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ORIGINAL ARTICLE

Disturbances to Urban Mobility and Comprehensive Estimation of Economic Losses

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Abstract

Civil infrastructure systems are disturbed by natural or man-made hazards at an increasing frequency and severity. Among these systems, transportation systems are especially vulnerable due to their nature and are of significant importance to urban built environments as they maintain the mobility of urban dwellers and goods. Mobility disturbances are significant not only due to the direct losses associated but also due to the greater economic impacts driven by indirect losses stemming from the economic interactions of regions and sectors. Therefore, understanding the economic impacts of urban mobility disturbances is critical. To achieve a better understanding of the status quo of the research on transportation disturbances and economic impact analysis, a literature review was conducted. The review indicates that most of the articles fail to leverage realistic hazard impact information and explicit network modeling, consequently jeopardizing the credibility of the results. To begin addressing the gaps in the field, an interdisciplinary framework was designed to investigate the economic impacts of mobility disturbances. To validate the framework, a case study was conducted to estimate the economic impacts of commuting-based mobility disturbances resulting from a potential earthquake scenario in the Greater Los Angeles Area. The direct and indirect economic losses were estimated to be 285.49 and 93.48 million dollars, respectively. The results indicated that the economic losses could vary significantly among regions as well as industries. Among the five counties in the study region, Los Angeles County suffered the most. In addition, industries related to finance, education and scientific services, etc. were estimated to experience larger losses.

Keywords Urban mobility · Hazards · Transportation · Economic impact analysis · Commuting

1 Introduction

Civil infrastructure systems are the fundamental facilitators in urban built environments. Transportation systems, among civil infrastructures, are essential to the functionality of cities, supporting the mobility of their inhabitants, and the exchange of goods and services. Due to their nature, transportation systems are vulnerable to hazards such as traffic accidents, terrorist attacks, extreme weather events, etc. Hazards disturb transportation systems at an increasing rate and severity to cause physical damage leading to losses in the functionality of transportation infrastructures. These physical damages result in direct economic losses that diffuse and expand continually through economic activities between different regions and industries, exacerbating the totality of losses. It is estimated that a hypothetical disruption of Seikan Tunnel in Japan can cause 1.33 billion dollars losses to China, Korea, and other regions based on a transnational and interregional input-output model (Irimoto et al. 2017). Therefore, investigating the economic impacts of hazards beyond the immediate (direct) losses and studying the diffusion of the impact among industries and regions are critical. A comprehensive accounting of total losses (including direct, indirect, and induced costs) requires the incorporation of interindustry economics in the form of economic impact analysis models.

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Economic impact analysis is widely used to estimate economic losses due to natural and man-made hazards. In the current state of economic impact analysis research, input-output models (IO) and the computable general equilibrium (CGE) models are the most common approaches. In this domain of economics research, Cochrane (1974) pioneered the use of interindustry economics in disasters context focusing on earthquakes. Hallegatte (2008) proposed the Adaptive Regional Input-Output model and applied the adaptive IO measures to the impact assessment of Hurricane Katrina. Park et al. (2005b) and Park (2008) constructed coupled demand-driven and supply-driven regional input-output models based on IMPLAN and CFS data, and applied it in the evaluation of the hypothetical terrorist attacks on civil infrastructure. In CGE modeling for disaster economics, Rose (2004) and Rose and Liao (2005) estimated the regional economic impacts of water supplies disruptions using a CGE model and considered resilience measures. Other researchers incorporated non-economic methodologies such as the Inoperability Input-Output model (Crowther et al. 2007). However, economic impact analysis literature related to disasters and their impacts on urban built environments focuses exclusively on individual components of infrastructure systems (e.g., a bridge instead of the road network). This leads to the inability to incorporate the spatially distributed and networked nature of civil infrastructures into the impact assessment. From a functionality perspective, this is a major shortcoming of the works in this domain, as components of infrastructure systems are fundamentally dependent on the status of the network to carry out the desired functions. Thus, e.g., if one studies the impact of an earthquake on a single freeway bridge or even a small group of bridges that do not represent the bridge network in an urban area realistically, the analysis cannot produce comprehensive insights related to the overall economic impact. This is because when an earthquake hits an urban area (or any other natural hazard with spatially distributed impacts), it affects a wide area and exposes the entire urban transportation network due to that possible propagation of failed individual components.

Only a handful of studies investigated the economic impacts of disturbances to spatially distributed and networked transportation systems. A predominant number of these studies assumed (hypothetically or based on hazard information) the failure of a small subset of infrastructure components and did not study the full spectrum of the potential impacts, i.e., functionality losses that spread well beyond a small subset of infrastructures, due to a locally relevant natural or man-made hazard. Naturally, this led to a lack of attention towards the fine-resolution analysis of urban transportation disturbances coupled with economic impact analysis. To address this gap, a multi-disciplinary framework is designed by the authors to investigate hazard-induced disturbances to urban mobility and overall their economic impacts in urban areas. To validate the designed framework, this paper conducts a case study, which focuses on the disruption of commuting in the Greater Los Angeles Area and the associated economic impacts throughout the region.[1] The paper is structured as follows. In the next section, the authors provide the background and the status quo in economic impact analysis of transportation disturbances, carefully categorizing published work in the domain. Then, the designed framework is introduced, and the Greater Los Angeles Area case study is discussed with extensive details before the results and the discussion thereof are presented.

2 Literature Review

In order to draw a picture of the status quo of this domain, the authors carried out a literature review. Prior research in the area that focuses on estimating the economic impacts of transportation disturbances was retrieved from Web of Science. An initial list of papers was derived by searching various sets of keywords and keyword groups such as "economic losses," "hazard," "disaster," "disruption," "transportation," "economic impact analysis," and "supply chain disruption."

The authors did not set a date of publication constraint on the relevant works. However, some articles were excluded from the review with respect to the following criteria. First, articles written in other languages than English were moved out. In addition, articles with explicit transportation network modeling but missing economic analysis were not included because these works only study the impacts of transportation disturbances from an engineering point of view, largely focusing on infrastructure management, transportation safety, traffic optimization, etc. Lastly, studies investigating the economic impacts of the disruptions to other kinds of infrastructure systems (e.g., power plants or water supply system disruptions) or papers without a clear analysis of the losses resulting from the disturbance of the transportation sector were removed from the review inventory (Aloughareh et al. 2016; Koks and Thissen 2016; Koks et al. 2016). This way, 25 articles were identified, and another 17 articles were found by surveying the references of the original 25 or by going through their listed publications of the authors. Out of the 42 publications identified in the end, 37 were peer-reviewed journals, 5 were conference papers, and 1 was a technical report.

The publications in the review inventory were categorized with respect to the following three dimensions. (1) Scope of Network Modeling and Analysis, to identify whether the article accommodates an explicit transportation network modeling approach; (2) Scope of Hazard Impact Information, to distinguish the articles based on the hazard data used for direct damages on the transportation infrastructure. Here, the

[1] Please note that this paper is complementing an earlier publication by the authors (Wei et al. 2018).

categorization is (i) simple assumptions for hazard impacts, (ii) reported or reviewed impacts, (iii) impacts found from realistic hazard simulations, or (iv) no hazard impact information; (3) Scope of Economic Modeling and Analysis, to identify the methodologies of economic impact analysis used in the articles. It should be noted that all these papers were put into six categories which are possible combinations of results from the first two scopes. Within each category, the scope of economic modeling was also used as another categorization criterion. The results of this scheme are presented in Tables 1 and 2. Detailed discussion of these papers were conducted in our previous work (Wei et al. 2018); thus, it would be not fully presented in this paper.

Considering the economic modeling approaches used in the reviewed studies, most articles only present an estimation of the "direct" impacts by simple mathematics. These articles do not take interindustry diffusion effects or interregional economic activities into consideration. Among the papers with intact economic impact estimation methodologies, IO modeling and IIM modeling are widely used approaches. In addition, there are several examples of CGE and SCGE models (spatial CGE) as well. However, most of these works leverage hypothetical hazard scenarios as the basis of their economic impacts analysis.

With respect to the hazard impact information that is incorporated into the studies, most of the articles are based on simplified assumptions such as the shutting down of a bridge over a week due to a hypothetical hazard. This type of approach does not utilize a sophisticated understanding of the hazard. In addition, only a small subset of the articles in the review inventory carry out their economic analyses based on reviewed or reported hazard information, i.e., hazards that have occurred in the past with documented and reported impacts. Out of the 42 publications reviewed, only 7 incorporated hazard impact information derived from realistic hazard simulations. Among them, 5 papers incorporated explicit network modeling. Zhou et al. (2010) calculated the social costs of drive delay and loss of opportunity caused by degraded network under a set of earthquake scenarios in order to evaluate the social-economic effect of seismic retrofit of bridges. Sohn et al. (2003) evaluated the significance of several bridges by quantifying the economic losses due to the 1812 New Madrid earthquake. Postance et al. (2017) conducted economic estimation for scenarios of road segments disruptions simply by multiplying increasing travel time with national user generalized cost without considering any ripple effects of transportation disturbances. Cho et al. (2001) and Gordon et al. (2004) estimated direct, indirect, and induced economic losses of Elysian Park earthquake scenarios.

On the other hand, it is noticed that papers without transportation network modeling outnumbers papers with explicit network modeling (as shown in Fig. 1). Within the subset of papers that do not accommodate explicit network modeling, only Gueler et al. (2012) and Park (2008) investigate multimodal issues (e.g., waterway, rail and truck). Among papers with explicit network modeling, most of the work focuses on the calculation of the direct transportation related costs such as increased travel or warehouse costs. Few studies estimated the indirect economic losses based on the direct losses (i.e., decreased proportion of initial production or demand), which were hypothetical or simply set according to historical records.

Based on this information, the authors drew the conclusion that only a few researchers conducted comprehensive economic analyses based on integrated transportation network modeling and realistic hazard simulations, especially focusing on the economic impacts of urban mobility disturbances.

Table 1 Illustrating the reviewed studies without explicit network modeling and analysis

		Scope of hazard impact information		
		Simple assumptions	Reported/reviewed impacts	Realistic (simulated) hazard impacts
Scope of economic modeling	Simple math	Gueler et al. (2012), Tan et al. (2015), Zhang and Lam (2016), Oztanriseven and Nachtmann (2017)	Jaiswal et al. (2010), Kajitani et al. (2013)	Zhang and Lam (2015)
	IO	Park et al. (2005a), Park (2008), Park et al. (2008), Li et al. (2013), Rose and Wei (2013), Irimoto et al. (2017)	MacKenzie et al. (2012), Tokui et al. (2017)	
	IIM	Santos and Haimes (2004), Lian and Halmes (2006), Wei et al. (2010), Pant et al. (2011), Thekdi and Santos (2016)	Yu et al. (2013)	
	CGE		Xie et al. (2014)	
	SCGE	Ueda et al. (2001), Tatano and Tsuchiya (2008)		
	CGE; IO			Rose et al. (2016)
	Others	Thissen (2004)		

Table 2 Illustrating the reviewed studies with explicit network modeling and analysis

		Scope of hazard impact information		
		Simple assumptions	Reported/reviewed impacts	Realistic (simulated) hazard impacts
Scope of economic modeling	Simple math	Xie and Levinson (2011), Ashrafi et al. (2017), Omer et al. (2013), Vadali et al. (2015)	Mesa-Arango et al. (2016)	Postance et al. (2017), Zhou et al. (2010)
	IO	Park et al. (2011), Cho et al. (2015)		Cho et al. (2001), Gordon et al. (2004), Sohn et al. (2003)
	CGE		Tirasirichai and Enke (2007)	
	SCGE	Tsuchiya et al. (2007), Kim and Kwon (2016)		
	Econometric	Greenberg et al. (2013)		

Simplified assumptions were widely used, and most of the research in the area did not leverage explicit transportation network modeling during this process, which compromised the reliability of the research outcomes. The authors designed a multi-disciplinary framework to fill these gaps. In the next section, the framework is discussed in detail.

3 Framework

In order to address the gaps discussed above, a multi-disciplinary framework was designed (Wei et al. 2018) and refined as shown in Fig. 2, and a full case study was implemented for validation. This multi-disciplinary framework makes use of state-of-the-art, realistically conducted hazard simulations together with explicit and holistic network modeling, and is able to estimate the economic impacts of hazard-induced transportation disturbances. In the case study that is conducted to validate the framework, a potential earthquake event is studied where the commuting in Greater Los Angeles Area is disrupted. The framework is broadly translatable to other types of hazards as well as different types of transportation modes and to different urban regions if data availability is assured.

It also should be emphasized that the discussions in this paper focus entirely on the economic analysis facet of a larger framework. The economic facet takes the increase in traveling costs quantifying the commuting disturbance resulting from the loss of functionality in the transportation network as inputs for economic impact analysis. There are two reasons for focusing on the consequences of commuting disturbances in the initial deployment of the framework. First, commuting disturbances can be easily triggered by physical damages to transportation systems, such as bridge disruptions,[2] or other events such as strikes or blackouts. The consequences of commuting disturbances cannot be ignored since they affect urban dwellers virtually five days a week and in many urbanized regions, dwellers take long distances to reach their workplaces on a daily basis. In addition, despite the previous research in the economic costs of commuting by economists and policymakers engaging in transportation for the purpose of household expenditure analysis, traffic optimization etc., the economic impacts of hazard-induced commuting disturbances have been rarely studied from a perspective that integrates science on hazards, engineering, and economics, which is also verified in the literature review presented. It is of critical importance to approach this problem in a more comprehensive manner, i.e., by accommodating results of realistic disaster simulations as well as taking insights from fine-resolution infrastructure network modeling coupled with mobility analysis into consideration. This way, a comprehensive evaluation of commuting disturbances can be carried out to better understand the influence on regional economies.

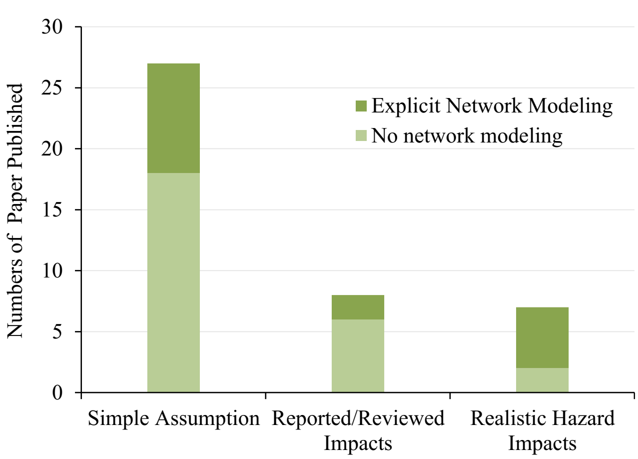

Fig. 1 Numbers of papers published by the scope of hazard impact information incorporated and explicit network modeling

[2] It is widely assumed as well as accepted in transportation safety domain that bridges are the most important components in transportation infrastructure.

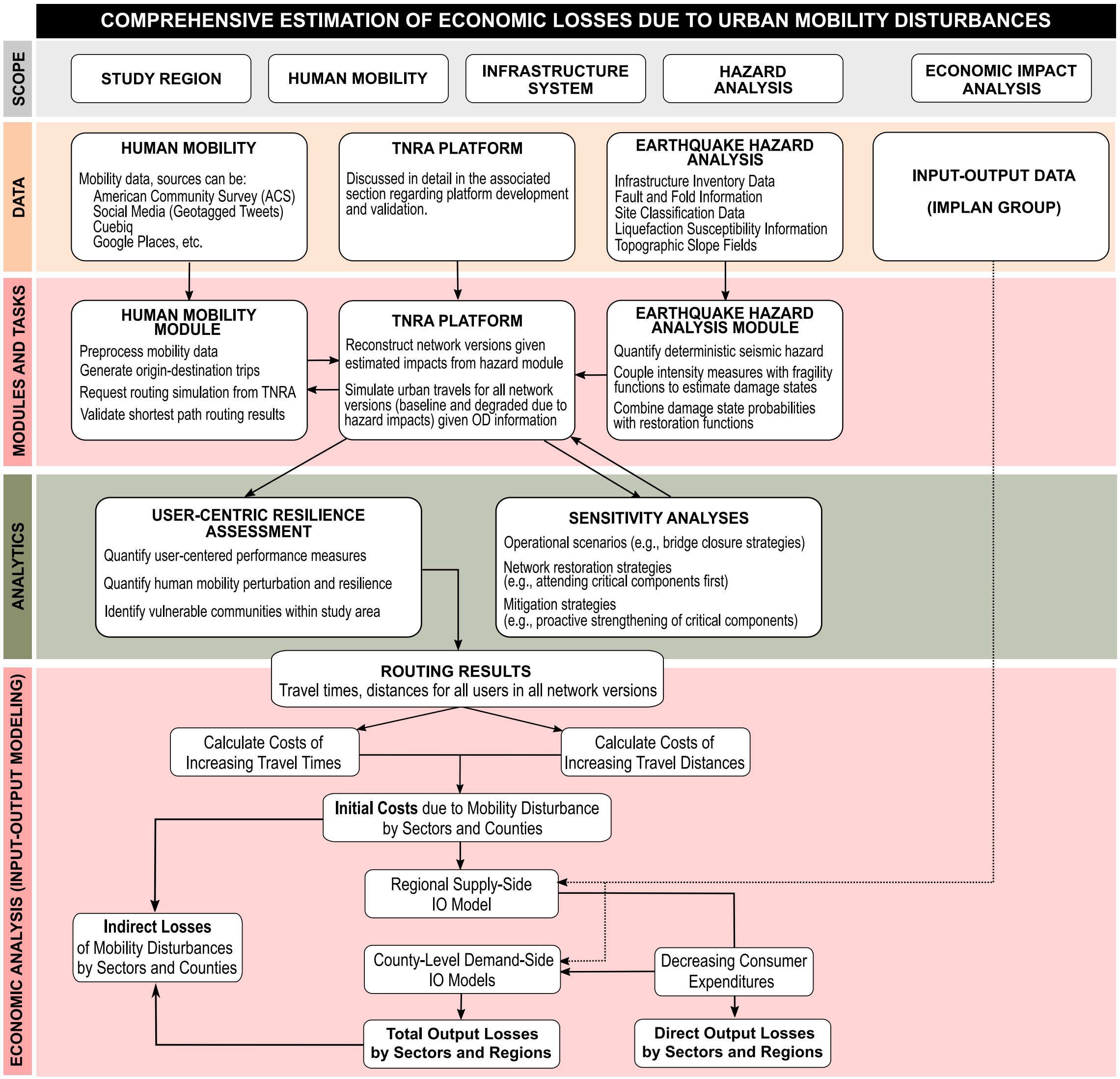

Fig. 2 Illustration of the conceptual framework

The economic impact analysis facet of the framework takes the increases in commuting times and distances (worsened due to hazard impacts) as its inputs to calculate the increase in commuting costs. These costs can be influenced by transportation network disruptions through two major ways. First, the driving operation costs increase with increasing driving distances. Commuters may have to change their daily driving routes in order to reach their workplaces if, e.g., a bridge on their original route is out of service for a certain period of time after an earthquake. These detours may result in increasing distances of travel. A detour can also happen if commuters want to avoid congestions since some of the transportation infrastructure components cannot fully perform their intended functions due to physical damages.[3] With increasing distances of travel, more fuel will be demanded, and the maintenance and repair costs will surge as well. Another contributor to the increasing economic costs of commuting could be the longer time spent on commuting due to detours and congestion. People may need to substitute the time spent on other activities such as leisure and entertainment, or on economic production. Thus, the value of travel time has to be taken into consideration.

Note that one of the major assumptions made here is the constant commuting demand before and after the disaster (e.g., commuters continue completing their home-workplace trips after an earthquake), which is a widely accepted assumption by researchers in the field (Stergiou and Kiremidjian 2006; Faturechi and Miller-Hooks 2014). However, the travel times and distances fluctuate as mentioned before. This causes a rise in commuting costs that are passed on to the consumers in the region. To capture the resilience of the network and the regional economy,

[3] The multi-disciplinary framework is unable to deal with this factor currently; however, this is a limitation that our future work will address.

commuting disturbances are collected in discrete time steps over the study period. This way, the improving commuting costs and the impact in the regional economy were observed as restoration of the transportation systems advances with time, e.g., bridges are repaired and opened to traffic again. Finally, the increasing commuting costs are taken as the direct losses caused by transportation network disruptions and the ripple effects on the economy are studied based on supply-side and demand-side input-output models.

3.1 Estimating Costs of Increasing Travel Distance and Time

The initial losses are calculated by increasing mobility costs, i.e., increasing travel distances and times due to mobility disturbances. Assume that there are M regions and N industries. In the following mathematical relations, i and j ($i, j = 1, 2, \dots M$) denote the origin and destination regions, respectively, and k ($k = 1, 2, \dots N$) denotes production sectors.

The following facilitation of the economic impact analysis methodology is carried out for commuting by driving only, towards the use of the framework in the case study. Note that the methodology is translatable to other urban mobility modes given data availability.

Economic costs of increasing travel distances are calculated by multiplying the total increasing travel distance with average operation costs:

$$\Delta TDC_{ij}^{k} = \Delta TD_{ij}^{k} \times AOC_{ij}^{k} \tag{1}$$

where

ΔTDC_{ij}^{k} is the cost of increasing travel distance (referenced to business-as-usual baseline network) from origin region[4] i to destination region j for sector k;

ΔTD_{ij}^{k} is the increase in total travel distance summed up for commuting trips from region i to j referenced to the baseline total, and AOC_{ij}^{k} is the average operation cost of driving. This is to account for the costs of fuel, maintenance, and other fees such as tires, in which higher fuel consumption is the largest contributor. Operation costs of driving are taken from the Bureau of Transportation Statistics[5] and from reports published by other research institutions.

It should be noted that there are some other costs of increasing driving distances such as mileage reimbursements. However, quantification of those are non-trivial due to the lack of open data sources and standard criteria on how much reimbursement is awarded by employers. In addition, the different treatment of reimbursements in different industries further complicates a global quantification. Therefore, only the operation costs are included in the framework.

Economic costs of increasing travel time are calculated simply by multiplying the total increasing travel time with the value of travel time. It is generally assumed that travel time has a negative demand because consumers are willing to pay for less of it (Fallis 2014). One way to quantify the value of travel time is by the monetary value of travel time savings (VTTS). However, this process is hard to practice due to lack of observable market prices (Tirasirichai 2007). There are multiple factors that can lead to variance in VTTS, for instance, travel modes, trip purposes, comfort levels, personal characteristics, and hourly wages. Therefore, simplifications are necessary. The US Department of Transportation published a set of guidance reports on value of time[6] in which the costs of employment are taken as the base value for quantifying VTTS. In this framework, values in the California Life-Cycle Benefit/Cost Analysis Framework are used. Consequently, the cost of increasing travel time is calculated as follows:

$$\Delta TTC_{ij}^{k} = \Delta TT_{ij}^{k} \times ATC_{ij}^{k} \tag{2}$$

where

ΔTTC_{ij}^{k} is the total cost of increasing travel time from origin region i to destination region j for sector k.

ΔTT_{ij}^{k} is the increase in total travel time summed up for commuting trips from region i to j referenced to the total for the baseline network.

ATC_{ij}^{k} is the average tradeoff value of time. This is to account for the time spent by commuters in driving instead of income generating or leisure activities.

This way, the total cost of increasing travel distances and times is

$$\Delta TC_{ij}^{k} = \Delta TDC_{ij}^{k} + \Delta TTC_{ij}^{k} \tag{3}$$

where

ΔTC_{ij}^{k} is the increase in total travel cost from origin region i to destination region j for sector k.

[4] The economic region in the full deployment of the framework will be the regions in Los Angeles that we have the input-output table for.

[5] These values are published annually by Bureau of Transportation Statistics. Average cost of driving includes fuel, maintenance, and tires. Available online at: www.rita.dot.gov/bts

[6] These values are conducted out by the California Department of Transportation and recommended to be used in statewide transportation projects analysis.

3.2 Estimating the Impact Through Interindustry Economics: Supply-Side IO Model

Ghosh (Ghosh 1958) proposed the supply-side input-output model in 1958, which has similar characteristics to the Leontief Input-Output model. The supply-side IO model is able to track the impacts of supply-side changes on the production of industries and quantify the corresponding output losses. Although it has been criticized for its plausibility following its proposition (Oosterhaven 1988), many researchers have addressed this problem by interpreting it as a price model (Dietzenbacher 1997).

In this framework, the supply-side IO model is employed to estimate the impacts of added commuting costs on the regional economy. Since consumers might spend their income in any county of the Greater Los Angeles Area, the influences of rising commuting costs on consumer expenditure are not quantified separately. To be specific, the increasing commuting costs caused by increasing travel distances and times for sector k are aggregated by regions, and then one supply-side IO model is used to estimate the decreased consumer expenditure in the Greater Los Angeles Area.

For sector k, the total increasing travel cost summed up for all commuters is aggregated as the following:

$$\Delta TC^k = \sum_{i=1}^{M}\sum_{j=1}^{M}\Delta TC_{ij}^k \tag{4}$$

Next, the decreasing consumer expenditure is calculated using a regional supply-side IO model:

$$\Delta CE^k = \Delta TC^k \times (I-B)^{-1} \tag{5}$$

where

ΔTC_{ij}^k is the total price inflation for sector k due to increasing travel distances and times.

ΔCE^k is the decrease in total consumer expenditure for sector k after costs inflation effect;

$(I-B)^{-1}$ is the output inverse matrix and B is the direct output coefficients matrix of the Greater Los Angeles Area.

Assume that there are no new producers entering the Greater Los Angeles Area market. Due to the different levels in local economic development (e.g., average hourly salary and average living costs can vary from region to region), the decreasing consumer expenditure is reallocated to each county according to their household final demand as follows:

$$\Delta CE_j^k = c_j^k \times \Delta CE^k \tag{6}$$

where

ΔCE_j^k is the decreased consumer expenditure in region j for sector k;

c_j^k is the household consumer expenditure ratio of region j to the Greater Los Angeles Area.

3.3 Estimating the Impact Through Interindustry Economics: Demand-Side IO Model

Next, demand-side IO models are employed in order to estimate the economic impacts based on reduced final demand.

Since Leontief proposed the input-output model in 1936 (Leontief 1936), it has been widely introduced into many domains. It is a transparent model that is easy to operate for estimating the indirect economic impacts of decreasing final demand. It is assumed that there are no substitution effects and consumer expenditures have direct impacts on final demand, which is an assumption that was previously proposed and used in the TransNIEMO model (Cho et al. 2015). This enables the calculation of the backward linkage impacts calculated based on demand-side IO models. In our framework, total output losses are estimated leveraging an approach similar to Park et al. (Park et al. 2005a).

For sector k, the total output loss in destination region j is

$$\Delta X_j^k = (I-A)_j^{-1} \times \left(-\Delta CE_j^k\right) \tag{7}$$

where

ΔX_j^k is the decrease in total output in destination region j for sector k;

$(I-A)_j^{-1}$ is input inverse matrix and A is direct input coefficients matrix in destination region j.

Finally, the economic impacts of commuting disturbances can be aggregated by regions and by sectors.

The total impacts by regions are

$$\sum_{k=1}^{N}\Delta X_j^k \tag{8}$$

The total impacts by sectors are

$$\sum_{j=1}^{M}\Delta X_j^k \tag{9}$$

4 Case Study

As discussed above, a case study was conducted to validate the designed framework. The case study focuses on the commuting disturbances caused by an earthquake scenario in the Greater Los Angeles Area. As the second-largest urban region in the USA, the region is known to suffer from traffic, with its dwellers having to endure long commuting times and distances to reach their workplaces. Public transit is still not a viable alternative and about 85–90% of the workforce uses the driving mode for commuting. The region encompasses five counties, namely, Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties. Model year is set to be 2017.

4.1 Assumptions and Data Sources

Several assumptions have been made in order to estimate the direct and indirect economic impacts. First, the travel demand remains constant after the hazard, as discussed above within the section that introduces the framework. In other words, commuting times and distances are affected by infrastructure system disruptions (i.e., functionality losses in bridges as the most critical links in the urban transport network), while the number of commuters, and their origins and destinations, is assumed to remain unchanged. This is a widely used assumption in transportation network resilience research (Stergiou and Kiremidjian 2006; Faturechi and Miller-Hooks 2014). Second, in terms of economic impacts, only the disturbance to the commuting by driving is considered for reasons described above related to the study region. Lastly, the extra costs of increasing travel times and distances are measured based on the value of travel time and value of operation, respectively. Other costs such as ownership costs (i.e., car depreciation, license and registration fees, etc.) are not included.

In this case study, the direct losses and indirect economic influences of commuting disturbance are estimated using supply-side and demand-side IO models based on their work. Regional input-output data are obtained from IMPLAN Group (Minnesota IMPLAN Group 2018). The 536 industries are aggregated into 7 industries by authors in order to ensure compatibility with the commuting disturbance results. The value of travel time ($13.65 per person hour by automobile in 2016) in vehicle operation cost parameters[7] published by California Department of Transportation[8] is used to calculate the initial losses of increasing travel times. The value of fuel price ($3.080 per gallon, including taxes)[9] from the US Energy Information Administration and value of driving operation costs ($7.91 cents per mile for maintenance, repair, and tires)[10] published by the American Automobile Association are used to calculate the initial losses of increasing travel distances.

4.2 Data Processing

The case is conducted as follows. First, for each industry, total travel times and distances between five counties are calculated by multiplying the numbers of commuters with average travel times and distances. This task is carried out five times for baseline and degraded network versions on day 0 before the hazard, and days 1, 7, 30, and 90 after the hazard. These discrete intervals result from the hazard simulations carried out using HAZUS parameters. HAZUS is a hazard-simulation software package distributed by FEMA in the US (Federal Emergency Management Agency 2018). This is done to cover the hazard timeline holistically as losses in transportation network functionality affect commuting patterns until full recovery (assumed to happen at the end of model year, on day 360). This way, changes in total travel times and distances during the hazard timeline can be calculated in a step-wise manner. For instance, from day 1 to day 7, the increase in total travel time from county i to county j for sector k is

$$\Delta TT_{ij}^{k,\ \text{day 1 to day 7}} = (7{-}1) \times \left(TT_{ij}^{k,\text{day 7}} - TT_{ij}^{k,\text{day 1}}\right) \tag{10}$$

Then, total direct costs caused by increasing travel distances and times can be calculated based on Eqs. (1) and (2), respectively. These costs are aggregated by all origins and destinations based on Eq. (4), which are taken as the initial losses caused by the disturbance of commuting mode of mobility.

Next, the decrease in consumer expenditures is estimated by Eq. (5) and are reallocated to five counties based on their final demand consumer expenditure, which are obtained from IMPLAN. Lastly, demand-side IO models are employed to calculate the total output losses as Eq. (7).

5 Results and Discussion

Figure 3 shows the direct, indirect, and total output losses in the Greater Los Angeles Area for one year.

[7] The Vehicle Operation Cost Parameters are statewide representative average values recommended by the California Department of Transportation to be used in the economic analysis of highway and other projects.

[8] California Department of Transportation, Vehicle Operation Cost Parameters, http://www.dot.ca.gov/hq/tpp/offices/eab/benefit_cost/LCBCA-economic_parameters.html, last accessed 2018/4/25.

[9] Retail Gasoline and Diesel Prices, U.S. Energy Information Administration, https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_y05la_a.htm, last accessed 2018/4/25.

[10] Your Driving costs Report 2017, American Automobile Association (AAA), https://exchange.aaa.com/automotive/driving-costs/#.WsNoF2hL82x, last accessed 2018/4/25.

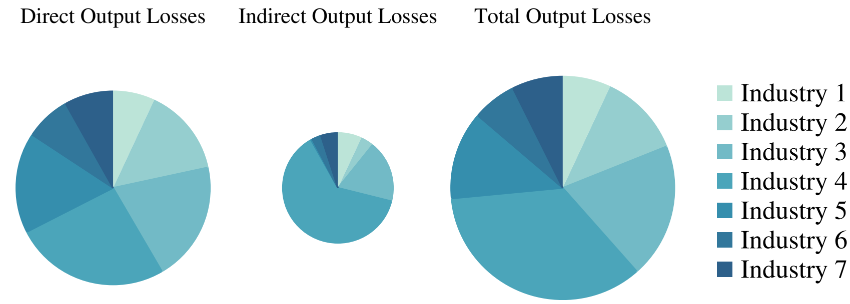

Fig. 3 Direct, indirect, and total output losses in the Greater Los Angeles Area (million USD). The area of the pie chart is proportional to the losses

Direct losses refer to the decreased consumer expenditure that includes the initial costs of increasing travel times and distances, and the direct losses caused by increasing travel costs. Indirect losses denote those losses caused by direct losses due to input-output activities between sectors. Total losses are estimated comprehensive economic impacts with the impacts of economic transactions taken into consideration. The indirect economic loss caused by commuting disturbance is about 93.48 million dollars, accounting for 24.67% of total economic losses. Industry-specific information is shown in Table 3. It should be noticed that the initial loss of Industry 4 (information, finance and insurance, real estate and rental, professional-scientific and technology services, management of companies, administrative and waste services) expands dramatically through the economic activities and results in great indirect and total losses, which indicates that Industry 4 is very sensitive to disturbances (Table 3).

Figure 4 shows the total output losses in five counties. Direct and indirect losses and other detailed information are shown in Table 4. Los Angeles County's total output loss is considerably larger than the other four counties'. This might be due to its relatively larger population and densely developed economy.[11] For the initial increasing traveling costs caused by commuting disturbances, over 80% happens within the Los Angeles County.

Table 3 Direct and indirect output losses of seven sectors (million USD)

	Direct losses	Indirect losses	Total losses
1. Agriculture, forestry, fish and hunting, mining, construction	19.80	6.51	26.30
2. Manufacturing	41.89	3.57	45.45
3. Transportation and warehousing, utilities, wholesale trade, retail trade	57.11	16.95	74.06
4. Finance and insurance, real estate and rental, scientific and technology services, information, management of companies, administrative and waste services	73.87	58.88	132.74
5. Education services, health and social services	47.94	0.41	48.35
6. Arts, entertainment and recreation, accommodation and food services	21.67	2.52	24.19
7. Other services	23.22	4.66	27.87
Total	285.49	93.48	378.97

Total output losses per industry are shown in Table 5 for the five counties. Although its total output losses are comparable to other industries, Industry 5 (education services, health and social services) experiences a relatively severe damage relative to its own output as indicated in Fig. 5. A potential reason is that the industry is one of the largest employers in the region being more exposed to the disturbance in commuting. Take Los Angeles County as an example, the proportion of employment in 2017 for Industry 3, Industry 4, and Industry 5 is 18.89, 18.79, and 17.88%, respectively.[12] Therefore, the direct losses of Industry 5 caused by commuting disturbance being greater than other industries aligns with the reasoning above. This is also verified by the relatively smaller indirect losses for Industry 5 compared to its direct losses as indicated in Fig. 3.

The aforementioned insights could enlighten the policy-making in the mitigation of economic impacts resulting from commuting disturbances, and improvement of the overall economic resilience to natural and man-made disasters. For industries that have great direct losses such as Industry 5, which indicates that transportation disturbances have huge direct influences on these industries, measures should be focused on mitigating the direct commuting-related losses. For example, have transportation network redundancy and diverse commuting modes, or set telecommuting systems so that people do not have to go to workplace under these circumstances. In addition, in order to mitigate the indirect economic losses for sectors very sensitive to transportation losses such as Industry 4, setting sufficient inventory and using diverse materials for production can get

[11] Los Angeles County is the most populous county as well as international trade center and manufacturing center in the USA. It is also home to many well-known companies such as Paramount Pictures and 21st Century Fox. https://www.lacounty.gov, last accessed 2018/4/25.

[12] California Employment Development Department, Labor Market Data and Information, http://www.labormarketinfo.edd.ca.gov/geography/lmi-by-county.html, last accessed 2018/4/25.

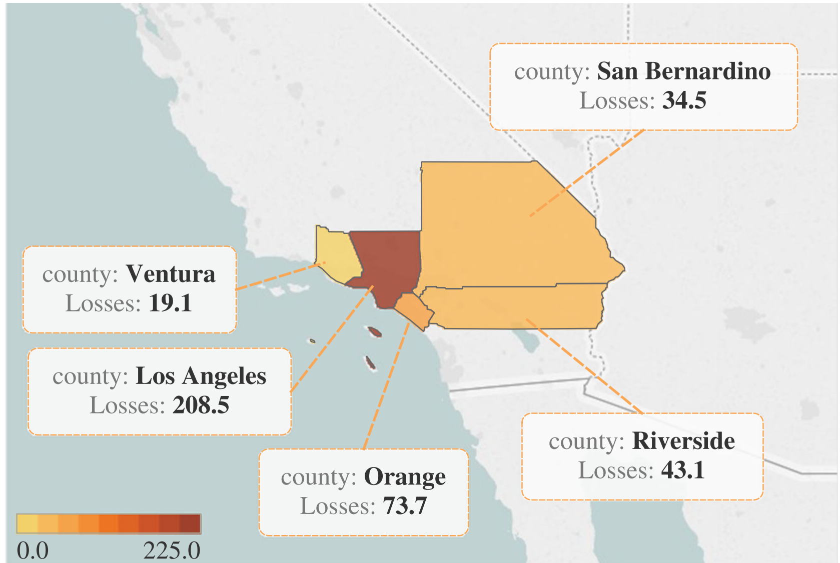

Fig. 4 Estimated total output losses in five counties (million USD)

Table 4 Direct and indirect output losses of five counties (million USD)

	Direct losses	Indirect losses	Total losses	% of the total losses for five counties	% changes in total output for its own	Total output
Los Angeles	154.35	54.18	208.54	55.03%	0.0184%	1,135,518.64
Orange	55.34	18.40	73.74	19.46%	0.0190%	388,417.91
Riverside	33.40	9.73	43.13	11.38%	0.0320%	134,657.37
San Bernardino	27.86	6.62	34.49	9.10%	0.0240%	143,945.37
Ventura	14.53	4.55	19.07	5.03%	0.0266%	71,796.56
Total	285.49	93.48	378.97	100.00%	0.0202%	1,874,335.85

producers well prepared for consequential shocks such as shortage of supplies.

6 Conclusion and Future Work

The transportation disturbances caused by natural and man-made hazards have been raising more attention due to the rising frequency and severity of adversities that expose the transportation infrastructure. This exposure calls for an integrated, multi-disciplinary investigation of urban mobility issues that bring together insights from fields of engineering and economics. Increased transportation costs, such as fuel costs, are only part of the total impacts of urban mobility disturbances. The propagation of disruptions based on the economic linkages between industries and regions cannot be ignored.

Table 5 Estimated total output losses in five counties (million USD)

	Los Angeles	Orange	Riverside	San Bernardino	Ventura
1. Agriculture, forestry, fish and hunting, mining, construction	13.96	5.07	3.33	2.60	1.34
2. Manufacturing	25.52	8.54	5.01	4.21	2.17
3. Transportation and warehousing, utilities, wholesale trade, retail trade	40.72	14.02	8.69	6.96	3.67
4. Finance and insurance, real estate and rental, scientific and technology services, information, management of companies, administrative and waste services	73.92	26.84	14.28	10.91	6.79
5. Education services, health and social services	26.16	9.37	5.65	4.72	2.46
6. Arts, entertainment and recreation, accommodation and food services	13.17	4.65	2.83	2.32	1.22
7. Other services	15.07	5.26	3.35	2.76	1.42
Total	208.54	73.74	43.13	34.49	19.07

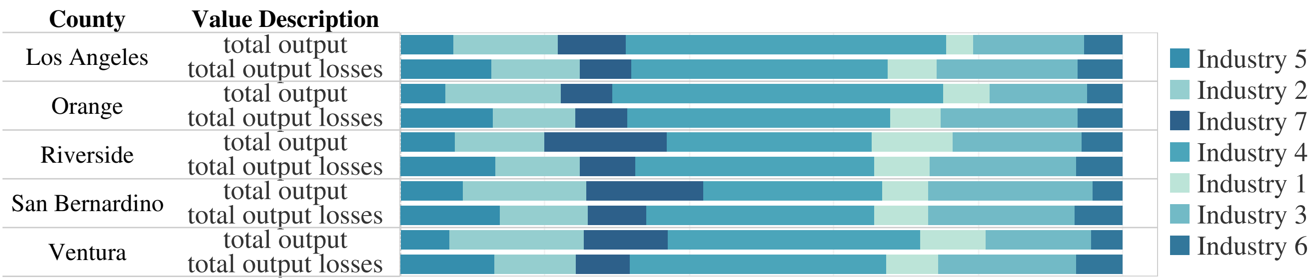

Fig. 5 Proportional distribution of industry losses and total output in five counties

In this paper, a comprehensive multi-disciplinary framework was proposed in order to investigate the economic impacts of unban mobility disturbances caused by the hazard-induced disruptions to transportation systems. Thanks to the multi-disciplinary collaboration, explicit network modeling and realistic hazard simulations are leveraged together with economic impact analysis methodologies. A metropolitan scale case study of a potential earthquake scenario in the Greater Los Angeles Area was conducted to validate the framework. It is found that indirect losses caused by commuting disturbances account for a significant portion of the total losses. In addition, economic losses caused by commuting disturbances vary significantly among different industries as well as among sub-regions of the metropolitan area, i.e., counties. In order to mitigate economic losses, policy-making could benefit from the insights generated with this study.

In terms of limitations, the inherent shortcomings of input-output modeling should be emphasized. IO models are linear and depend on constant coefficients of production which makes the approach rigid. Other modeling approaches such as CGE methods may be leveraged in our future work. In terms of the mobility and the infrastructure networks, multi-modal analysis is a current limitation that is being worked on as well as the current inability to deal with the route choice behavior of millions of urban dwellers, i.e., accounting for the congestion effects. However, these limitations do not invalidate the study as the current version of the framework only provides a conservative estimate of the losses. Working on the limitations, the estimated total losses are expected to increase, potentially calling for proactive actions in terms of urban policy-making.

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