PROBABILISTICALLY ACCOUNTING FOR BUSINESS INTERRUPTION AND BRIDGE DAMAGE IN ROAD NETWORK PERFORMANCE

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Abstract: *Both building and bridge damage can affect the post-earthquake performance of a regional road network. Bridge damage may render routes impassable or reduce their capacities until repairs can be made, changing how drivers navigate. Building damage may displace people from their homes and communities and alter their origins or destinations. The severity and pattern of post-earthquake road network disruption will also evolve as bridges and buildings are repaired and people adjust their movements. For example, people who previously drove between their homes and workplaces may choose not to commute because all reasonable routes between the two are impassable due to bridge damage or because their workplace is not functional due to building damage. The consequences of people not being able to access their workplaces may have significant and longer-term implications for a region's economic recovery. Methods for quantifying post-earthquake road network disruption often neglect the changes in demand between origins and destinations that may arise from changes to the damage states of buildings in those locations. For example, the post-earthquake origin-destination (OD) matrix for a road network may be assumed to be the same as the pre-earthquake OD matrix. While predicting where people might relocate or want to go is complex, this assumption may result in inaccurate estimates of the benefits of seismically retrofitting bridges. We present a probabilistic method for simulating the effects of post-earthquake bridge damage and post-earthquake business interruption due to building damage on commuter traffic in a region. In the proposed method, we modify the OD matrix for a region to account for how business interruption due to building damage will affect commuters using HAZUS data. Through a case study of the San Francisco Bay Area, we show how the proposed method can be integrated into probabilistic seismic risk assessment frameworks and regional recovery simulations. The proposed method illuminates whether bridges or buildings are driving post-earthquake road network disruptions, enabling decision-makers to address the root cause of those disruptions by allocating limited retrofit budgets more effectively.*

1 Introduction

Given the diversity of impacts attributed to post-earthquake road network disruption, methods for seismic risk assessment of road networks are similarly diverse in terms of the measures of road network disruption they use as decision variables or as bases for computing decision variables, in addition to varying in terms of their geographical scale, time frame considered (e.g., emergency response or long-term recovery), and the needs they aim to address (e.g., emergency planning, network expansion, risk mitigation) (e.g., Argyroudis et al., 2015; Faturechi & Miller-Hooks, 2015). Approaches to quantifying the impacts of road network disruption fall into three categories of increasing computational complexity: topological approaches characterize the road network using graph theoretic metrics like connectivity, which indicates how well origins and destinations in the network are connected; functional approaches characterize the level of service provided to users of the road network using measures like travel time, travel distance, mode-destination accessibility, and flow; and economic approaches aim to estimate the economic losses incurred by post-earthquake road network damage (Chang et al., 2012; Chang, 2016; Faturechi & Miller-Hooks, 2015; Miller, 2014).

Seismic risk assessments can use these measures of disruption directly – for example, travel time is the most commonly used decision variable in the literature on transport infrastructure system performance in disasters (Faturechi & Miller-Hooks, 2015). Measures of disruption can also serve as inputs to a cost model (Argyroudis et al., 2015). Cost models typically sum two types of cost (or loss): the cost of restoring the functionality of damaged components (i.e., direct costs) and the costs associated with ongoing network disruption while damaged components undergo repair (i.e., indirect costs) (Hackl 2018; Dong et al., 2014; Kiremidjian et al., 2007). Classical sources of indirect costs include travel time delay (the increase in time required to make all trips demanded on the damaged road network compared to normal conditions) and unmet demand (Hackl 2018; e.g., Deco & Frangopol, 2013). Proposed additions to the category of indirect costs typically focus on societal impacts of road network disruption and include costs associated with the lost economic value of activities (e.g., working or shopping) not performed when trips are not made (Zhou et al., 2010), accidents that result in casualties (Deco & Frangopol, 2013), road network operations (Deco & Frangopol, 2013), carbon dioxide emissions, fatalities following an earthquake (Dong et al., 2014), and energy waste due to repair of damaged components (Dong et al., 2014).

While travel time delay and the cost of road network performance can be useful measures of disruption, they may not improve our understanding of how network disruptions impact individuals or different groups of network users. If used as a decision variable, travel time delay implicitly assumes that all travellers have an equal value of time (VoT). VoT quantifies the willingness of a traveler to pay to reduce the time they spend in transit by one unit and is also referred to as the subjective (or behavioural) value of travel time (SVTT), and the subjective (or behavioural) value of travel time savings (e.g., Jara-Diaz & Guevara, 2003; Small, 2012). A traveller may be willing to pay to reduce the time they spend in transit because transit itself has low utility (i.e., they derive little satisfaction or pleasure from transiting) or because they could spend the time saved in more pleasurable or more useful (i.e., utility-enhancing) ways (Mackie et al., 2001). VoT can depend on qualities of the trip, such as its purpose (for work or for recreation), mode (e.g., car or bicycle), duration, or the time at which it is made (Mackie et al., 2001; Small & Verhoef, 2007). VoT can also vary depending on the characteristics of travelers themselves, including their individual preferences, demographic characteristics (e.g., age, sex, level of education, employment), and hourly income (Belenky, 2011; Small & Verhoef, 2007). Similarly, models of indirect cost in which travel time delay is multiplied by a single VoT to arrive at a monetary loss (Hackl2018) do not account for variations in VoT or for the diminishing marginal utility of income.

If the characteristics of travellers that affect their VoT are not accounted for when traffic on the road network is simulated, subsequent disaggregation of travel time delay (or other summary measure of network performance) by those characteristics is not possible. Disaggregation of network performance measures is necessary to conduct equity analysis, the goal of which is to understand how fairly and/or justly the impacts of a particular policy – i.e., its costs and benefits – are distributed among members of society, including both users and non-users of the road network (Bills & Walker, 2017; Litman, 2002). Equity analysis is particularly important in light of historically inequitable transport planning processes and outcomes that have resulted in less-advantaged members of society having experienced disproportionately high shares of the costs and disproportionately low shares of the benefits of transport projects (e.g., Bills & Walker, 2017).

Disasters are widely acknowledged to exacerbate existing societal inequities (e.g., Lindell & Prater, 2003), and assessing and limiting inequities in transport systems has been the subject of state and federal legislation in the US (Bills & Walker, 2017). Therefore, how risk assessment methods for road network account for impacts on different groups of people should be a key concern for researchers, given its importance to decision-makers. In transport systems, equity has two primary dimensions: horizontal equity considers how impacts are distributed among groups that are deemed equal in ability and need, while vertical equity considers how impacts are distributed among groups that differ in ability and need, e.g., people of different income levels (Bills & Walker, 2017). For example, Miller and Baker (2016) conduct a vertical equity analysis by examining how an individual's income class (low, medium, high, or very high) and their household's ratio of cars to workers affect their expected post-earthquake mode-destination accessibility decrease in the San Francisco Bay Area.

We previously presented a method for better characterizing the impacts of post-earthquake road network disruption on individual network users within a probabilistic seismic risk assessment framework (Silva-Lopez et al., 2022). We used welfare loss (as formulated by Galvez and Jara-Diaz (1998)) as a measure of road network performance within a probabilistic seismic risk assessment framework. Welfare loss (in units of utils) describes the value to society of individual travellers' increased travel times and is a function of increased travel times as well as travellers' SVTT, their marginal utilities of income, and the value placed by society on the utility of individual travellers (Mackie et al., 2001). As a summary statistic of network performance, welfare takes into account that the same change in commute time can impact commuters with different characteristics in different ways. Setting up the seismic risk assessment of a road network such that welfare losses can be computed also enables the disaggregation of summary statistics such that the impacts of disruptions on different groups can be articulated – a necessary prerequisite for devising more equitable network management policies.

In this work, we continue to think about how metrics of road network disruption can better capture individuals' experiences. While disruptions to workplaces are often framed in terms of business interruption, being unable to access workplaces may also have consequences for individuals' livelihoods. In a study of transport-related business impacts of the 1994 Northridge earthquake, Gordon et al. (1998) surveyed individual commuters, who reported missing an average of 11.2 days of work after the earthquake due to damage to the work site, damage to their residences, and/or damage to their commute route, among other reasons. Connectivity losses may capture this disruption, but only in aggregate terms. Accounting for post-earthquake demand changes has been an area of substantial interest in the literature. One approach is to re-assess the trip generation model by modifying trip production (or push) and attraction (or pull) factors throughout the area of interest. For example, Guo et al. (2017) create a static origin-destination matrix for the immediate post-earthquake demand based on a gravity model that considers damaged facilities and evacuated households as push factors and medical care and emergency shelters as pull factors. A common way to model post-earthquake traffic demand is to simply scale the pre-earthquake origin-destination demand data. For example, Kilanitis and Sextos (2019) scale the pre-earthquake origin-destination demand matrix by a factor between 0 and 1 that varies with the time that has elapsed since the earthquake, thereby reflecting restoration of the network capacity and the resumption of pre-earthquake traffic patterns. This scaling assumes that the changes in traffic that follow an earthquake consist solely of decreases in traffic volume, not shifts in underlying patterns.

In this study, we directly explore how post-earthquake road network disruption and business interruption resulting from building damage affect commuters' ability to access their places of work at a regional scale. We propose a method for modelling shifts in commute demand that may occur after an earthquake. In this method, we modify the demand on the road network by excluding the trips of commuters whose workplaces remain interrupted due to building damage at the time of interest post-earthquake. We then assess how many commuters' trips exceed their maximum acceptable commute time, a measure of road network performance that we refer to as the number of jobs affected by road network disruption (as distinct from those jobs affected by building damage).

2 Methods

We integrate two measures of road network performance – welfare loss and the number of jobs affected by roda network disruption – with an established event-based probabilistic seismic risk assessment framework. We previously integrated welfare loss into a probabilistic seismic risk assessment framework (Silva-Lopez et al. (2022)). Figure 1 shows how we extend previous frameworks to account for the number of jobs affected by road network disruption.

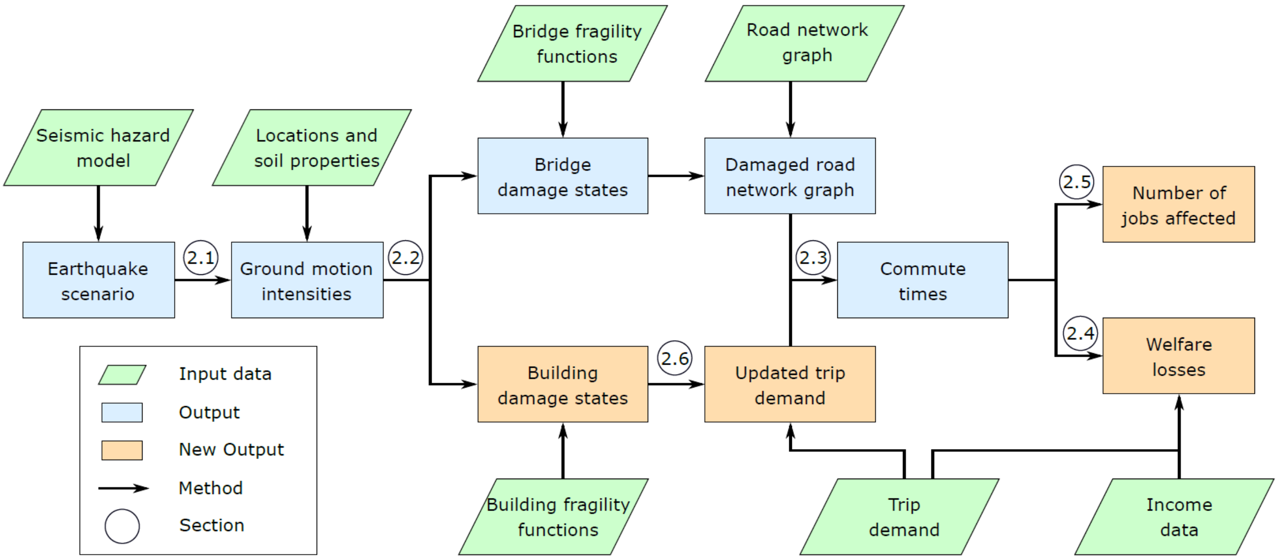

Figure 1 -- Diagram summarizing the evaluation of the impact of an earthquake scenario on users of the road network.

2.1 Ground-motion intensity maps

The first step involved in the seismic risk assessment of road networks is to use a seismic source model to generate n_s earthquake scenarios that are consistent with the seismic hazard of the region where the road network is located. This seismic source model provides the rates, locations, faulting-types and magnitudes of earthquakes that can occur in the area. For each earthquake scenario j, a ground-motion model (GMM) is used to model the ground-motion intensity IM at each location of interest b. A GMM predicts the mean of the log ground-motion intensity ($\ln Y$) as well as the ground-motion intensity within- (σ) and between-event (ϵ) residual standard deviations. A GMM is function of many inputs, including the moment magnitude of the earthquake scenario M_j, a metric of distance from location b to the fault plane R_{bp}, and the average shear wave velocity down to 30 meters at the b^{th} location $V_{s30,b}$. For each j of the n_s earthquake scenarios, m ground-motion intensity maps can be sampled by sampling m realisations of the spatially-correlated ground-motion intensity residual terms (Han and Davidson (2012) provide a survey of sampling methods). The set of $n_s \times m$ ground-motion intensity maps is indexed using n (i.e., $n = 1, \ldots, n_s \times m$). Given the residuals, the total log ground-motion intensity at a bridge b in a particular scenario n can be computed per the following equation,

$$\ln Y_{bj} = \overline{\ln Y(M_j, R_{bp}, V_{s30,b}, \ldots)} + \sigma_{bj}\epsilon_{bj} + \tau_j \eta_j$$

where σ_{bj} is the within-event residual standard deviation, ϵ_{bj} is the normalized within-event residual in $\ln Y$, τ_{bj} is the between-event residual standard deviation, η_j is the normalized between-event residual in $\ln Y$, and the other parameters are as described above. Both ϵ_{bj} and η_j are standard normal random variables. ϵ_{bj} represents location-to-location variability; its vector can be modelled using a spatially-correlated multivariate normal distribution. η_j represents between-event variability; its vector can be modelled using a standard univariate normal distribution. This procedure produces a set of $n_s \times m$ ground-motion intensity maps. The annual rate of occurrence for the k^{th} ground-motion intensity map is the original occurrence rate of the associated earthquake scenario j_s divided by m, since there are m ground-motion intensity maps simulated for every earthquake scenario.

2.2 Damage maps

For each ground-motion intensity map, we sample a damage map which can be expressed as a vector of *B* binary variables, each indicating the functionality of a bridge or building. The probability that a component experiences a damage state that reduces its normal functionality given a particular ground-motion intensity can be quantified using a fragility function, as given in the following equation.

$$P\left(DS_b \geq ds \middle| Y_{bj} - y\right) = \Phi\left(\frac{\ln\left(\frac{y}{f_b}\right)}{\beta_b}\right)$$

where Y_{bj} denotes the ground-motion intensity at site b in ground-motion intensity map j, Φ denotes the standard normal cumulative distribution function, and $\ln f_b$ and β_b are the mean and standard deviation, respectively, of the $\ln Y_b$ value required to cause the damage state of interest, ds, to occur or be exceeded for the b^{th} component. Bridge damage results in partial or total closure of the roads carried by the damaged bridge, while building damage result in business interruptions. More severe damage results in greater loss of functionality.

2.3 Model of road network performance

A traffic model typically includes four sub-models for trip generation, trip distribution, modal split, and traffic assignment, in that order (Patriksson, 2015). The case study in the following section uses a simplified traffic model that takes advantage of publicly available empirical data on commuters' residences and places of work at the census block level to replace the trip generation, distribution, and modal split sub-models. However, more complex traffic models are compatible with the proposed method for evaluating road network performance. Here we briefly describe the simplified traffic assignment procedure used in the case study.

Traffic assignment model

A traffic assignment model takes as input a directed graph of the road network, *G*, and the demand between a set of origins and destinations. It returns measures of road network performance, such as the aggregate travel time, total vehicle-miles travelled, and the number of completed trips. The road network graph comprises a set of vertices, *V*, and a set of edges connecting them, *E*. Each edge has associated properties – including length, capacity in vehicles per unit of time, free-flow traversal time, and flow (the number of vehicles assigned to it by the traffic assignment model) – that determine how quickly vehicles traverse it. The traffic assignment model assigns trips to edges according to a rule or set of rules. A common rule is to assign trips to the shortest-time path between an origin and destination. Assigning trips to edges within a path modifies their properties, e.g., increasing their traversal times. The demand on the road network can be defined in an origin-destination matrix, a two-dimensional array in which each element is the number of trips desired between a particular origin and corresponding destination in a given time period.

Road network performance

Once the traffic assignment model has distributed trips to edges within the road network, the aggregate travel time, *T*, can be computed using the following equation:

$$T = \sum_{e \in E} q_e t_e$$

where *e* is an edge in the set of all edges in the network, *E*, q_e is the flow over edge *e*, and t_e is the traversal time over edge *e*. The change in aggregate travel time on a version of the road network that includes damaged bridges compared to the undamaged road network is determined by computing *T* for each version of the road network and calculating their difference.

2.4 Welfare model

To better capture how the travel time delays previously described impact network users with different characteristics, we previously adopt the welfare model presented by Mackie et al. (2001) (Silva-Lopez et al., 2022). This welfare model weights the change in a network user's travel time by factors that account for how valuable the time saved or additional time spent is to the particular user, as determined using information about their individual earnings. This model is particularly useful because it can be used with traffic models of varying sophistication, from the traffic assignment model used in the example of Section 3 to more sophisticated activity-based travel demand models that planners may wish to use. To implement the welfare model of Mackie et al. (2001), we first augment the origin-destination matrix that is an input to the traffic model with information about the individual earnings of each traveler. Information on commuters' incomes is necessary to estimate the change in welfare, ΔW , as defined by Mackie et al. (2001) in the following equation,

$$\Delta W = \sum_{q} \Omega_q \lambda_q SVTT_q \Delta T_q$$

where ΔW is the change in welfare, q denotes different income groups, Ω_q is a weight assigned to group q, $\lambda_q$is the marginal utility of income among members of group q, $SVTT_q$ is the subjective value of travel time for members of group q, and ΔT_q is the change in the aggregate travel time of members of group q. Further details of the welfare model are given in Silva-Lopez et al. (2022).

2.5 Impact of business interruption on commutes

Building damage can lead to business interruptions, which in turn reduce the number of commuters using the road network: commuters who know their workplace has sustained significant damage will not drive to work (e.g., Gordon et al., 1998). To capture this effect, the damage state of each building is used to obtain its business interruption time, which depends on the building occupancy type (e.g., Federal Emergency Management Agency, 2015). Realizations of building damage are obtained simultaneously with realizations of bridge damage. The performance of the road network is estimated for a particular time of interest, defined as the number of days post-earthquake. People who work in buildings with business interruption times greater than this number of days are removed from the demand on the road network. This process could be repeated at multiple times of interest to estimate demand as businesses recover functionality. Since the number of workers is typically known at the census tract level rather than for each building, the number of workers who stop using the road network is assumed to be proportional to the fractional loss of building space in the census tract. Thus, the updated number of commuters that need to travel to a destination *D* is:

$$d'_{\cdot D} - d_{\cdot D}\left(1 - \frac{\sum_{i=1}^{n_D} f_i s_i}{\sum_{i=1}^{n_D} s_i}\right)$$

Where $d_{\cdot D}$ is the number of people who work in census tract *D* in normal conditions, n_D is the number of buildings in census tract *D*, s_i is the number of stories of a given building, and f_i is a binary variable equal to 1 if building *i* has business interruption and 0 if not. To use these results ot reduce the trip demand as described by the OD matrix, the people who stop using the road network also need to be assigned to an origin census tract. The assignment is assumed to be proportional to the trip demand under normal conditions. In other words, at each destination census tract, the number of people that stop commuting from all other census tracts is assumed to be proportional to the original number of commuters. Thus, the updated demand from all origin-destination pairs is computed as:

$$d'_{OD} - d_{OD}\frac{d'_{\cdot D}}{d_{\cdot D}}$$

where d_{OD} is the demand between origin *O* and destination *D* in normal conditions. Through direct modification of the OD matrix demand due to building damage, we can explicitly distinguish commutes that are made longer due to bridge damage to those that are not made due to business interruption. We refer to the former as jobs affected by road network disruption (*J*), or simply jobs affected, and describe how to compute them in the following subsection. By modifying the demand on the road network in this fashion, we can better distinguish the post-earthquake traffic disruptions that can be mitigated by improving the resilience of the road network from those that are a consequence of building damage. Drawing this distinction can help set expectations for what different seismic risk mitigation strategies can reasonably achieve.

2.6 Jobs affected by road network disruption

To quantify the number of jobs affected by road network disruption, J, we assume that a person will commute if the utility of going to work exceeds the utility of staying at home. The longer the commute, the smaller the utility associated with commuting. The behavioral mechanisms that define an individual's exact willingness to commute are complex and further complicated by the post-earthquake context that we are modeling. For this study, we use a simple model to characterize individuals' willingness to commute: if an individual's commute time from an origin O to a destination D, t_{OD}, exceeds a universal maximum acceptable commute time t_{max}, then that individual will not commute and their job will be counted as affected by road network disruption. This model is similar to that used by Kroll et al. (2020), who compare a commuter's travel time after an earthquake to their optimal commute time to determine whether said commuter would find the change in time acceptable and still make the trip. This model for the number of jobs affected by road network disruption is given in the following equation,

$$J_{OD} = \begin{cases} 1 \text{ if } t_{OD} \geq t_{max} \\ 0 \text{ if } t_{OD} < t_{max} \end{cases}$$

where J_{OD} is an indicator for whether the job of the worker going from O to D is affected (1) or not (0). In the case study of the following section, we use a maximum acceptable one-way commute time of four hours for all commuters, based on the assumptions (consistent with those made in the economic data we use) that each worker has an eight-hour work day, requires eight hours of rest, and returns to their home after work, leaving a maximum of eight hours in which to travel from home to work and back. More complex models of individuals' willingness to commute may better capture individual sentiment; the proposed method is compatible with these more sophisticated models.

3 Case Study: San Francisco Bay Area

We use the nine-county San Francisco Bay Area as a testbed in which to demonstrate the proposed method and the potential insights that could be gleaned through its implementation and use.

3.1 Ground-motion intensity and damage maps

For this case study, we generate one ground-motion intensity map and corresponding damage map for a 7.0 Mw rupture on the Hayward Fault. We simulate spatially- and cross- correlated ground motions at all 1743 bridges and at all 1582 census tract centroids in the Bay Area, based on the 2010 census. The ground-motion intensity measure for the maps used to simulate bridge damage is the 5%-damped pseudo absolute spectral acceleration (Sa) at a period of 1 second, the required input to the bridge fragility functions provided by Caltrans (Miller, 2014). The ground-motion intensity measure for the maps used to simulate building damage is the peak ground acceleration (PGA), which is used as the input to HAZUS building fragility functions (Federal Emergency Management Agency, 2015). To model spatial correlation we used the model proposed by Jayaram and Baker (2009), and to compute cross correlations between PGA and Sa = 1s, we used the study developed by Loth and Baker (2013). We assumed that all buildings in a particular census tract experience the same ground-shaking in a particular scenario. To reduce the computational burden of this analysis, a hazard-consistent subset of a full earthquake rupture forecast could be obtained using an optimization procedure such as that detailed by Han and Davidson (2012) or Miller (2014).

3.2 Traffic assignment model

Graph of road network

The San Francisco Bay Area road network is modelled as a directed graph G ~ (V,E) and shown in Figure 2 (Miller 2014). The road network includes 1743 state-owned highway bridges, and the region contains 2,129,609 buildings, resulting in a total of 2,131,352 components whose damage we simulate. Each edge in E has properties that determine its traversal time given a traffic volume according to the commonly used Bureau of Public Roads travel time function,

$$t_a = t_f(1 + 0.15\left(\frac{q_a}{c_f}\right)^4)$$

where t_f denotes the free-flow travel time, t_a denotes the capacity-dependent travel time, c_f is the hourly capacity, and q_a is the hourly flow on the edge (Bureau of Public Roads, 1964). All bridges in the road network are associated with edges in E. To model a complete road closure due to a damaged bridge, the associated edges are modified to have an hourly capacity $c_f = 0$ and both free-flow and capacity-dependent travel times $t_f, t_a = \infty$ to ensure no trips are assigned to those edges.

Demand on road network

We obtain the demand on the road network from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) data set, Version 7.5 (U.S. Census Bureau, 2010). The LODES data set tabulates the census tract in which a commuter lives, the census tract in which they work, and their membership in one of three income groups (low, medium, or high) based on their annual individual earnings (U.S. Census Bureau, 2010). We can therefore define an origin-destination matrix for the region of interest in which each trip is associated with the income group of the commuter demanding it. Since the edge capacities of the linksin G are hourly, we scale the daily demand by a factor of 0.21 to get the hourly demand during the 6 am - 10 am window, a peak commuting time (Wang et al., 2012).

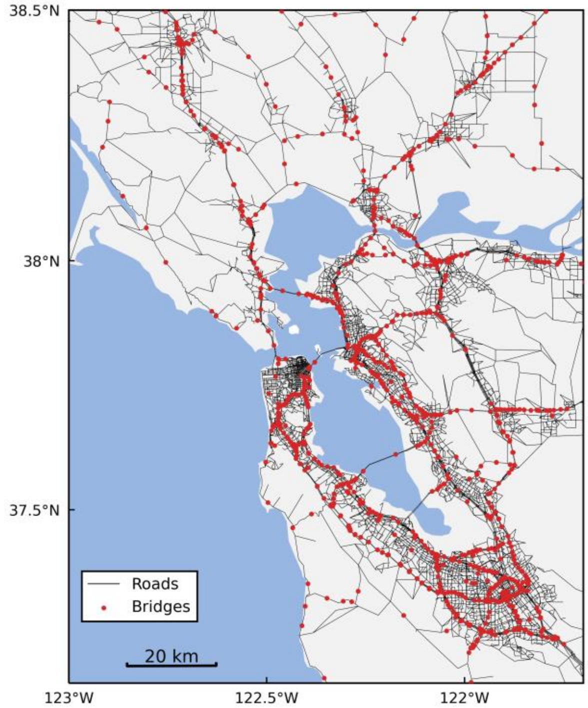

Figure 2 -- Map of the San Francisco Bay Area road network used in this study (Miller, 2014).

3.3 Results

Figure 3 shows the number of trips lost by origin census tract immediately following a 7.0 Mw earthquake on the Hayward Fault when the original origin-destination matrix is used (left) and when the origin-destination matrix is modified to account for business interruption (right). We observe that when business interruption is considered in the origin-destination matrix, the number and spatial distribution of trips lost is different than when traffic is simulated using the origin-destination matrix derived under normal circumstances. For example, the number of lost trips that begin in census tracts north and east of the San Francisco Bay is markedly reduced when the origin-destination matrix is modified to account for business interruption as compared to when the origin-destination matrix is left unchanged. This suggests that many trips originating in those areas are more affected by building damage than by bridge damage, at this particular point in the post-earthquake timeline. In contrast, the number of trips lost that originate along the southern edge of the San Francisco Bay is largely unchanged when the origin-destination matrix is modified to account for business interruption. This suggests that trips originating in the southern part of the study area are more impacted by bridge damage than by business interruption.

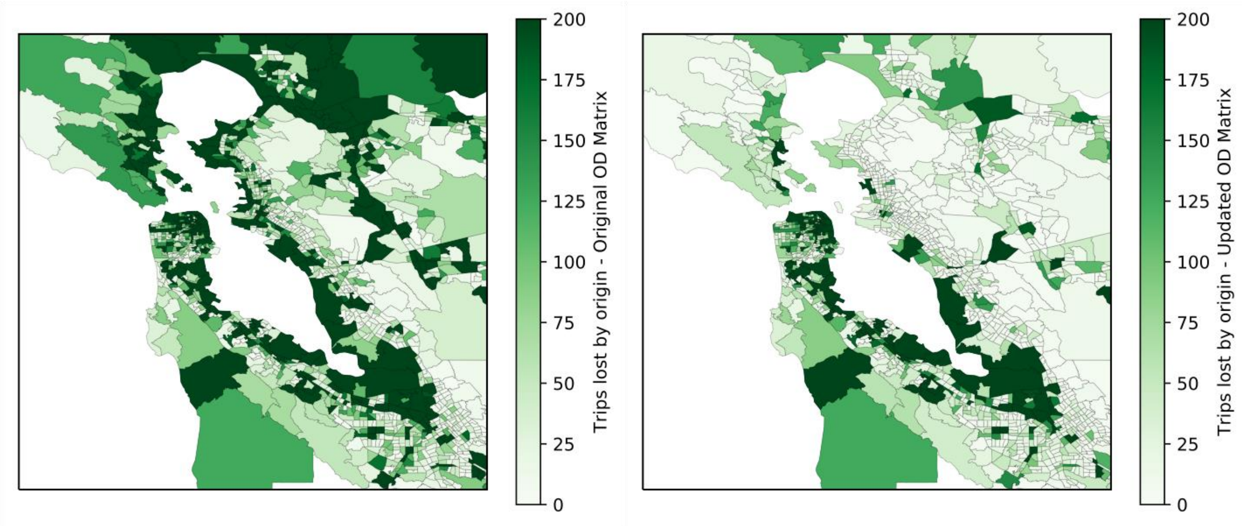

Figure 3 – Maps of the San Francisco Bay Area showing the difference in the number of lost trips at the census-tract level when the original OD matrix is used (left) and when the modified OD matrix, which accounts for building damage and resulting business interruption, is used (right).

4 Discussion and Conclusions

In this work, we present a rational method for modifying the demand on a road network after an earthquake to account for how business interruptions stemming from building damage will affect commuters. A case study of the San Francisco Bay Area immediately following a 7.0 moment magnitude earthquake on the Hayward Fault shows that accounting for the change in commute demand on a road network due to business interruption at commuters' workplaces can have significant impacts on both the magnitude of the number of trips that cannot be made on the road network and the spatial distribution of those lost trips. While we demonstrate the proposed method for a single point in the post-earthquake timeline, it can be applied at multiple such points to develop a more comprehensive view of how the impacts of bridge damage and business interruption due to building damage evolve over time. Future work will address how to optimally select points along the post-earthquake timeline at which to simulate bridge and building damage, as well as the performance of the road network, to minimize computational burden while maximizing information gained about the impacts of the earthquake on the study region.

Not modifying the commute demand on a road network after an earthquake risks painting a misleading picture of who is impacted by bridge and building damage, as well as of the magnitude of those impacts throughout the affected region. For policy-makers, decision-makers, and asset managers tasked with reducing the community and economic impacts of earthquakes, understanding which assets – bridges or buildings – are driving those impacts is a necessary first step in developing appropriate and equitable mitigation strategies.

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