TEMPORAL CHANGES IN THE SERVICE ELASTICITY OF TRAVEL DEMAND DURING DISASTER

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The heavy rain disaster 2018 in Japan caused disruption in the transportation network. In this research we attempt to calculate the service elasticity of travel demand in Hiroshima Metropolitan Area as the affected area due to heavy rain disaster July 2018 in Japan. The elasticity is used to explore the changes in travel demand with respect to the expected minimum generalized cost that is expected to be improved as the recovery process proceeds. To achieve the goal, first, we introduce a resilience concept to reflect the temporal changes of the recovery process. We then calculated the elasticity over time concerning the logsum-based network performance measure obtained through recursive logit model. Moreover, the elasticity values used to define the stages of the system under disrupted condition. The main results show that the elasticity values follow the tilde-shape, where in the emergency situation the elasticity is less elastic and more elastic at the adaptation and recovery stages. These findings will help policymakers to understand the situation under disrupted condition.

Key Words: *Service Elasticity of Travel Demand, Expected Minimum Generalized Cost, Heavy Rain Disaster, Resilience*

1. INTRODUCTION

The heavy rain occurred in July 2018 in Hiroshima Prefecture caused serious damages not only on lives and assets of victims, but also on transport infrastructure. Based on the report of Cabinet Office Japan (*1*), the number of housing damage is 15,176, and the number of deaths is 109. A massive transport network also occurred in this area on July 6 and 7, 2018 (*2*), resulting in more than 100 transport link disruptions (*3*), including both road and train links. Since transport network plays a significant role in evacuation activities and good transport management, a quick recovery of disrupted transport links is needed during disaster to support emergency activities. The disaster would change not only transport supply, but also travel demand. There would be two major reasons causing changes in travel demand during disaster: (a) travel demand decreases because people cancel their trips partially due to transport network disruptions, and/or (b) travel demand increases because people still have to travel for example for emergency and recovery activities, even though transport network is disrupted. This implies that the relationship between transport supply and demand would be changing over time during disaster: (a) indicates people may tend to consider travel as a luxury good that can be canceled when the service level is worse due to disaster, while (b) indicates travel tentatively be a kind of a necessity good even the service level is very poor. In other words, borrowing the concept of elasticity which has been widely used in economics, we could say that (a) indicates that the service elasticity of travel demand is relatively high (i.e., travel is relatively considered as a luxury good), while (b) indicates that the elasticity is relatively low (i.e., travel is relatively considered as a necessity good).

In this study, we use the service elasticity of travel demand as an indicator representing the relationship between transport demand and supply. While there is vast literature about the elasticity as discussed in the next section, little study has explored changes in elasticities during disaster. We argue that changes in elasticities would be a useful indicator of phase transition during disaster since they would depict changes in consumers' tastes for transportation services: transportation services tend to be necessity goods particularly soon after the disaster, while it would back to normal after the emergency phase, or even they may consider the services as luxury goods since they may start to recognize that their road use would lead to serious congestions that would have negative impacts on the recovery process.

In this study, we analyze changes in service elasticity of travel demand over time under heavy rain disaster July 2018 in Hiroshima, Japan. To facilitate the discussions, we use the concept of the resilience. The concept of resilience is defined as the *"... system's capability to persist when exposed to changes or shocks"* (*4*). System performance drops to a certain point due to disruption and then goes back to the normal condition aligned with the recovery process. We particularly attempt to depict and understand phase transition by exploring changes in the service elasticity of travel demand. The service level is measured by the expected minimum generalized cost that varies over time due to road network disruptions and transport network recovery. We repeatedly compute the logsum-based network performance measure whenever a link is recovered (also called accessibility in this study) by using recursive logit model.

The structure of the paper is as follows. The next section presents a literature review related to this study, followed by the methods used to obtain elasticity values during the disaster. We then introduce the data used in this study. The following section discusses the results, and the last section will conclude the paper with findings, policy recommendations, and future prospects.

2. LITERATURE REVIEW

(1) Studies related to elasticity

As discussed in Introduction, we use the concept of elasticity to explore the relationship between transport supply and demand. The elasticity is generally used to measure the sensitivity of demand with respect to changes in price or income in the economic field (*5*). There is vast literature about elasticity of demand. Libardo and Nocera (*6*) defined elasticity as the percentage change in the transportation demand with respect to the unit fluctuation of economic price. Beuthe et al. (*7*) calculated the elasticity of demand in a multimodal transportation network analysis. Instead of using price elasticity, they defined the elasticity as generalized cost elasticities, which not only covering the monetary loss but also the value of time of the travelers. Matas and Raymond (*8*) estimated a dynamic model to identify short-term and long-term changes in the elasticity with respect to the price, quality of the alternative routes and mode, and income. The results show that the demand is elastic with respect to the level of economic activity (GDP, income). They also stated that the traffic is sensitive to time-varying pricing schemes. The elasticity concept has been used in studies under disaster conditions as well. Soltani-Sobh, et al. (*9*) used the elasticity to capture the response of the travel demand to the changes in the travel cost while also considering the demand uncertainty, refers to the unknown effects of the trip behavior of the users following the disruption. Chen and Rose (*10*) used elasticity to analyze the link between accessibility, vulnerability, and resiliency. They created a computable general equilibrium framework to measure the ability of a system to recover from a disruption, given that the transportation infrastructure plays a significant role in facilitating economic growth and development. The economic elasticity is also used in Wu et al. (*11*), focusing on the earthquake disaster in China. Other researchers measured both short-run and long-run elasticities of travel demand with respect to the cost in rail transportation (*12*), resulting in an elastic value for the long-run and inelastic value for the short-run. Voith (*12*) described that the long-run elasticity of demand with respect to the cost is defined as the response to the changes in long-term impacts, such as residential choice, job location, and spending on private transportation. In contrast, the short-run elasticity of demand with respect to the cost refers to the changes in the modal choice or number of trips. Some other studies also focused on the elasticity of transportation and gasoline demand (*13–15*). As briefly reviewed above, while vast literature about the elasticity exists, little study has focus on changes in elasticities during disaster.

(2) Studies related to resilience concept

In order to understand resilience phases, we review existing works on the resiliency of the system, which typically consist of several phases toward recovering its function. Hosseini et al. (*16*) conducted a comprehensive review on the concept, and defined resilience as *"the ability of an entity or system to return to normal condition after the occurrence of an event that disrupts its state"*. As summarized by Hosseini et al. (*16*), there is vast literature about resilience and its assessment. Table 1 summarize existing studies of resilience and its phases when a system got disrupted, and Figure 1 illustrates one typical example of phase transitions considered in the resilience concept (*17*). Although different names and definitions have been used, most of the works commonly divide the period into at least the following three phases. The first is *normal phase*, also called anticipation, prevention, or original phase, the phase before disaster occurred. The second is *emergency phase*, also called absorption, degradation or survivability phase, the phase soon after the disaster where emergency activities are carried out. The third is *adaption and recovery phase*, also called restoration or recover ability, the phase sometime after disaster where recovery activities are carried out.

Table 1 Phases of Disrupted System

Author(s)	Phases of Disrupted System			
	First	Second	Third	Fourth
Najarian & Lim (*18*)	Anticipation	Absorption	Adaptation	Recovery
Bešinović, N. (*19*)	Robustness	Survivability	Response	Recovery
Bawankule, et al. (*20*)	-	Absorb & learn	Adapt	Recovery
Bevilacqua, et al. (*21*)	Prevention	Mitigation	Recovery	Long-term impact
Pant, et al. (*22*)	Reliability	Vulnerability-survivability		Recover ability
OECD (*23*)	Original	Disrupted		Recovery
Hossain, et al. (*24*)	Prevention	Degradation	Restoration & Adaptation	
Ouyang, et al. (*25*)	Prevention	Damage propagation		Recovery

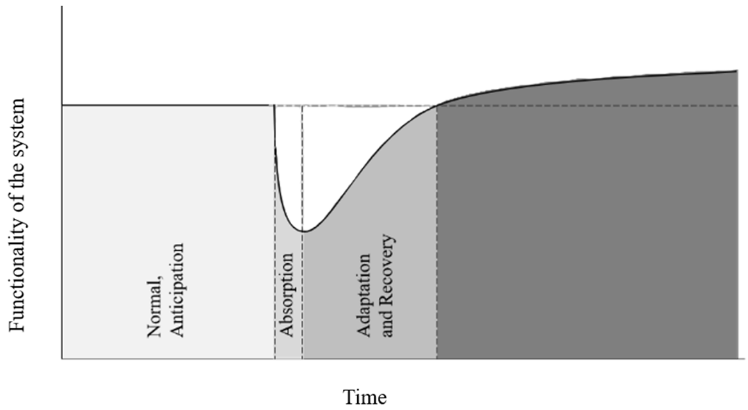


Figure 1. The phase transition of a system (adapted from Najarian and Lim (*17*))

study explores changes in the accessibility level during disaster using the recursive logit model.

In the recursive logit model, given the transport network structure containing a link set A, a traveler at link k ($\in A \cup j$) is assumed to choose the next link a ($\in A \cup j$) under the random utility maximization framework, where j represents the destination of the traveler. More specifically, the utility function can be defined by the Bellman equation as follows:

3. METHOD

(1) Recursive Logit Model

In this study, we utilize recursive logit model to calculate the logsum-based accessibility measure. The model was originally proposed by Fosgerau et al. (*17*). They modeled route choice behavior as a series of link choice problems on a road network through the Bellman equation.

Their paper proves that the recursive logit model is consistent with the multinomial logit model with an infinite route choice set. Mai et al. (*26*) further propose that there is an efficient procedure to obtain logsum values using the inverse matrix algebra, and thus the model framework would be suitable to the current study where the accessibility index needs to be repeatedly computed whenever a link is recovered. Following the work of Safitri and Chikaraishi (*27*), this

$$u(a|k) = v(a|k;\beta) + V^j(a;\beta) + \mu\varepsilon(a) \tag{1}$$

$$\begin{aligned} V^j(k;\beta) &= E\left[\max_{a\in A(k)} \left(v(a|k;\beta) + V^j(a;\beta) + \mu\varepsilon(a)\right)\right] \\ &= \mu \cdot \ln \sum_{\substack{a\in A(k) \\ \forall k \in A}} \delta(a|k) e^{\frac{1}{\mu}\left(v(a|k;\beta)+V^j(a;\beta)\right)} \end{aligned} \tag{2}$$

where $v(a|k;\beta)$ represents the instantaneous utility, $V^j(k;\beta)$ represents the expected maximum utility from link k to destination j, β is a vector of parameters, $\epsilon(a)$ is the random term which assumed to be i.i.d extreme value type I, μ denotes the scale parameter, and $A(k)$ is a set of outgoing links from link k.

Using the recursive logit model, we can now straightforwardly define the accessibility index $ac_{ijc\tau}$ from origin i to destination j at date c and time of day τ as follows:

$$\begin{aligned} ac_{ijc\tau} &= V^j(\tilde{k};\beta) \\ &= \mu \cdot \ln \textstyle\sum_{a \in A_{c\tau}(\tilde{k})} \delta(a|\tilde{k}) e^{\frac{1}{\mu}\left(v(a|\tilde{k};\beta)+V^d(a;\beta)\right)} \end{aligned} \tag{3}$$

where $\tilde{k}$ is a link representing origin i (i.e., a road link in front of city hall) and $A_\tau(\tilde{k})$ represents a set of outgoing links from $\tilde{k}$ under the disrupted transport network at date c and time of day τ. $ac_{ijc\tau}$ would vary across time, since $A_{c\tau}(\tilde{k})$ varies depending on network disruptions due to disaster and recovery activities.

(2) The Expected Minimum Generalized Cost

In this study, we defined the generalized cost as the cost travelers have to pay due to changes in the travel time in the network, converting the travel time to the cost. We straightforwardly calculate the generalized cost with the function of time and date $x_{ij}(c\tau)$ through equation below:

$$x_{ij}(c\tau) = \frac{1}{\beta_c}\left(ac_{ijc\tau}\right) \tag{4}$$

where β_c is the cost parameter in 100 Japanese Yen (JPY) adopted from Oka et al. (*28*), e.g., -18.45, where the parameter along with other parameters was estimated using freight vehicle GPS trajectory data; $ac_{ije\tau}$ represents the accessibility index at date c time τ. This generalized cost is varying over time along with the recovery of the link in the network.

(3) Elasticity

To obtain the elasticity value, we utilize the following multilevel model:

$$Q_{ijc\tau} = \beta_0 + (\beta_1 + u_{1ij\tau})x_{1ijc\tau} + \varepsilon_{ijc\tau} \tag{5}$$

where $Q_{ijc\tau}$ is the log of total trips from origin i to destination j at date c and time of day τ; $x_{1ijc\tau}$ is the log of expected minimum generalized cost from origin i to destination j at date c and time of day τ; β_0 and β_1 are the fixed effects from origin i to destination j at time of day τ, qhwew β_1 represents the service elasticity of travel demand; $u_{1ij\tau}$ is the random term representing the deviation of the elasticity values across origin, destination, and time of day, following the normal distribution with zero mean and variance σ_u^2, and $\varepsilon_{ijc\tau}$ is the white noise (residual), following the normal distribution with mean zero and variance σ_{e0}^2. Although different elasticity values across ODs can be produced under the above model setting, this study sorely focuses on changes in the average elasticity value to simply the discussions. We divided the whole study period (June 1, 2018 to September 30, 2018) into 120 three-day consecutive periods (i.e., June 1-3, June 2-4, ..., September 27-29, September 28-30), and develop a model for each to obtain a time-dependent service elasticity of travel demand. Additionally, we also consider the differences between weekend and weekdays, given that weekday trips might have different elasticities than weekend trips (*5*) by adding weekend dummy in the model.

In this study, we set the following two hypotheses:

H1*: The service elasticity of travel demand becomes less elastic soon after the disaster. People still travel partially because they have to conduct emergent disaster-related activities even though travel cost is higher than normal.*

H2*: The service elasticity of travel demand becomes more elastic after the emergency. People cancel their trips partially because they realize that their road use leads to serious congestions that may negatively influence the recovery process.*

By confirming the above two hypotheses, we argue that elasticities will vary over time during disaster, and changes in elasticities would be a useful indicator of phase transition since changes in elasticities depict changes in consumers' tastes for transportation services, which would be essential information for transport management during disaster. For example, ride sharing could be a good option to efficiently utilize the limited transport supply during disaster (*29*), but it could nudge people to travel more and thus it may have to be implemented after the transition to the recovery phase. Our proposed indicator can be used to identify the appropriate timing of implementing such a policy measure.

4. STUDY AREA AND DATA

This study focused on Hiroshima Prefecture, particularly affected area during heavy rain disaster July 2018. The study area covers: (1) Hiroshima City, (2) Higashi-Hiroshima City, (3) Kure City, and (4) Aki District, shown in Figure 2.
The data used in this study were (1) transport network data, and 2) Mobile Spatial Statistics obtained from

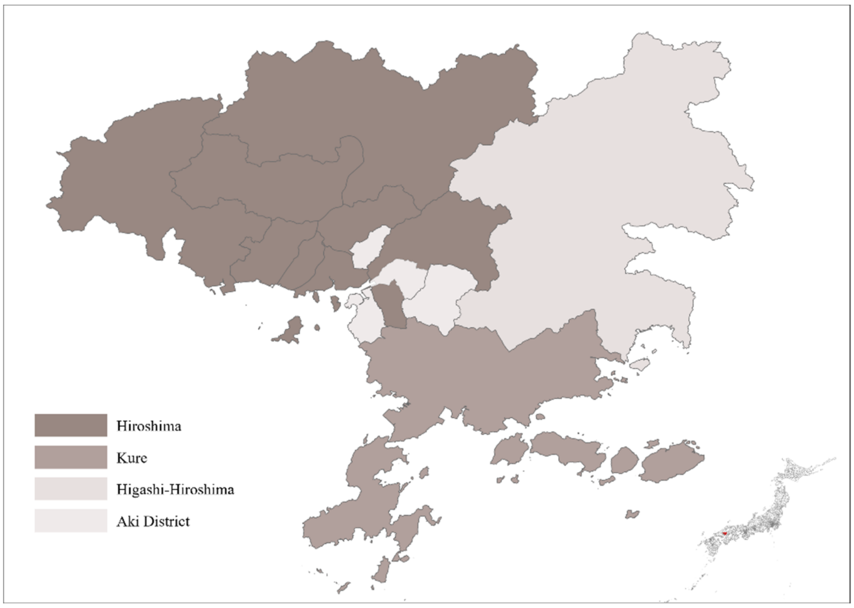


Figure 2. Map of Study Area

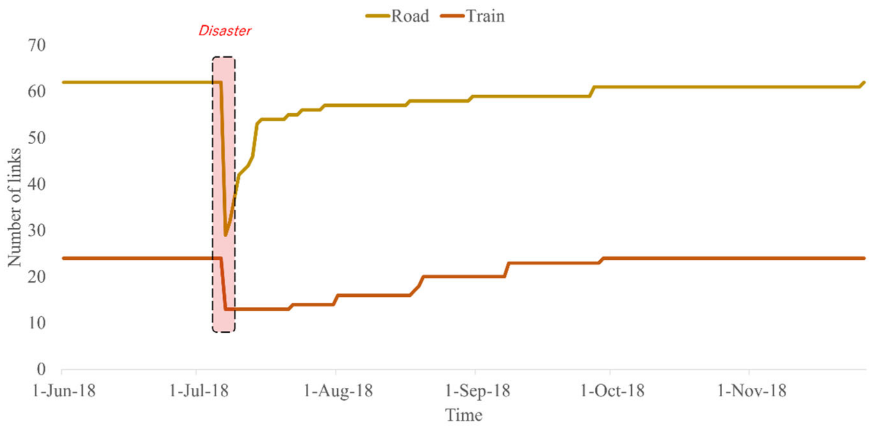


Figure 3. Number of available links over time

Docomo Insight Marketing Inc., as presented below.

(1) Transport Network Data

The transport network data are prepared together with an information about link closures and recoveries during disaster, which is critical to explore temporal changes in the transport network performance. Figure 3 shows the number of available links over time in the study area. There are 86 links in the network, consist of roads and railroads (train). Note that we only reflect arterial roads such as expressways, prefectural, and national roads. As Figure 3 indicates, the available links when the disaster occurred were only 35 out of 86, and it gradually increase over time as the recovery proceeds. We can also confirm that recovery activities in road were faster than railroad in the network, probably due to the differences in the complexity of the system.

Figure 4 shows the connectivity in transport network in different periods. Figure 4(a) shows transport network before disaster occurred. All 86 links were available connecting the 27 study areas, which the ID of the area can be seen in Table 2. Figure 4(b) shows the connectivity soon after the disaster occurred, which indicate that Kure city (IDs 1-7) only had limited links to other cities. Note that this study does not cover every small road links in the network and water transportation. Thus, some travel demand to/from Kure city were observed in Mobile Spatial Statistics data, even though the connectivity of transport network observed in the Figure 4(b) does not have any connection. Figure 4(c) shows the connectivity in the network, seven days after the disaster occurred. Some links were recovered, and all areas were connected.

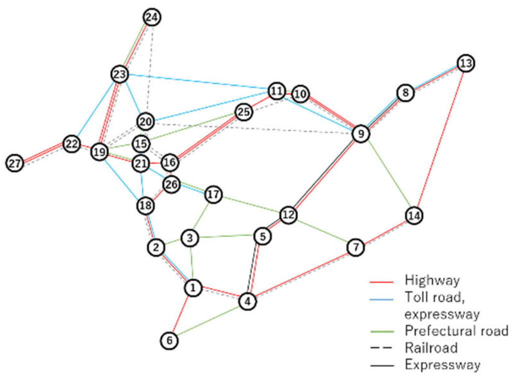
(2) Mobile Spatial Statistics Data

The Mobile spatial statistics are the population movement statistics generated from mobile terminal network operational data. The data contains estimated origin-destination (OD) travel demand among 27 zones, regardless the travel modes.

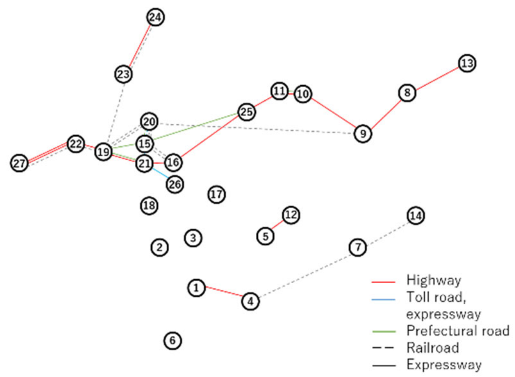
Due to the Docomo Insight Marketing Inc. privacy policy, we exclude some area (e.g., Gohara, Shiwa, and Nakano, refers to Table 2) given that these data were masked due to low travel demand. The data is available from June 1, 2018, to September 30, 2018. As mentioned earlier in this paper, the travel demand under disrupted condition might have two kind of conditions, e.g., (a) the travel demand will decrease because people may cancel their trips, and/or (b) the travel demand will increase, because people still travel even though the service level is worse, which might include trips for emergency/recovery activities. Using mobile spatial statistics, we found that the travel demand increased in some origin-destination (OD) soon after the disaster, but mainly travel demand decreased in most areas. Figure 5 shows the number of trips over time in the affected area (Kure, Higashi-Hiroshima, and Aki district) and non-affected areas (Hiroshima city).

Table 2 List of Study Area

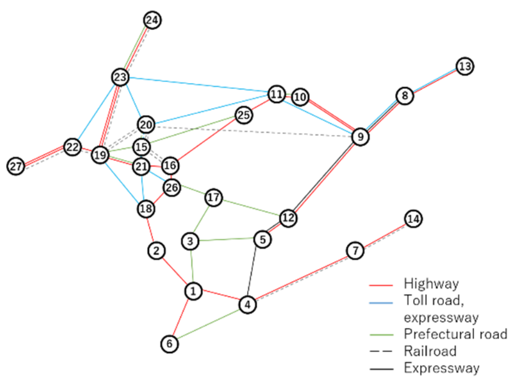
ID	New ID	Area	City	ID	New ID	Area	City
1	1	Kure/Chuo	Kure	15	13	Fuchu	Aki District
2	2	Tenno	Kure	16	14	Kaita	Aki District
3	3	Yakeyama	Kure	17	15	Kumano	Aki District
4	4	Hiro	Kure	18	16	Saka	Aki District
5	-	Gohara	Kure	19	17	Naka ward	Hiroshima
6	5	Ondo	Kure	20	18	Higashi ward	Hiroshima
7	6	Yasuura	Kure	21	19	Minami ward	Hiroshima
8	7	Takaya	Higashi-hiroshima	22	20	Nishi ward	Hiroshima
9	8	Saijo	Higashi-hiroshima	23	21	Asa Minami ward	Hiroshima
10	9	Hachihon-matsu	Higashi-hiroshima	24	22	Asa Kita ward	Hiroshima
11	-	Shiwa	Higashi-hiroshima	25	-	Nakano	Hiroshima
12	10	Kurose	Higashi-hiroshima	26	23	Yano	Hiroshima
13	11	Toyosaka. Fukutomi. Kochi	Higashi-hiroshima	27	24	Saiki	Hiroshima
14	12	Akitsu	Higashi-hiroshima				



(a) before disaster (June 30, 2018)



(b) after disaster (July 7, 2018)



(c) seven days after disaster (July 14, 2018)

Note) The location IDs are provided in Table 2.

Figure 4. Changes in transportation network by July 2018 heavy rain disaster – all conditions show the weekend information.

These classifications were made based on link availability obtained from the transport network data. Figure 5 also shows the number of trips in both affected and non-affected areas were decreasing not only on the day when the July heavy rainfall happened but also on other days, e.g., due to typhoon on July 29, 2018, and September 28 to October 1, 2018; and Obon festival (festival in Japan) on August 13 to August 15, 2018. Although some disruptions affected All matrices shown in Figure 6 was generated from weekend data, e.g., June 30, 2018, as before the disaster occurred; July 7, 2018, as the day when the disaster occurred; July 14, 2018, a week after the disaster, and August 11, 2018, a month after the disaster occurred; since that the day when disruption occurred is in the weekend so that we can compare all the travel demand mentioned, given that weekend and weekdays, data may have a different pattern of travel

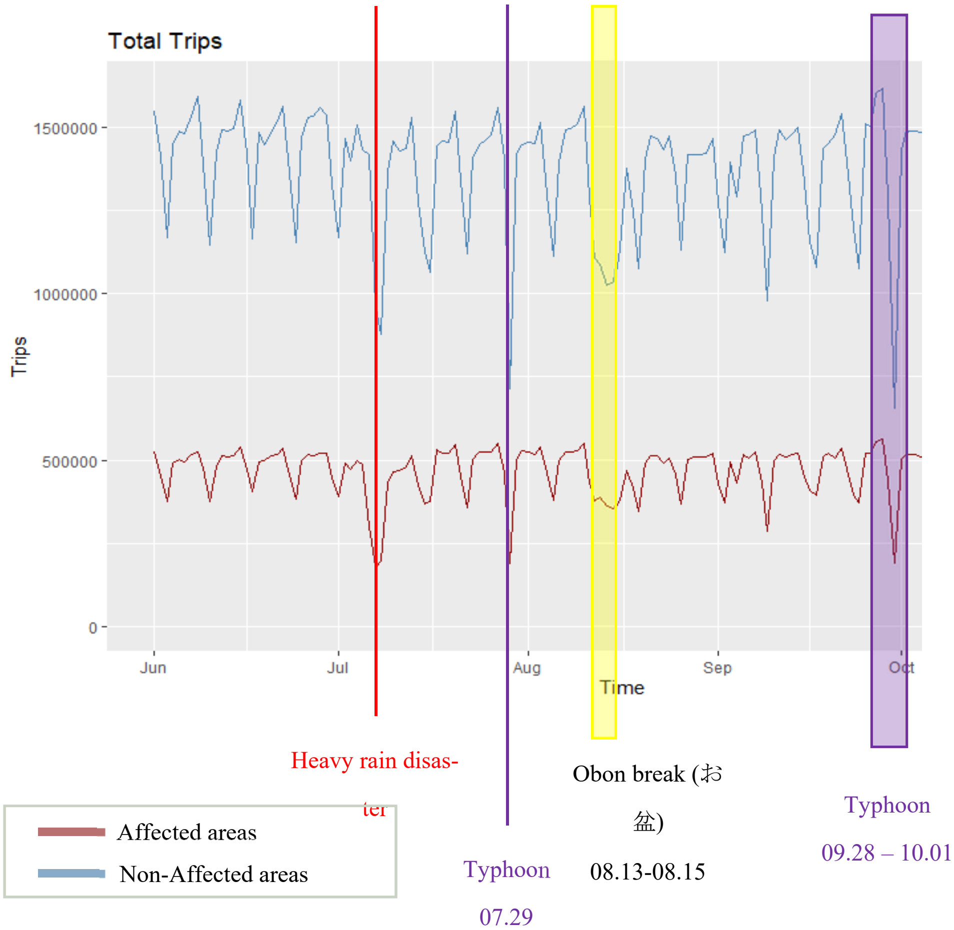
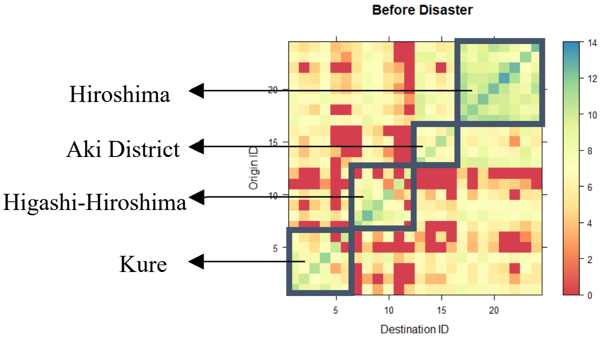


Figure 5. Changes in total number of daily trips in the target area

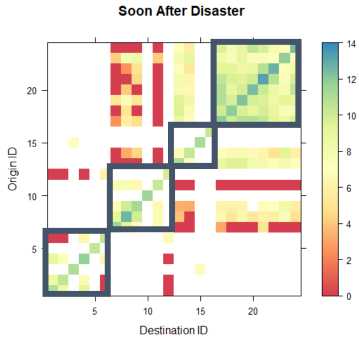
the travel demand, the heavy rain disaster in July 2018 still leaves some damaged roads, and until September 2018, the transport network was not fully recovered. Note that the weekend data is included in this figure so that some drops were captured apart from the previously mentioned events. In the heavy rain disaster, we encountered a number of trips mixed with the recovery and emergency activities. Thus, the decrease in the number of trips was not so different from other disruptions.

Meanwhile, Figure 6 shows the travel demand at four different times. Figure 6(a) shows the travel demand before disruption occurred. The X-axis shows the destination ID; Y-axis shows the origin ID, while the level shows the logarithm value of travel demand. Red color indicates lower travel demand, and blue color indicates higher travel demand.

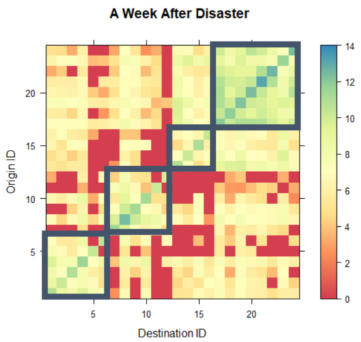
demand. In Figure 6(a), we can confirm that condition that intra-trips travel demand has higher travel demand than the demand to or from other areas. The higher travel demand is in the Hiroshima city area. We can also confirm that, when the disaster occurred and many links were disrupted, the travel demand drastically decreased. Figure 6(b) showing the travel demand on the day when the disruption occurred, and many ODs were not connected at all, indicated by white color in the matrix. The intra-trips, especially in Kure, have low travel demand due to the severity of the damage that affects the links' connectivity. A similar condition also happened in Higashi-Hiroshima and Aki District, where some links are disrupted. However, again, we confirm that intra-trips still higher than the travel demand to or from other areas. Figure 6(c) shows travel demand a week after



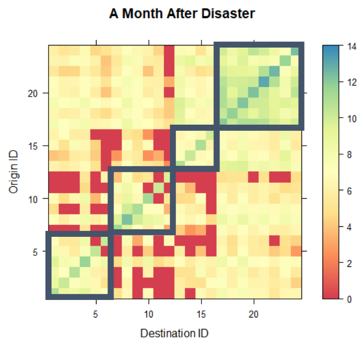
(a) Before disaster (June 30, 2018)



(b) Soon after disaster (July 7, 2018)



(c) A week after disaster (July 14, 2018)



(d) A month after disaster (August 11, 2018)

Note: The IDs (New IDs) of origins/destinations are provided in Table 2.
Figure 6. Travel demand matrices by July 2018 heavy rain disaster.

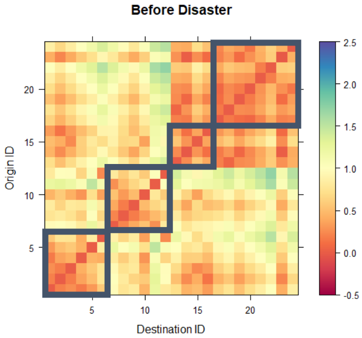
disruption occurred. Although not all the links were recovered, each O-D has at least one link. So that, people can travel despite sometimes they have to take a detour to reach the destination. Travel demand increased a month after the disaster (Figure 6(d)) compared to a week after the disaster (Figure 6(c)). At that time, most of the links were recovered.

5. RESULTS AND DISCUSSION

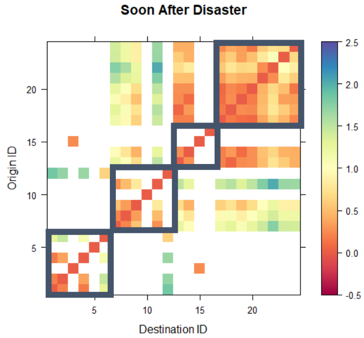
(1) The Expected Minimum Generalized Cost

The expected minimum generalized cost was straightforwardly obtained from the accessibility index calculated from the recursive logit model. The accessibility index refers to the easiness of reaching the destination. The higher index indicating the access to a specific destination is easier (more accessible) and vice versa. Many roads were damaged when the disruption occurred and cannot be used; thus, the accessibilities are smaller than the accessibility before disruption occurred. Note that in the calculation of the accessibility index, we also used travel time and travel cost to generate the logsum value (accessibility); the details can be seen in our previous study (*27*).

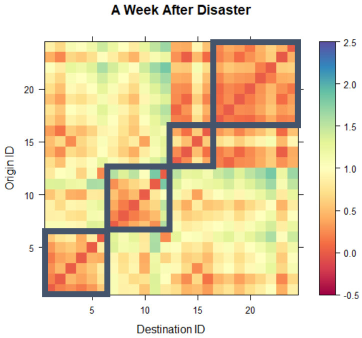
In analyzing the expected minimum generalized cost, we adopted parameters from Oka et al. (*28*), where the parameters were empirically estimated using freight vehicle GPS trajectory data. The generalized cost indicates the cost people have to pay when they make the trips. Figure 7 shows the calculated



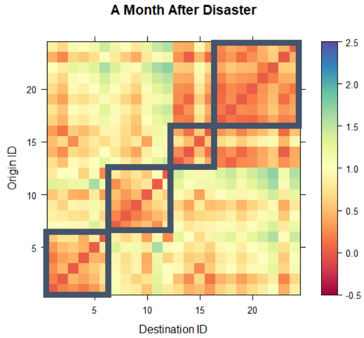
(a) Soon after disaster (June 30, 2018)



(b) A day after disaster (July 7, 2018)



(c) A week after disaster (July 14, 2018)



(d) A month after disaster (August 11, 2018)

Note: The IDs (New IDs) of origins/destinations are provided in Table 1.
Figure 7. Generalized cost matrix by July 2018 heavy rain disaster.

generalized cost in each point of time. The level shows the logarithm of expected minimum generalized cost. Figure 7(a) shows the condition before disruption occurred, while Figure 7(b) demonstrated the condition soon after the disaster occurred. Due to the massive network disruption, we can confirm that some of the OD pairs have no connections, indicated by the white cells. Figure 7(c), shows the expected minimum generalized cost a week after the disaster, representing that some pairs still have higher expected minimum generalized cost. Meanwhile, Figure 7(d) represents the condition a month after the disaster. The expected minimum generalized cost in this condition almost goes back to the condition before the disaster occurred, where all connectivity has its own expected minimum generalized cost and in the intra-trips have a lower value of expected minimum generalized cost.

(2) Elasticity

The temporal changes of elasticity used the three-day consecutive periods from June 1, 2018, to September 30, 2018. This study decided to use three-day length data to analyze the elasticity since the patterns could better explain the condition. Additionally, we confirmed that the elasticity in the seven days and two weeks length data would produce the similar elasticity values, and thus the results are less affected by the length. Table 3 showing the result of the model for three out of 120 period, indicating that the elasticity value a) before the disruption (period 7; June 7-9, 2018), b) soon after the disruption (period 35; June 5-7, 2018), and c) about a month after the disruption (period 70; August 9-11, 2018).

These results indicate that the elasticity value is increasing soon after the disaster but then might higher after the disaster, which follow the tilde shaped (~shaped). Soon after the disaster (b), the elasticity value is -0.802, meaning that a 1% increase in the expected minimum generalized cost will reduce 0.802% demand. This result is also showing that the elasticity is less elastic compared to the average elasticity value before disruption (-0.989), meaning that people tend to travel although the expected minimum generalized cost as the service level changes. This would be partially because travel demand includes the evacuation and emergency activities, changing the nature of transportation services from luxury goods to necessity goods to some extent.

This finding confirms the first hypothesis, *H1: The service elasticity of travel demand becomes less elastic soon after the disaster. People still travel partially because they have to conduct emergent disaster-related activities even though travel cost is higher than normal.* The finding shows that even though the expected minimum generalized cost changes due to changes in the service level, people still tend to or need to travel.

This condition is then followed by the cancelation trips, supporting the hypothesis *H2: The service elasticity of travel demand becomes more elastic after the emergency. People cancel their trips partially because they realize that their road use leads to serious congestions that may negatively influence the recovery process.*

During the recovery process, people may consider the services as luxury goods since they may start to realize that their road use would lead to serious congestions that may negatively influence the recovery process. As a result, the travel demand would voluntarily decrease. Considering the resilience concept and its phases, we divided the elasticity graph over time into three phases based on the existing studies. Figure 8 shows the results together with the log of generalized cost, travel demand, and link availability. We also added the moving average of the elasticity, showing the average elasticity for seven days value. We then defined three main phases when a transpor-

Table 3. Estimation Results

(a) before the disruption (period 7; June 7-9, 2018)				
	β	t-value	σ^2	Std. Dev
Fixed effects				
(Intercept)	3.648	344.791		
$x_{1ij\tau}$	-0.964	-42.792		
Random effects				
Origin-destination-time			1.901	1.379
Residual			0.321	0.567
R-square	0.883			
Final log-likelihood	-24,888.4			
Number of observations	19,804			

(b) soon after the disruption (period 35; June 5-7, 2018)				
	β	t-value	σ^2	Std. Dev
Fixed effects				
(Intercept)	3.758	292.452		
$x_{1ij\tau}$	-0.802	-36.338		
Random effects				
Origin-destination-time			1.270	1.127
Residual			0.428	0.654
R-square	0.852			
Final log-likelihood	-20,346.8			
Number of observations	14,963			

(c) about a month after the disruption (period 70; August 9-11, 2018).				
	β	t-value	σ^2	Std. Dev
Fixed effects				
(Intercept)	3.656	394.69		
$x_{1ij\tau}$	-1.076	-49.61		
Random effects				
Origin-destination-time			1.896	1.377
Residual			0.326	0.571
R-square	0.875			
Final log-likelihood	-25,126.2			
Number of observations	20,396			

tation system got disrupted based on changes in elasticity values. *First,* the normal condition. This condition is generally defined as the condition when there is no disruption occurred in the network. In this phase, all links are available, and the demand elasticity is less elastic, meaning that people remain travel despite its expected minimum generalized cost. *Second,* the

In the emergency phase, the demand reduced on average, but people may tend to consider transportation services as necessity goods even though the network was disrupted and total travel cost was higher, which further, the congestion cannot be avoided (*30*). In this emergency state, it is better to prioritize the emergency vehicles. However, at the certain point, when

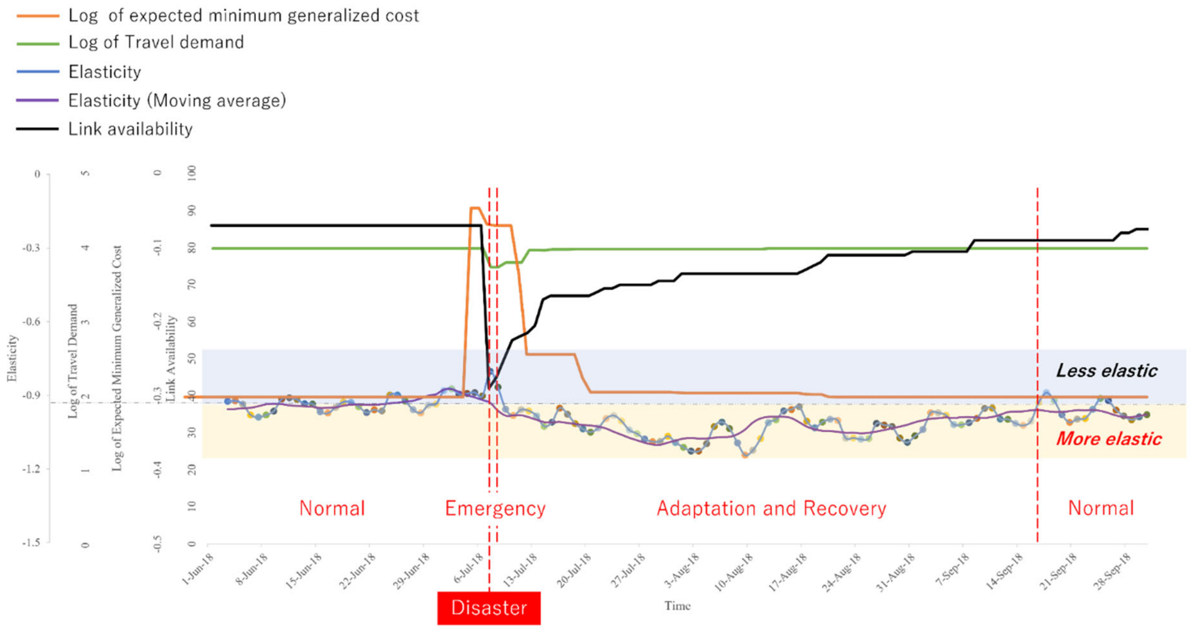


Figure 8. Changes in service elasticity of travel demand during heavy rain disaster occurred in July 2018 in Hiroshima

emergency phase, meaning that the phase when the disruption occurred. We simply defined the emergency phase based on the elasticity values, where the elasticity value is less than the average elasticity value before disruption, which is considered less elastic, meaning that people tend to consider travel as a necessity good. This is partially evidenced by the increased travel demand in some O-D pairs soon after the disaster. Nevertheless, as we discussed previously, the majority of the travel demand in this phase decreased.

Note that we do not separate the evacuation activity and the demand from the travelers in this study. *Third*, after some time, the elasticity is greater than the average elasticity value before disruption, indicating that people start to adapt (trip cancelation, etc.). This condition would imply the end of the emergency phase, or shift to the adaptation and recovery phase, since the degree of the necessity of transportation services goes back to normal.

The results of this study would help policymakers to better understand the situation. In heavy rain disaster July 2018 Japan, Tennou-Kure as one of the affected area experienced congestion due to high travel demand, and it continued for several months.

the phase transition to adaptation recovery phase occurred, people tend to voluntarily cancel the travel (*31*). Implying that people start to adapt with the condition of the recovery process. In this phase, an efficient tentative transport service, such as a temporal BRT service introduced in Hiroshima-Tennou-Kure during heavy rain disaster in 2018 (*32*), would need to be introduced as an transportation management measure during disaster.

CONCLUSION

The primary objective of this paper was to explore the changes in service elasticity of travel demand, where the service level is defined as the expected minimum generalized cost obtained from the recursive logit model. To facilitate the understanding of changes in service elasticity of travel demand, we introduce a resilience concept and identify several transition phases during disaster. The empirical analysis was conducted focusing on the heavy rain disaster 2018 in Hiroshima Metropolitan Area, Japan.

The study has two hypotheses regarding changes in the elasticity value: (1) the service elasticity of travel demand becomes less elastic soon after the disaster. People still travel partially because they have to conduct emergent disaster-related activities even though travel cost is higher than normal, and (2) the service elasticity of travel demand becomes more elastic after the emergency. People cancel their trips partially because they realize that their road use leads to serious congestions that may negatively influence the recovery process. The empirical results done using a multilevel log-log regression model support these two hypotheses and confirm that the identified temporal patterns of elasticities follow the tilde shape: it increased soon after the disaster (i.e., transportation services tend to be necessity goods), decreased rapidly after the emergency phase (i.e., transportation services tend to be luxury goods), and gradually returned to the original level. This implies that people tend to be less sensitive to the network disruption in the emergency phase, but then people start to adapt the condition in the adaptation and recovery phases. Identifying these transitional phases will help policymakers to understand and able to respond to each phase, since primary goal of disaster management would be different by phase.

In future, we need to conduct more empirical studies with focusing on different disasters and different regions to confirm that whether or not the identified tilde shape changes in elasticity are a robust finding. Also, this study does not take into account the congestion aspects, though it was serious problem during the disaster (*30*). Even though we have such limitations, we believe that this study has an important contribution to organizing and consolidating different phases of transport management during disaster.

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