate normal distribution.

The result is a set of m ground-motion intensity maps (e.g., Figure 2(a)). Since we simulate an equal number (b) of ground-motion intensity maps per earthquake scenario, the annual rate of occurrence for the j^{th} ground-motion intensity map is the original rate of occurrence of the earthquake scenario, divided by b. We denote the rate associated with the j^{th} ground-motion intensity map as w_j.

2.2.2. *Implementation*

To generate a stochastic catalog of ground-motion intensity maps, we use the OpenSHA Event Set Calculator [28]. This software outputs the mean, $\overline{\ln Y_{ij}}$, and standard deviation values, σ_{ij} and τ_j, for all locations of interest for a specified seismic source model and ground-motion prediction equation, which are needed inputs for Equation 1. The intensity measure is the 5%-damped pseudo absolute spectral acceleration (Sa) at a period $T = 1s$, which is the required input to the fragility functions below. This spectral acceleration value represents the maximum acceleration over time that a linear oscillator with 5% damping and a period of 1 second will experience from a given ground motion. We calculate these values at each component location (bridges and other structures). Using one ground-motion intensity measure per component is a common simplification of the time-varying acceleration dynamics [e.g., 29, 9] that may have lower errors for components with a natural period near 1 second as opposed to long-span bridges. We use the UCERF2 seismic source model [30], Wald and Allen topographic slope model for the the shear wave velocity $V_{s30,i}$ [31], and the Boore and Atkinson [20] ground-motion prediction equation. We simulate the ground-motion intensity maps by combining the mean terms from the Event Set Calculator and spatially-correlated residual terms of the ground-motion intensity (using [27]) according to the basic ground-motion model (eq. 1).

2.3. *Damage maps*

2.3.1. *Theory*

Calculating network performance risk requires assessing the structural damage of relevant components after future earthquakes. The link between ground-motion intensity and structural damage is often provided by *fragility functions*. Fragility functions express $P(DS_i \geq ds_c | Y_{ij} = y)$. We assume one component, such as a bridge, per site location, so we will identify both components and site locations via the index i. Using that notation, DS_i is a discrete random variable whose value represents the damage state for the i^{th} component and ds is a damage state threshold of interest. The damage state is conditioned on a realization, y, of the random variable Y_{ij}, the ground-motion intensity at the i^{th} site

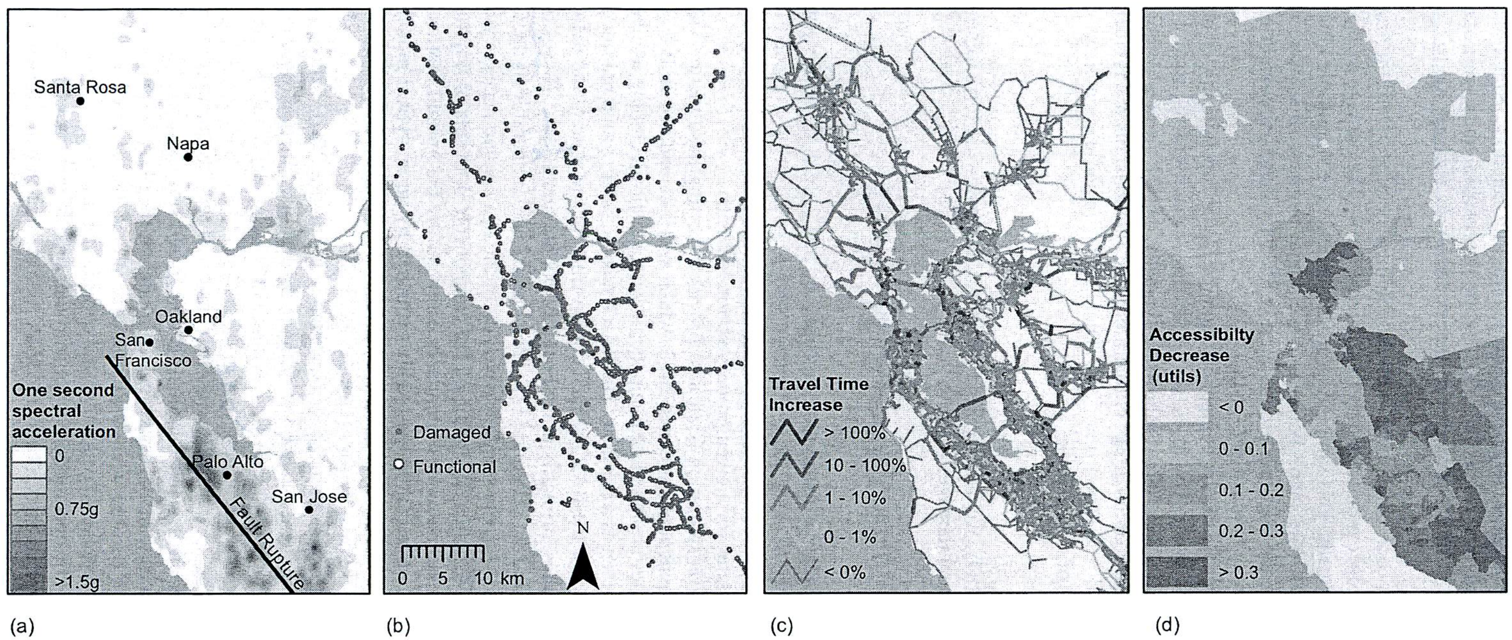

Figure 2. Illustration of the risk framework for one earthquake event including a) One-second spectral acceleration (ground-motion intensity) map with earthquake rupture, b) bridge (component) damage map, c) map of travel time increase (network-performance measure) values, and d) map of accessibility values averaged over all market segments by travel analysis zone (TAZ).

Too much detail for an approach you don't use

and j^{th} ground-motion intensity map. Researchers have calibrated fragility functions using historical post-earthquake dat[...] ok [...]rimental and analytical results [e.g., 33], hybrid approaches, and expert opinion. I~~t is possible to~~ ~~s[...]ates from a joint distribution that includes correlation, such as due to similarities in design or~~ ~~c[...]tices [e.g., 34]~~.

By sampling a damage state for each component, with probabilities obtained from the fragility functions given the ground-motion intensity, we produce a damage map (e.g., Figure 2(b)). The damage map has a realization of the damage state of each relevant component. This sampling process can be repeated multiple times to simulate multiple damage maps per ground-motion intensity map. For example, if equal numbers of damage maps are sampled per ground-motion intensity map (c damage maps per ground-motion intensity map), the weight of the j'^{th} damage map should be adjusted accordingly to $w_{j'}$, where $w_{j'} = \frac{w_j}{c}$, and $j' = 1, \ldots, J$.

Functional percentage relationships link the component damage to the functionality of network elements. For example, in a road network, when a bridge collapses, the traffic flow capacity of the road it carries and it crosses can be modeled as reduced to zero. These relationships are typically derived from a combination of observation and expert opinion, often due to data scarcity [35]. Furthermore, the relationships are typically deterministic for a certain component damage state and restoration time [35]. Thus, in this paper, each damage map corresponds to a functionality state for every element of the network.

2.3.2. Implementation

Component damage. For the case study, we use fragility functions of the following form to provide the link between ground-motion shaking and component damage:

$$P(DS_i \geq ds_\varsigma | Y_{ij} = y) = \Phi\left(\frac{\ln y - \lambda_{\varsigma,i}}{\xi_{\varsigma,i}}\right), \tag{2}$$

where Φ is the standard normal cumulative distribution function, $\lambda_{\varsigma,i}$ and $\xi_{\varsigma,i}$ are respectively the mean and standard deviation of the $\ln Y_{ij}$ value necessary to cause the ς^{th} damage state to occur or be exceeded for the i^{th} component, and the other variables are defined above. By using the previous equation and the inverse method, we can sample realizations of component damage states for a given ground-motion intensity.

The California Department of Transportation (Caltrans) provided the fragility function values $\lambda_{\varsigma,i}$ and $\xi_{\varsigma,i}$ used in this study for the highway components in summer 2012, which was last updated in 2007 and includes various retrofitted bridges [36]. The $\lambda_{\varsigma,i}$ values are based on component characteristics including number of spans and age as detailed in [32]. The $\xi_{\varsigma,i}$ values are given as a constant. The BART seismic safety grou[...] ok [...]ility function values $\lambda_{\varsigma,i}$ and $\xi_{\varsigma,i}$ used in this study for the BART-related components for the state[...]mmer 2012. Data is available for the aerial structures, primarily in the East Bay, but not tunnel s da[...]pond to the safety performance goals under the recent retrofit program [37]. The numbers are comparable to the Caltrans fragility data. For the BART components, however, $\xi_{\varsigma,i}$, the standard deviation of the $\ln Sa$ value necessary to cause the extensive damage state to occur or be exceeded, varies depending on the component. Both sets of fragility functions are based on the assumption that damage can be reasonably accurately estimated by the ground motion intensity at each site independently, and that the damage state can be reasonably estimated by an analytical model considering a single ground-motion intensity measure. In addition, the fragility curve[...]not directly consider the effects of [...] Current work is ongoing to refine these assumptions [e.[...] ok

what is "These" referring to?

bart fragility fcns. I added text

Per ground-motion intensity map, we sample ~~1~~ one dam[...]ure 2(b)), which has [...] component damage state at each component locatio[...]cording to the fragility function (eq. 2). Th[...] functions do not consider correlation of the structural capacities, but other models could be used [...].

Transit network damage. Each of the 43 transit systems we considered will be impacted differently. For Caltrain, conversations with managers suggest that given that there is one shared track system, the system would either be fully operational or not at all. Similarly, managers suggested modeling the VTA system as fully functional or not. Depending on where the BART train cars are when the earthquake strikes, the agency could accommodate different emergency plans. However, BART representatives suggested considering that if any part of a route is damaged, the entire corresponding route would not be operational (but other routes on different tracks might be still operational). In other words, each BART route as well as the Caltrain and VTA routes are each a weakest-link system, so the failure of a single component will cause the route to be non-operational. We modeled the ferry systems as fully functioning for all earthquake events. For all earthquake events including the baseline, trans-bay and cross-county bus lines were discontinued, but main lines in urban areas as well as other local bus networks were maintained per recommendations from the MTC, though they may face delays due to [illegible] congestion.

Road network damage. Each component's damage ok [illegible] to the traffic capacity on associated road segments. We use a functional percentage relationship to compute the traffic capacity of relevant road segments. Based on discussions with Caltrans, we consider travel conditions one week after an earthquake, since it is a critical period for decision making. For example, one week after most events, bridges should have been inspected and surface damage should be repaired, but major reconstruction would not have yet begun. According to our functional percentage relationship, at this point in time, the components have one of two classes of functionality, zero traffic capacity and full traffic capacity [35]. We can thus summarize the component damage using two damage states ds_s, $ds_{damaged}$ and $ds_{functional}$, which correspond to the common HAZUS *extensive* or *complete* damage states and the *none*, *slight*, or *moderate* damage states respectively [35]. Thus, the functional percentage relationship assigns zero traffic capacity on road segments that have at least one component in the $ds_{damaged}$ damage state, and full traffic capacity otherwise. We do not consider network damage from sources other than main structural damage from ground shaking, such as tunnel displacement or liquefaction, but the framework allows including such considerations.

2.4. *Network performance*

2.4.1. *Theory*

The final step for the event-based risk analysis is to evaluate the network performance measure, X. For this application, we consider a metric popular in urban planning, *mode-destination accessibility change* [e.g., 15, 41, 42] (e.g., Figure 2(d)). Mode-destination accessibility, hereafter referred to as accessibility, measures the distribution of travel destination opportunities weighted by the composite utility of all modes of travel to those destinations, i.e., the ease of someone getting to different destinations weighted by how desirable those destinations are [16, 14]. The utility function for the mode-destination choice may be estimated using a multinomial random utility model where the logsum represents the accessibility value [43, 16, 14]. Namely, accessibility for a particular agent a is

$$Acc_a = \ln\left[\sum_{\forall \in C_a} \exp(V_{a(c)})\right], \tag{3}$$

where $V_{a(c)}$ is the utility of the c^{th} choice for the a^{th} person for $a = 1, \ldots, A$, and C_a is the choice set for the a^{th} person [16]. Choices refer to travel destinations and the mode of travel (driving, walking, bus, etc.). The units are a dimensionless quantity, *utils*. As an extension, the accessibility values from the previous equation can be converted into equivalent time and dollar amounts using *compensating variation* for cost-benefit studies; for the case study, 0.0134 *utils* (generic measure of utility) equals the value of one minute per day [14, 44, 45] and we conservatively value one hour of time as approximately \$15 [46]. In other words, one *util* is worth approximately \$20 per person per day based on these assumptions. With nearly 7 million people in the region, even small changes in *utils* lead to large economic losses. Since accessibility measures how easily people can get to the destinations they desire, accessibility is used as one of the measures of human welfare [e.g., 14].

Once the accessibility network performance measure is computed for each damage map, we aim to estimate the exceedance rate of different levels of performance. The annual rate, λ, of exceeding some threshold of network performance is estimated by summing the occurrence rates of all damage maps in which the performance measure exceeds the threshold:

$$\lambda_{X \geq x} = \sum_{j'=1}^{J} w_{j'} \mathbb{I}(X_{j'} \geq x) \tag{4}$$

where x is an accessibility value threshold of interest and $X_{j'}$ is the accessibility value realization for the j'^{th} damage map. The variable $w_{j'}$ is the occurrence rate of the j'^{th} damage map.The indicator function $\mathbb{I}$ evaluates to 1 if the argument, $X_{j'} \geq x$, is true, and 0 otherwise. By evaluating λ at different threshold values, we derive an exceedance curve (e.g., Figure 6).

Income class	Income range, 1989 USD	Income range, 2014 USD
Low	0 - $25,000	0 - $47,334
Medium	$25,000 - $45,000	$47,334 - $85,202
High	$45,000 - $75,000	$85,202 - $142,004
Very high	more than $75,000	more than $142,004

Table 1. Income class d[illegible]ase study region, as defined by the local planning organization, the MTC [45] and also translated to current 2104 USD us[illegible]lex.

2.4.2. Implementation

We compute accessibility using *Travel Model One* (version 0.3), an activity-based model used by the Metropolitan Transportation Commission (MTC), the local metropolitan planning organization (MPO) [47]. It represents the full road network as well as the public transit networks, biking, and walking. Travel demand data consists of the locations of different households in the case study area, their destination preferences and utilities, their number of vehicles, and their income and other demographic data [47, 45]. More details can be found in [48]. This data was collected by the MTC from surveys and census information. We assume that the distributions of travel preferences do not change after an earthquake, although the actual destinations and trips may vary. For example, if a trip takes a very long time after a simulated earthquake, it is less likely that ~~the~~ a person will choose to take the trip ~~will occur~~. The r[illegible]is a *variable* travel demand model. This model uses a combination of Java code called CT-RAMP [49], [illegible] Voyager and Cube Cluster software programs, which are part of a leading commercial software s[illegible]n planning [47]. This model differs from previous representations of this network [e.g., 9, 50], ~~since~~ it includes not only major roads but also local roads and transit lines. We have provided further details about computing mode-destination accessibility using this high-fidelity model in [17].

This analysis considers 40 interesting and hazard-consistent events, as defined by 40 sets of ground-motion intensity maps, damage maps, accessibility performance measure realizations, and corresp[illegible]s of occurrence. We selected this set of events with the optimization-based procedure ~~we~~ intro[illegible]ers are referred to [17] for more details about this set of events.

In the following sections, we first compare region-wide results, and then focus on p[illegible]icular characteristics of three communities ~~(Figure 1 shows the study area and three communities)~~. Finall[illegible]izable trends.

3. Results and Discussion

3.1. Overview of results region-wide

In this section, we analyze region-wide trends in accessibility l[illegible]es for the case study area. We fi[illegible]nalyze each of the 12 socio-economic groups used in practice for [illegible] [45]. These soci[illegible] correspond to all combinations of four ~~different~~ income cl[illegible] three ~~different~~ cla[illegible] availability in the household (zero automobiles, fewer a[illegible]omobiles than household members t[illegible]t work, ~~a greater or equal number of~~ as ma[illegible] automobiles ~~as compared to the number of~~ than household members that work).

We first assess the data availability for each of the segments. Each data point represents a trip by a person of a household, who is modeled as an agent in the high-fidelity transportation model. The results suggest co[illegible] holds with at least one car, because for households without cars (no cars), only the low income cl[illegible] many trips.

unclear. Plus you show all the cases!

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

First, we notice that the ratio of cars to the number of people who work in a household is correlated with accessibility risk; a higher ratio corresponds to higher expected decreases in accessibility. This corresponds to going across a column in Figure 3. For example, for the first row representing low income households, we notice a marked change in accessibility across the columns, as indicated by an expanded area of darkened TAZs from left to right (Figure 3(a-c)). Note that 1 *util* corresponds to a consumer value of compensating variation of approximately $20 per person per day, which assumes low (conservative) estimates of the value of time for travel delays and value of getting to destinations.

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

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

ok

consistent

Thus, for a given TAZ, the differences across incomes are not that great. At the same time though, there is an unequal geographic distribution of wealth in the San Francisco Bay Area. Because of this, when we aggregate accessibility risk across TAZs, we see that accessibility risk rises with increasing household income (Figure 6(b)). Therefore, even though the poor... tural disasters including hurricanes, floods ... ome

order figures

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now as 5: fig:scen_acc. 4 x2 maps. line 107 first reference. fig on line141

order on discuss them. This should be figure 5.

In co... the higher relative annual frequency of events on the Hayward Fault; this is correlated to bridge damage and thus road closures. Furthermore, the data suggests that both the more common moderate-magnitude East Bay events and the rare higher-magnitude San Andreas events can cause accessibility problems for the East Bay. Figure 5 shows one sample realization of a M6.85 Hayward event and one sample realization of a M7.45 San Andreas event—both follow the general trend of high predicted accessibility losses in the East Bay. In contrast, while any events could contribute to the risk in San Francisco, our model results show the main accessibility losses in San Francisco corresponding to the San Andreas events. Figures 5(c,d) provide one such example. Figures 5(e,f) show an example of a lower magnitude event farther away from the main population centers, a M6.35 event in the Great Valley Pittsburg-Kirby Hills Fault. This shows how the range of more minor faults in the East Bay can contribute to that area's risk. Also, we have shown the results for one socio-economic group in Figure 5, but the other socio-economic groups follow the same general patterns, albeit with different specific values.

Finally, we can examine the rates of loss exceedance (eq. 4). Figure 6 shows a similar shape to the loss exceedance curves for other metrics such as portfolio losses and travel time delay [17]. Note that the results are primarily valid in the 100 to 2475 year return periods, since this is the range chosen for the map selection optimization problem. Recognizing that the impact varies significantly by TAZ, as indicated by Figure 3, we also examine the accessibility loss exceedance curve for three communities: part of the San Francisco financial district, Danville, and Pacifica (Figure 1). These correspond to TAZ IDs 2, 1161, and 224 respectively. This part of the San Francisco financial district represents an area with relatively low expected changes in accessibility (Figure 3), whereas Danville and Pacifica are at an elevated risk in almost all socio-economic groups (Figure 3). The general trends are corroborated by the loss exceedance curves for these three communities (Figure 6(a) shows an example for the socio-economic group with medium income households with fewer cars than workers). In other words, the average middle-class person from Danville in a household with fewer cars than people who work is expected to experience travel-related losses up to 1 *utils* per day after a rare earthquake, which he or she values at approximately $20 per day considering a conservative estimate of travel time and destination value. In contrast, his or her fellow Bay Area resident in San Francisco has expected losses of only a tenth as much as experienced by a Danville resident. At return periods greater than 100 years, we notice that Danville and Pacifica follow a similar general pattern, which differs dramatically from that of San Francisco.

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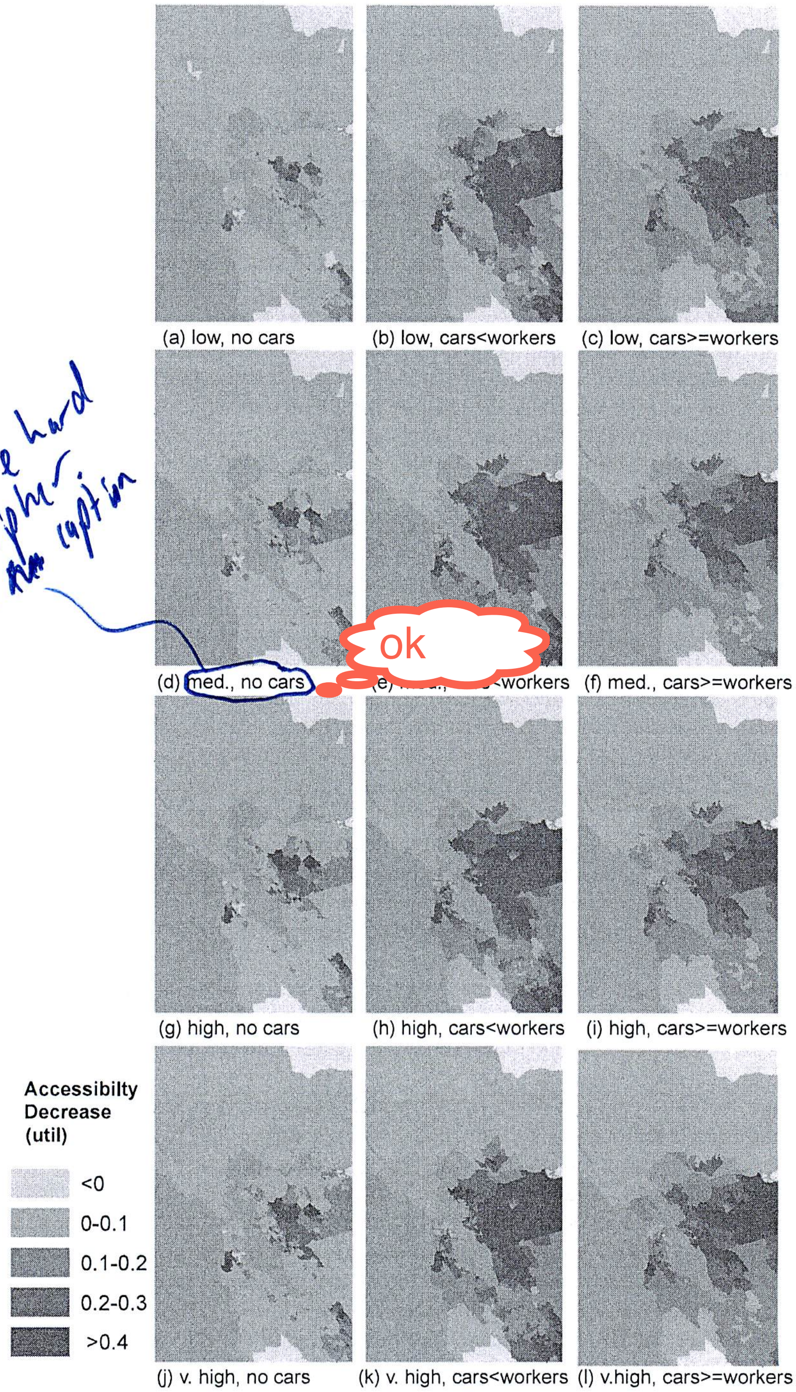

Figure 3. Expected changes in accessibility per person per day for each combination of income class and car ownership group. The darker the color, the greater the losses in accessibility.

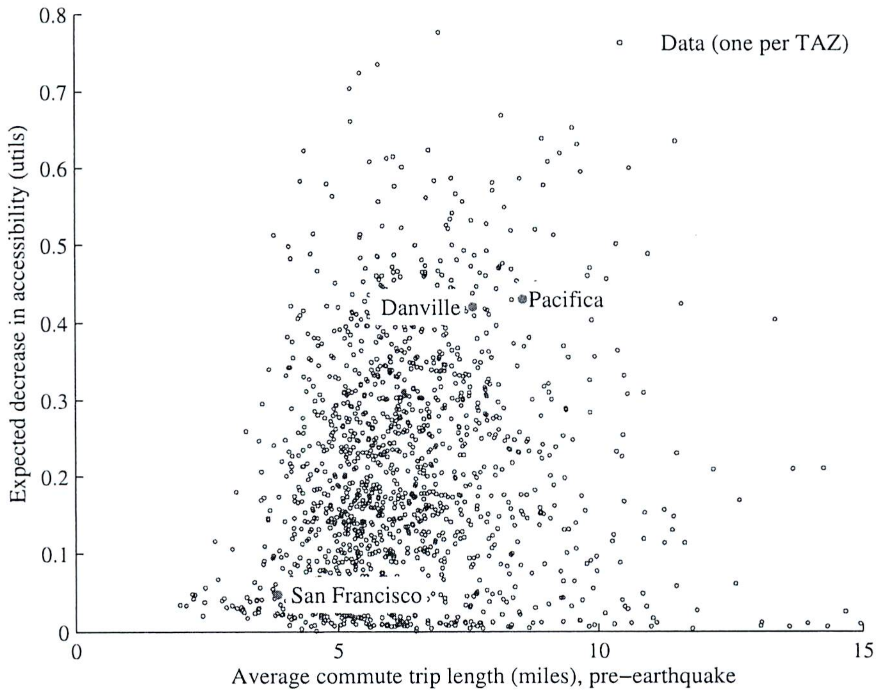

Figure 4. Trip length (pre-earthquake) versus change in total accessibility per person per day. Each dot represents data from one TAZ, and red dots highlight the data points for the three case study communities: San Francisco financial district, Danville, and Pacifica.

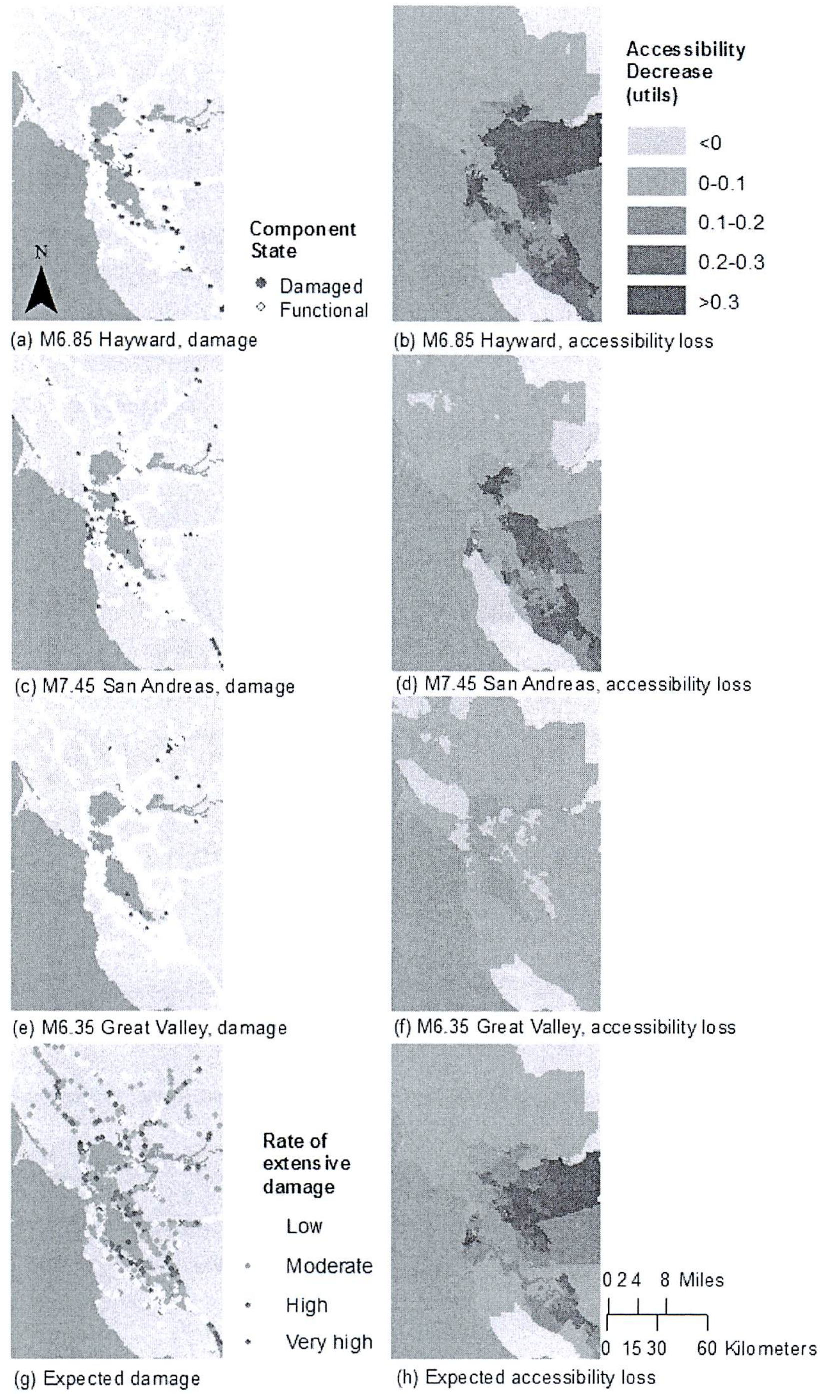

Figure 5. Bridge damage (red = damaged) and corresponding accessibility losses per person per day by TAZ for medium income households with fewer cars than workers. The bottom row has expected values calculated as a weighted average over all events.

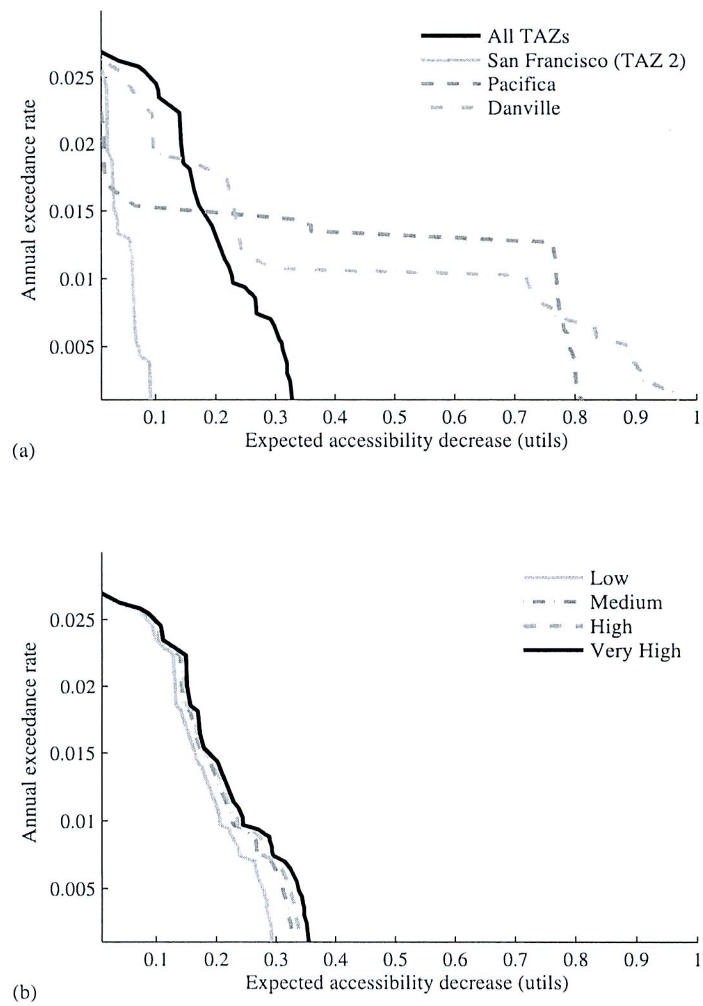

Figure 6. Accessibility annual loss exceedance curve with a comparison by (a) case study TAZs and average over all TAZs and (b) income class; all curves are in *utils* per person per day for medium income households with fewer cars than workers .

you can get rid of these everywhere

ok

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

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

Second, the average time for a trip to and from work is about average for a TAZ in this region and also follows a similar distribution to that of the other TAZs; the average trip distance for trips is only 7% lower than the average for all trips region-wide. Since the trip time and length are relatively typical, but the accessibility is much lower than average, the trip time and length do not explain the differences in accessibility losses.

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

ok throughout to removing CA

3.3. *Analysis for Pacifica, ~~CA~~*

We might not suspect that Pacifica, ~~CA~~ would be at an extremely elevated risk of accessibility losses across most market segments, as compared to other communities, because it is not unusually close to a major earthquake fault. In addition, the percentage of pre-earthquake car-based trips is around average for the case study area (88% versus an average of 85%). In contrast to most other regions, however, Pacifica is wedged between the Pacific Ocean to the West and the coastal mountains to the East. Indeed, the main access road is California Highway [illegible] has various vulnerable bridges included in the case study dataset. There are no viable alternative rou[illegible] Since almost all trips are by car from Pacifica and the average trip length is much longer than the re[illegible] (108% longer), the road issue is particularly serious.

It's right on top of the San Andreas!!

TODO

As a comparison, consider the next main town along the Pacific coast, Half Moon Bay, about 13 miles South. Half Moon Bay has significantly lower expected accessibility losses compared to Pacifica (0.11 *utils* per day for a person in Half Moon Bay in middle income household with fewer cars than workers, given an event in the dataset, versus 0.43 *utils* per day for a similar person in Pacifica). While the seismic hazard is similar, the population is about one third the size, so there is less demand for the limited road capacity [51]. Furthermore, and likely most significantly, Half Moon Bay has a key alternative to California Highway 1, California Highway 92, which links to Silicon Valley and the main highways of that region (US-101 and I-280). Our results indicate that since Pacifica, CA is unusually reliant on one road with key vulnerabilities for access, it has an elevated risk for losses in accessibility.

3.4. *Analysis for Danville, ~~CA~~*

We will first examine the trip length characteristics for Danville, ~~CA~~. The distribution of pre-earthquake commute trips from Danville, ~~CA~~ is shifted towards both longer distance and longer time than the communities we have studied so far; for example, the average length of a trip from Danville is 85% longer than the average over all trips originating from any TAZ. More specifically, there is a relatively higher proportion of trips taking 60-74 minutes and traveling over 40 miles than in the other communities. The consequence of these longer trips is more opportunities to be impacted by a road closure, simply because more roads and bridges will be used. Moreover, the road layout near Danville, CA mandates many highway trips, which increase the likelihood of crossing bridges; bridges are the part of the network for which we model the vulnerability.

Next, we look at patterns of expected bridge damage. Bridge damage is important for many regions, including Danville, because the percentage of car-based trips is high (85% of all trips on average, and also 85% of Danville-origin trips). For damage map realizations for the three earthquake events we introduced—M6.85 Hayward Fault, M7.45 San Andreas Fault, M6.35 Great Valley Fault—some bridges in the Oakland area are in the extensive or greater damage state (Figure 5(a,c,e)). These correspond to bridge closures in the model. In addition, in the first two cases, there are closures to the north of Danville, which represents one of the two main travel routes from Danville. There are also scattered closed bridges to the west of Danville, a top travel corridor for people of Danville because of

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 2. 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).

the workplace centers in San Francisco, Oakland, and Silicon Valley (all to the west). As for transit, in the first two events, all BART lines are closed, so there are limited alternatives to the popular road routes. The result is that the residents of Danville, CA have reduced access to their normal destinations after all these events.

We can also look at bridge damage in a probabilistic event-set-based manner. The expected damage over all events represents the annual rate of a bridge being in the extensive or complete damage state for an extensively-sampled, hazard-consistent set of 113,940 damage maps (Figure 5(g)). This figure indicates that bridges in the Oakland-Berkeley area ~~are particularly~~ likely to be damaged. We also see a few high likelihood bridges to the North of Danville. Thus, the data suggests that the relative position of high-risk bridges to Danville contributes to this community's accessibility risk.

It's tricky to bring this in here. Can you just use your 40 maps? That would be simpler to explain and more internally consistent

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

First, we compare patterns of transit system damage with patterns of travel mode shifts after earthquake events.
Over all the simulated events, taking a weighted average by th ... lihood of each event, we see a reduction in
transit ridership (25% weighted average decrease from ... prising. The heavy rail systems
(BART and Caltrain) are n ... heavy
ridership. The light rail s ... It is
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respec ... Haywa ... pact. Similarly, the
transit i ... nt. This Northe ... had o ... nes, all Caltrain, and all
Light Rail lines not operational, whereas this Hayward Rogers-Creek event had all 14 of the 14 BART lines,
Caltrain, all VTA Light Rail and 3 of the 8 Muni light rail lines not operational. Thus, the Hayward Rodgers-Creek event featured significantly higher losses to the transit network. Moreover, the differences in accessibility results could not have been predicted from simpler models focusing on bridge portfolio losses, because the percent of damaged bridges was about the same, and the San Andreas event actually corresponded to a greater increase in fixed-demand travel time.

It's hard to re-create figures now that I don't have access to the iMac. Doing it with the 40 maps also means doing new calculations.
I've tried deleting the number.
If it's still a problem, however, one option would be to connect the iMac to wifi and I could make the fixes by logging in remotely.
Not too bad! Another option would be to figure it out from the backed-up files.

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 8). 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 [7]. In conclusion, the data suggests that TAZs, i.e. communities, which have a greater walkability are also more resilient to earthquake-related accessibility risk.

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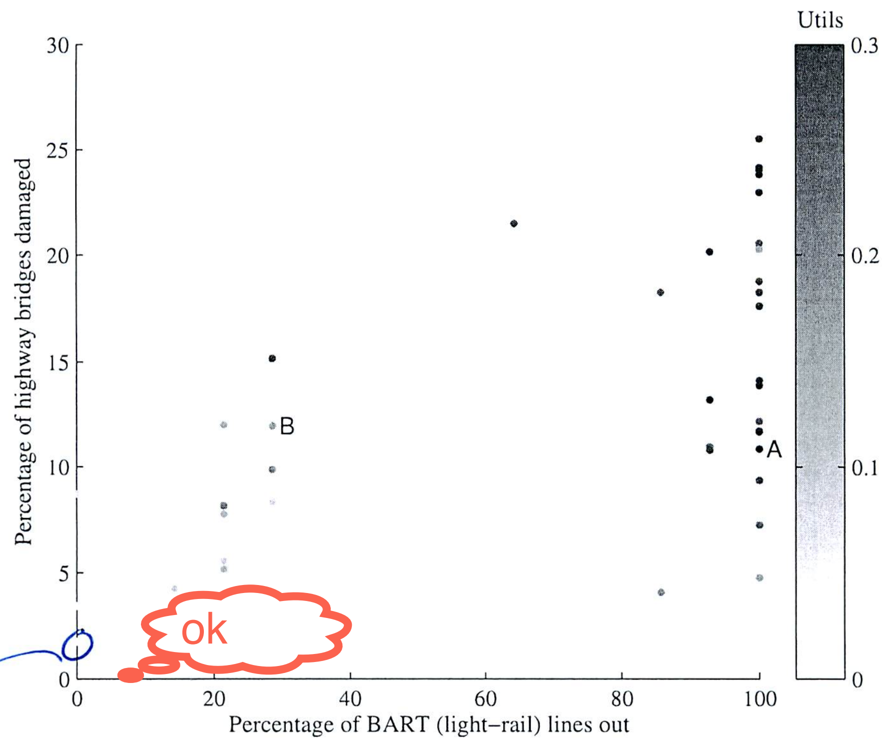

Figure 7. Percentage of BART (heavy-rail) lines not operational versus percentage of highway bridges damaged, where each data point corresponds to one earthquake damage map. The values are color-coded by the average loss in accessibility per day per person over all TAZs for households with the fewer cars than people who work. Two events discussed in this section are marked by the letters A and B.

use your new version of this figure with circles around the points

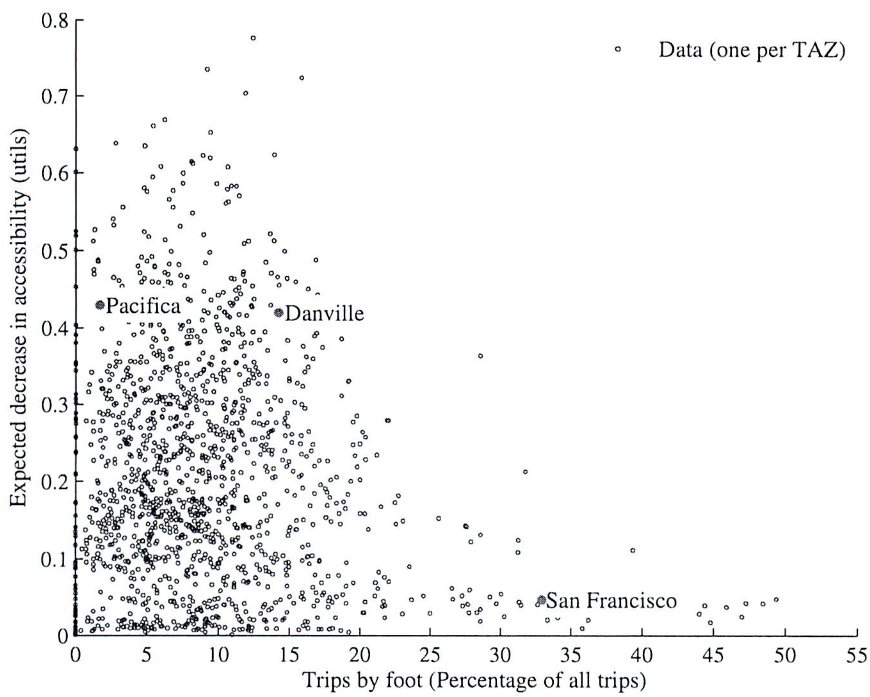

Figure 8. Percentage of total trips by foot (pre-earthquake) versus decrease in total accessibility, measured in *utils* per day (for households with the number of cars less than the number of workers). Each dot represents data from one TAZ, and red dots highlight the data points for the three case study communities: San Francisco financial district, Danville, and Pacifica.

4. Conclusions

Here we have shown how mode-destination accessibility links post-earthquake infrastructure damage to the impact on human welfare and enables identifying at-risk geographic and demographic groups in a region. Adopting this state-of-the-art performance metric from the urban planning community, we have illustrated its use for seismic risk assessment and mitigation through a case study of the San Francisco Bay Area. For the case study, we consider a set of 40 hazard-consistent earthquake scenarios, ground-motion intensity maps, damage maps, and corresponding annual rates of occurrence. For each damage map, we processed the data for analysis in a high-fidelity, activity-based travel model that includes the road network, transit networks, walking and biking options, variable travel demand, and mode choice. We used this data and model to compute the mode-destination accessibility, a performance measure for each community and each socio-economic group (defined by income class and car ownership).

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

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

In conclusion, mode-destination accessibility offers important applications for further investigation into the impact to human welfare of engineering losses and mitigation efforts. This work lays the foundation for future work in risk mitigation and policy to reduce the vulnerability of at-risk communities. It also suggests that initiatives making communities more conducive for cycling and walking to work can increase resiliency.

Thanks!

Nice conclusion!

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