THE IMPACTS OF TRANSPORT NETWORK DISRUPTIONS ON TRAVEL DEMAND: A CASE OF JULY 2018 HEAVY RAIN DISASTER IN JAPAN

Nur Diana SAFITRI[1], Makoto CHIKARAISHI[2]

[1] Division of Advanced Science and Engineering, Hiroshima University
(1-4-1 Kagamiyama, Higashi-Hiroshima 739-8529, Japan)
E-mail: dianasafitrinds@gmail.com
[2]Member of JSCE, Division of Advanced Science and Engineering, Hiroshima University
(1-4-1 Kagamiyama, Higashi-Hiroshima 739-8529, Japan)
E-mail: chikaraishim@hiroshima-u.ac.jp

In July 2018, a heavy rain disaster in southwestern Japan caused floods and landslides, resulting in large-scale transport network disruptions. The network disruptions affected the socioeconomic aspect, leading to economic loss. Using the concept of resilience triangle and the Markovian route choice model (recursive logit model), this research explores the impacts of transport network disruptions on transport demand. We quantify the monetary loss caused by the road network disruptions using the logsum values obtained from the recursive logit model. The results indicate that the total monetary loss is around 5.7 billion Japanese Yen, even without considering the cost of congestion. This indicates that the resilience of transport network is one of the crucial components in estimating the benefits from transportation infrastructure investment.

Key Words : *Heavy Rain, Resilience, Recursive Logit Model, Monetary Loss*

1. INTRODUCTION

The torrential rains and heavy flooding in southwestern Japan in July 2018 created a condition of extreme disruption for the cities[1)], including several areas in Hiroshima Prefecture. Based on the flash report of damage situation by heavy rain in Hiroshima Prefecture from the Cabinet Office Japan[2)], the number of housing damage is 15,176 and the number of death is 109. Particularly in the three cities and one special area, namely Hiroshima, Higashi-hiroshima, Kure, and Aki District, massive transport network disruptions were occurred on July 6 and 7, 2018[3)], and it led people to postpone or cancel their trips.

The problem of transportation network disruptions has been discussed from the viewpoint of transport network vulnerability. There are four methods of vulnerability analysis as mentioned by Taylor[4)], i.e., a) risk-based inventory assessment, which more considers in the infrastructure assets, b) topologically based assessment, considers the network structure and connectivity, also identify the critical links and nodes in the network, c) serviceability-based assessment, which considers the impacts on the degradation of the network operation, and d) accessibility-based assessment that has similarity with the serviceability and more focus on the socioeconomic impacts.

Moreover, recently the rapidity of the recovery process becomes an important topic, which has been discussed under the concept of resilience triangle. Bevilacqua, Ciarapica, and Marcucci[5)] developed an extended framework of resilience triangle in the supply chain, which focus on the assessment of supply chain performance under disruptions. Li et al.[6)] used resilience triangle to build a resilience framework in frequent disaster conditions, where a resilience triangle is extended to a long-term paradigm to take into account the impacts of frequency on the system performance. Zobel[7)] developed a method to analyze and visualize the resilience triangle, which takes into account the two main characteristics of the resilience triangle, i.e., the robustness of the system and the rapidity of the recovery. However, these frameworks do not really adopt the monetary value of resilience improvement, preventing to convey policymakers to take actions improving the resilience of transport networks.

Given the above background, this study attempts to identify the impacts of transport network disruotion on travel demand under the resilience triangle concept. We first show a framework that considers both the initial impact of disaster and the subsequent time to recovery. We propose a simple logsum-based network performance measure (also known as accessibility index) obtained from the recursive logit model, to quantify the impacts in each point in time. This index is computationally efficient, though we do not consider the effect of congestion. The index can also be used to compute the monetary loss by transport network disruption, since the model is consistent with the random utility maximization theory. Then, the multilevel regression analysis was conducted to identify the impacts of network disruptions on travel demand with the use of Mobile Spatial statistics data obtained from mobile phone company which does not require any direct inputs from the affected people through questionnaire surveys.

The structure of this paper as follows; next section presents a conceptual framework, followed by the methods that we used to obtain accessibility index and to identify the relationship between the transport network disruption and travel demand. We also introduce a way to calculate the monetary loss due to disruptions. We then introduce data used in this study. The following section shows and discusses the results. Last section will concludes the paper findings, policy recommendations, and future prospects.

2. FRAMEWORK

The extended framework of resilience triangle which proposes to identify the monetary loss by transport network disruption is illustrated in Fig. 1. There are three stages in the framework. The first stage identifies changes in multimodal transport network. The second stage quantify the network performance level under disrupted transport network. The last stage is to explore the impacts of network performance on travel demand. In the last step, we perform the multilevel regression analysis to identify the impacts of network disruptions on travel demand and quantify the monetary loss. The first two stages are to explore the impacts of disaster on the transportation supply side, while the last step explores the impacts on the demand side, i.e., how the degradation in the network performance will affect the socioeconomic aspects such as working, education activities, shopping, and vacationing[4].

The key aspect of this proposed framework is in the consideration of temporal aspects of network recovery: Soon after the road network disruption, the network performance would drop to a certain point, then, the performance level will increase as roads are recovered. At a certain time, the network performance will return to its original state (condition before the disruption). This temporal aspects of recovery has been discussed under the concept of resilience triangle in the existing literatures[8),9),10),11),12),13]. Balal et al.[10] defined resilience as the ability to respond and recover to the previous condition before disruption happened. Najarian and Lim[15] in their paper, stated four abilities of a resilience system, as follows: a) Anticipation; phase before anything happens; b) Absorption; phase when the system absorbs the impact of the events/hazards/disasters; c) Adaptation; phase after disasters just before the recovery; d) Recovery; phase in which gradually return to the initial state[15]. Tierney and Bruneau in Ayyub[13] stated the functionality of a system could measure the resilience after getting shocked to the normal or initial level of per-

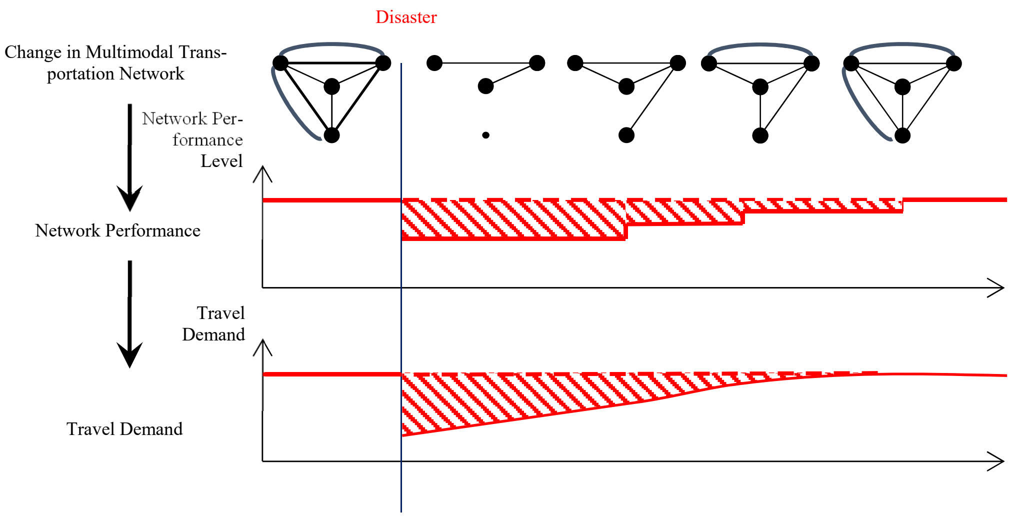


Fig.1 A resilience triangle to identify the impacts of network disruptions on both supply and demand of transport systems.

formance using resilience triangle. The resilience triangle was proposed by Bruneau et al.[8] and defined into the destruction of function in the incident and recovery process[16].

Besides, a comprehensive work that empirically identify the impacts of transport network disruption on both demand and supply side has not really been conducted. One major point would be in measuring network performance level and travel demand over time efficiently. Various network performance measures have been proposed under transport network vulnerability studies[4], but repeated applications of these methods are computationally expensive and thus a method that efficiently quantify the performance is needed. In this study, we propose to use a simple logsum-based network performance measure obtained from the recursive logit model. This approach also allows for quantifying the total monetary loss caused by network disruptions. Hence the comprehensive assessment on the impacts of disaster on both transport supply and demand is becoming possible.

3. METHOD

To quantify the network performance level, we utilize recursive logit model, which proposed by Fosgerau et al.[17]. Then, a multilevel regression analysis was conducted to analyze the impact of transport network disruptions on travel demand. Brief explanations on these methods are given in the following subsections.

(1) Recursive Logit Model

The recursive logit model, initially proposed by Fosgerau et al.[17], is known as a dynamic discrete choice model, where the traveler's path choice problem is represented by a series of link choice problems on a network through Bellman equation. In their paper, it is proved that the recursive logit model is consistent with a multinomial logit model with infinite choice set. One very nice aspect of the model is in the efficient calculation of the logsum measures. Mai et al.[18] proposes an efficient way to calculate logsum values, which all logsum values can be obtained through one inverse matrix calculation. This allows us to efficiently compute logsum values under various network disruption patterns. In the empirical analysis, values cost and time parameters are adopted from Oka et al.[19], where these parameters are estimated by using Freight vehicle GPS trajectory data.

(2) Multilevel Regression Analysis

To identify the relationship between transport network disruption and travel demand (the log of total OD trips), we develop a multilevel regression model, where we introduce four random terms varying across (1) dates, (2) destinations, (3) origins, and (4) the ID which showing combinations of origins and destinations. These random terms are introduced to efficiently control unobserved factors affecting the travel demand. Explanatory variables include (1) the logsum value obtained from recursive logit model, (2) the completely destroy (house damage) in destination and origin information, (3) floor flooded (house damage) in destination nad origin information, (6) weekdays dummy, i.e., 1 if Monday-Friday and 0 otherwise, (7) active time dummy, i.e., 1 if 05.00-21.00 and 0 otherwise. The damage of the disaster was obtained from several reports from the city's Government, that is Higashi-hiroshima[20], Hiroshima[21], Aki District[22], and Kure[23].

(3) Monetary loss from the network disruption

Since the reduction of the logsum due to disaster can be directly used to calculate the additional cost people have to pay for travel for each OD pair, and the travel demand for each OD pair can be obtained from Mobile Spatial Statistics (which will be explained in the next section), we can straightforwardly obtain the monetary loss from the transport network disruption. In this the empirical analysis, we calculate the monetary loss for each OD pairs in the study area and find out which connectivity that has the worst monetary loss. First, we calculate the generalized cost, which shows the loss of money for one trip canceled. We then calculate the monetary loss by taking multiplication of the average number of trips before disaster and the changes in generalized cost for each OD pair.

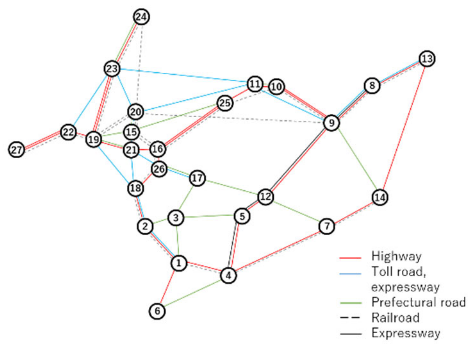
4. DATA

The study of this research is in Hiroshima Prefecture, which focused on the road network of Hiroshima, Higashi-hiroshima, Kure, and Aki District. Data that we used in this study covers the mobile spatial statistics data and transport network data. Both data were taken in the same period in the research area. The mobile spatial statistic data were obtained from Docomo InsightMarketing Inc. This data covers not the road users only, but also users of all other modes. The network data consist of a map showing the network which has the information of link name and node. The list of the area can be seen in Table 1. In this research, we only consider 24 areas excluding area numbers 5, 11, and 25 since a large number of data are omitted from the data due to the privacy policy of Docomo InsightMarketing Inc.

Table 1 List of the Network Data Area

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

Looking at he network data, the closure information was provided from the day when the disaster happened until 3,418 hours after the disaster happened, which indicates that the network was fully recovered within four and half months. In the normal condition, the network has 86 links and its connecting 27 nodes/area (Fig. 2(a)). As shown in the Table 1 for the ID area of the network data, Kure city, which has ID of 1-7, only has several links that connecting the area in intra city network (Fig. 2(b)). Moreover, the connectivity to the area outside of Kure city is very limited. Then, the recovery process began and the broken links were recovered over time. Three days after disaster (Fig. 2(c)), Kure city began to have access to other cities, even though the access was very limited. Fig. 2(d) and (e) showing the condition 7 days/one week and two weeks after the disaster happened. Herein, Kure city has more access to connect to other cities and connect to the area in intra-city. One month after the disaster (Fig. 2(f)), 73 links were recovered, and only 13 links were under recovery process.



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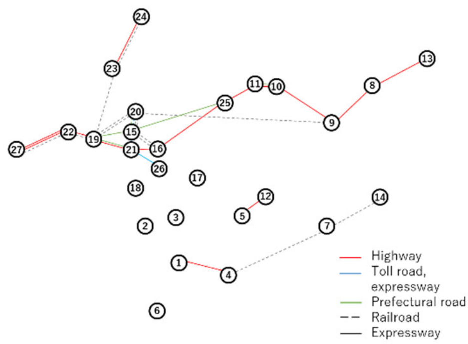

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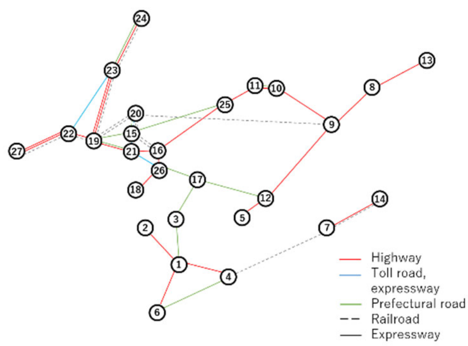

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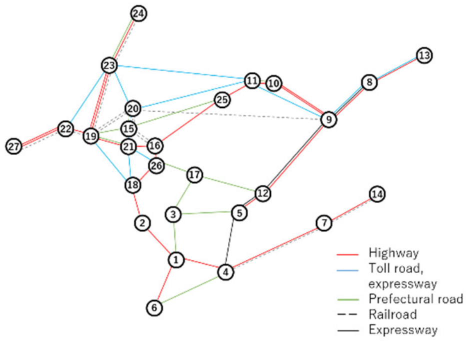

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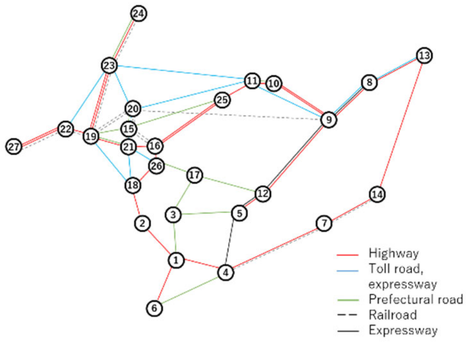

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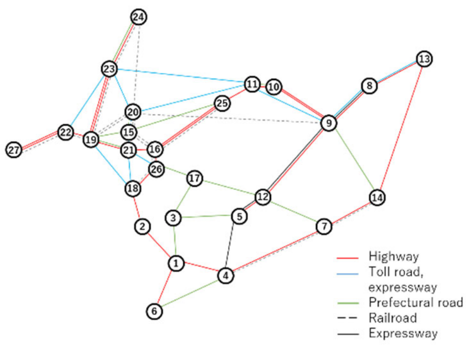


(f)

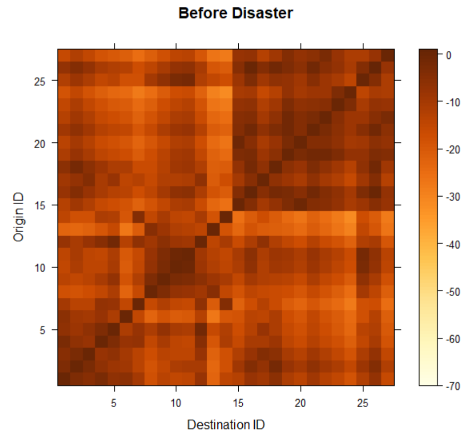
Fig.2 Network in the normal condition (before the disaster happened) (a), soon after disaster happened (b), 3 days after disaster (c), 7 days after disaster (d), 2 weeks after disaster (e), and 1 month after disaster (f).

5. RESULTS AND DISCUSSION

(1) Accessibility Index

The accessibility index refers to the logsum-based network performance measure obtained from recursive logit model. For the network development, we represent a road network as a directed graph. We compute the accessibility index repeatedly whenever a part of transport network was recovered over time.

Fig. 3(a) shows the accessibility index for each pair when no disruption occurs. The light color in the matrix showing the lower accessibility index, and the



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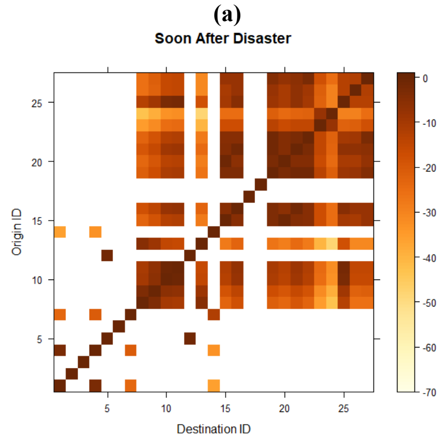

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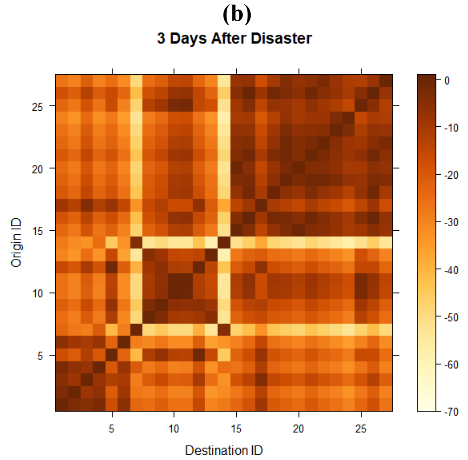

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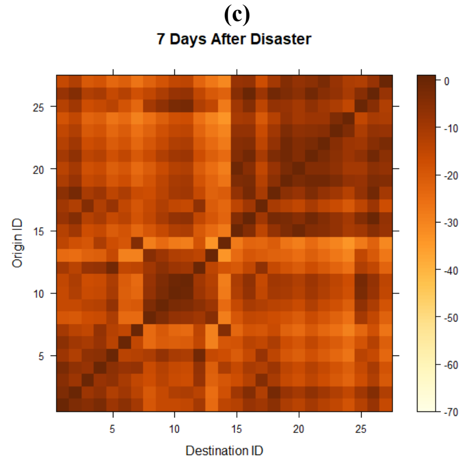

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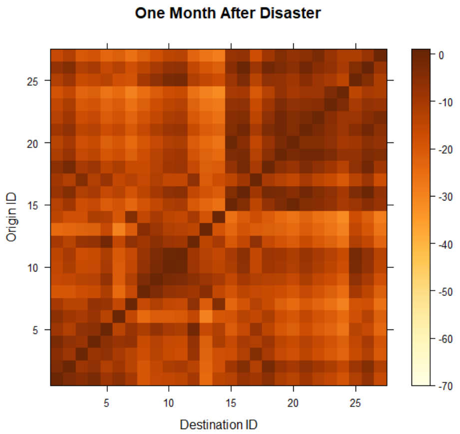


(e)

Fig.3 Accessibility Index Matrix Before Disaster Happened (a), soon after disaster (b), 3 days after disaster (c), 7 days after disaster (d), and 1 month after disaster (e).

dark color showing the high accessibility index. In this condition, all links are accessible. Fig. 3(b) shows the situation soon after the disaster, where only 35 links out of 85 were available. We can confirm that several destinations are not accessible (white color in the figure) mostly located in Kure city. The accessibility index itself had improved over time due to the progress in network recovery. Fig. 3(c) shows the accessibility index in 7 and 14 are still lower even three days after the disaster. Destinations 7 and 14 are Yasuura (7) and Akitsu (14), and we can confirm that it is because less routes are available to these destinations (Fig. 2(c)). The connection between location 14, which dependent on location 7, went on for 172 hours (7 days) after the disaster. Here, it can be seen that location 14 was very dependent on its connection to location 7. From Fig. 3(d) and Fig. 3(e), we can confirm that the accessibility index are almost recovered within one month after the disaster.

(2) Impacts of accessibility loss on Travel Demand

Table 2 shows the estimation results of multilevel regression model, where the unit of analysis is hourly. The results of the marginal R-square show the variance of fixed effects, while the conditional R-square provides for the overall model (fixed and random effects)[24]. The results indicate that the travel demand would increase if the value of accessibility index increase. In case of the severity of the house damage, the completely destroyed for both origin and destination will directly affect the travel demand, which means that if the house damage were getting severe, the travel demand would decrease. Besides, we also confirm that the impact of the flood, weekdays, and time will not affect the travel demand.

(3) Monetary loss by road network disruption

We also compute the monetary loss for all 24 × 24 origin destination pairs. Note that the monetary loss calculated here is the loss of money due to the increase in travel time, not the reduction of travel time. We decided to calculate the monetary loss from the supply side perspective, since as we confirmed in the previous section, travel demand can sometimes increase due to recovery activities and so forth and thus losses calculated from the demand side information may not be very much stable.

The differences in generalized cost before and after disaster can be directly used to quantify the cost of additional travel time. At the OD pair level, the total loss of money per trip ranges from 0 to 3,712 yen. The largest value of the reduction in generalized cost is in the pair of Saka and Aki ward. We then calculate the total monetary loss by taking multiplication of the average number of trips before disaster and the changes in generalized cost for each OD pair. The results are shown in Fig. 4, which could be idenfitied that the monetary loss was decrease over time since the recovery was conducted. Dark color indicates the lowest monetary loss and light color show higher monetary loss. Meanwhile, white color in the matrix show the monetary loss per day greater than one million yen. The highest monetary loss in this condition is pair between Asa Minami Ward (23) to Naka ward (19). Both of them are located in Hiroshima city. If we look at the reduction in number of trips based on trip generation and attraction, the highest monetary loss also corresponds to this, where Asa Minami ward shows the largest trip reduction for trip generation and Naka ward shows the largest trip reduction for trip attraction. Fig. 4(c) shows that the monetary loss was decreased and only one area that has monetary loss greater than one million yen (Saijo (9) and Akitsu (14)). This loss happened due to the closest link which connecting those areas.

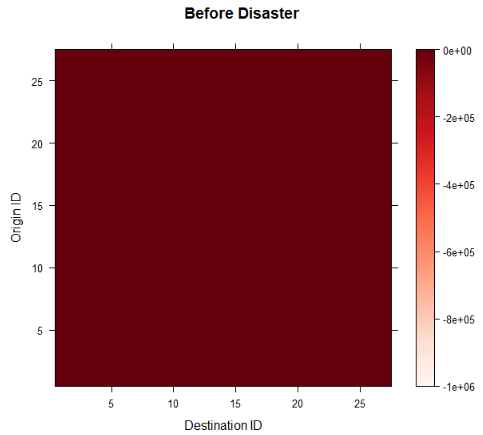
The monetary loss can also been shown using resilience triangle to understand rapidity of the recovery and the severity of the impacts. We exemplify the monetary loss over time in 4 distinct OD pairs. One of the most affected areas is Tenno, Kure[25]. Herein, we looked at the monetary loss to Tenno from the center of Hiroshima city, i.e., Naka Ward. Also, we looked at the monetary loss from Saijo to Akitsu (Higashi-hiroshima), where the recovery of the road connecting these two areas took a longer time than the others. The connectivity between these areas can be confirmed in Fig. 4. Two weeks after disruption, the link between node 9 (Saijo) and 14 (Akitsu) is still

Table 2 Multilevel Regression Results

	β	t value	
Fixed effects			
Intercept	3.0875	16.5120	***
Accessibility index	0.0151	20.8060	***
Completely destroyed in destination	-0.0041	-1.6060	
Completely destroyed in origin	-0.0041	-1.6080	
Floor flooded in destination	0.0004	0.3780	
Floor flooded in origin	0.0003	0.3180	
Weekdays	0.1506	5.8030	***
Active Time	1.3561	479.7110	***
Random effects (Variance)			
Origin-Destination	1.4169		
Date	0.0121		
Destination	0.2138		
Origin	0.2206		
Residual	0.4923		
Marginal R-square	0.0990		
Conditional R-square	0.8120		
Final log-likelihood	-617,554		
Number of observations	577,923		

not available. A similar situation happened in node 2 (Tenno) and node 3 (Yakeyama). The links that directly connect between these areas was not available even one month after the disaster happened. Further, we also look at the monetary loss changes over time in the connectivity between Hiro (Kure) and Kurose (Higashihiroshima), which have the biggest total monetary loss.

In the comparison, the monetary loss between Naka ward and Tenno decreased rapidly, but it takes a long time to reach zero. Meanwhile Saijo-Akitsu and Hiro-Kurose decrease slowly and relatively faster to reach zero. Tenno-Yakeyama decreases slowly and has a tardy graph of monetary loss. It because the link that directly connects these two areas was broken for a long time. Later, the monetary loss reaches zero in November 26, 2018 or when all links was recovered. This indicate that, although in mass medias the connection between Tenno-Yakeyama was not really highlighted compared to the connection between Naka ward-Tenno, the cumulative impacts can be get higher due to the tardy recovery. Identifying it might be useful to consider the optimal order of recovery process, since the marginal benefits from the network recovery getting smaller and smaller as the network is recovered. The total of all monetary loss for all pairs shows that the monetary loss is nearly 6 billion yen, and might higher after consider the congestion. Even though still it would give policymakers to have an intuitive understanding on the loss we had during the disaster.



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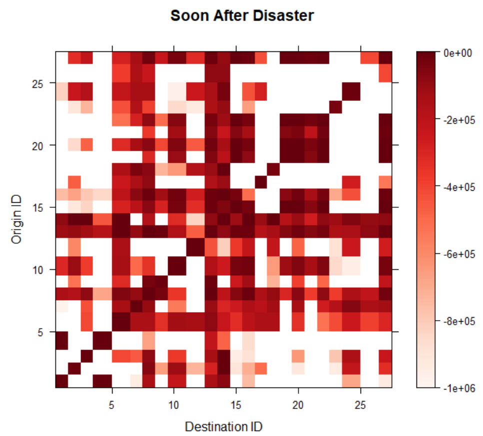

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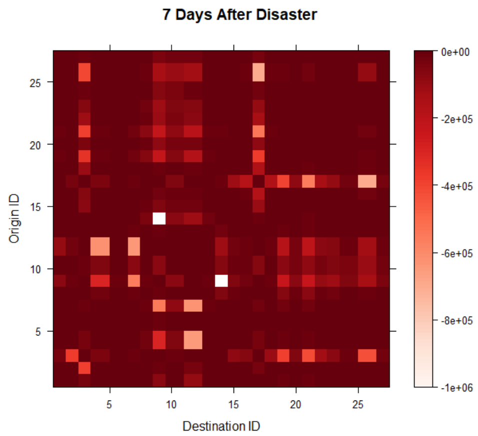

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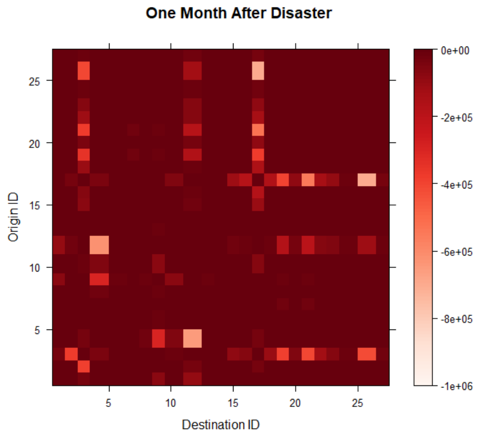

(d)

Fig.4 Monetary Loss Before Disaster Happened (a), soon after disaster (b), 7 days after disaster (c), and 1 month after disaster (d).

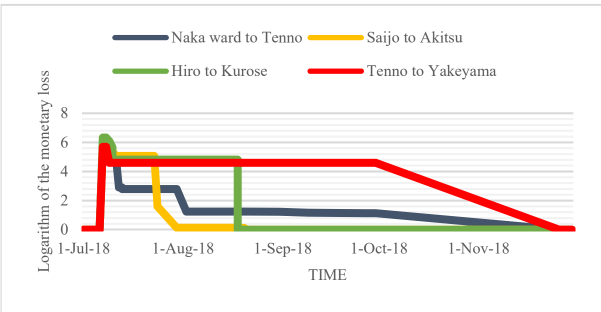

Fig.5 Monetary Loss Over Time in 4 OD Pairs

6. CONCLUSION

This research identified the impacts of transport network disruptions on the travel demand with particular focus on July 2018 heavy rain disaster happened in the Hiroshima Area, resulting in a massive transportation network disruptions. Particularly, we first introduced a resilience concept to reflect the recovery process of transport network over time. We then proposed a simple logsum-based network performance measure (also known as accessibility index) obtained from the recursive logit model. Although this index does not consider the effects of traffic congestions, it is computationally efficient and monetary loss caused by transport network disruptions can be calculated since the model is consistent with the random utility maximization theory. We then conduct the multilevel regression analysis to identify the impacts of network disruptions on travel demand by using Mobile Spatial Statistics data obtained from a mobile phone company. The results show that the accessibility will have the direct impact on travel demand. Moreover, the network disruptions significantly reduce travel demand, and show that the total monetary loss is at least 5.7 billion JPY, which might higher after considering the traffic congestions. The results also show that, for some of the disruptions, the impacts are modest but the total loss is getting larger due to tardy recovery. This indicates that putting the higher priorities to the recovery of main transport corridors is not always a better option, since the marginal benefits would be smaller and smaller as the network is recovered. These results would help policymakers to facilitate the recovery process of disrupted transport networks.

Though significance is aimed, this research also have limitations. First, in the analysis of the impacts using multilevel regression, the dependent variable (number of trips), a number of trips would actually be recovery activities. Actually, exploring transportation demand during disaster is still not very much elaborated, and more empirical analysis is needed to improve our current understanding. Second, our current accessibility index does not take into account traffic congestions, which could be simply solved by using real time travel time information for example from GPS trajectories.

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