People's Risk Recognition Preceding Evacuation and Its Role in Demand Modeling and Planning

Urata, Junji; Pel, Adam

DOI
10.1111/risa.12931

Publication date
2017

Document Version
Accepted author manuscript

Published in
Risk Analysis: an international journal

Citation (APA)
Urata, J., & Pel, A. (2017). People's Risk Recognition Preceding Evacuation and Its Role in Demand Modeling and Planning. *Risk Analysis: an international journal*, *38*(5), 889-905. https://doi.org/10.1111/risa.12931

Title:

People's risk recognition preceding evacuation and its role in demand modeling and planning

Abstract:

Evacuation planning and management involves estimating the travel demand in the event that such action is required. This is usually done as a function of people's decision to evacuate, which we show is strongly linked to their risk awareness. We use an empirical dataset, which shows tsunami evacuation behavior, to demonstrate that risk recognition is not synonymous with objective risk, but is instead determined by a combination of factors including risk education, information, and socio-demographics, and that it changes dynamically over time. Based on these findings, we formulate an ordered logit model to describe risk recognition combined with a latent class model to describe evacuation choices. Our proposed evacuation choice model along with a risk-recognition class can evaluate quantitatively the influence of disaster mitigation measures, risk education, and risk information. The results obtained from the risk-recognition model show that risk information has a greater impact in the sense that people recognize their high risk. The results of the evacuation choice model show that people who are unaware of their risk take a longer time to evacuate.

Keyword:

risk recognition, evacuation behavior, evacuation planning, ordered logit model, latent class model

1. INTRODUCTION

There is an increasing body of literature on understanding the process of evacuation, and it focuses both on people's behavior and emergency management. The important issues to be addressed include the design of evacuation plans and strategies for evacuation operations. At an operational level, the key goal is to manage the travel demand and transportation infrastructure. Road network performance is significantly reduced by traffic overload, and this situation occurs when there is a high traffic demand for travel, leading to delayed arrival at safe locations. We thereby facilitate the necessary inflow of emergency services and the outflow of evacuation traffic. Preceding these operations, at the planning and policy stages, we need to consider aspects of risk education, disaster forecasts and information provision, emergency warning, and anticipatory measures for disaster mitigation. Both stages can be supported by transportation models; planning is typically done using traffic assignment and flow models, while policy development is typically carried out using travel demand forecasting models.

Two approaches can be distinguished in evacuation transportation modeling studies: optimization-based and simulation-based approaches. Optimization-based approaches determine normative evacuation decisions and traffic flows in terms of, for example, the staging of travel demands,[(1)] the usage of dedicated evacuation routes and exit points,[(2)] and the deployment of traffic control measures.[(3)] Several of these studies incorporate sources of uncertainty, which may also be related to evacuation compliance behavior.[(4)] On the other hand, simulation-based approaches specifically aim to capture evacuation behavior as they intend to model the outcome of people's decision-making, and generally use discrete choice models[(5)] to describe travel choices under evacuation situations. Recent literature reviews[(6),(7)] on simulation-based evacuation models show that these models tend to conceptually follow the classical four-step framework that consists of trip generation, trip distribution, modal split, and traffic assignment. It is clear that variations and adaptations are made in some of the underlying assumptions in order to represent evacuation behavior. An example is to incorporate pick-up behavior[(8)] and re-evacuation behavior[(9),(10)] that influence the travel demand patterns, especially during short-notice or totally unexpected disasters. These simulation-based models are useful to analyze the impacts of policy and management measures in light of evacuation response behavior.[(11),(12),(13)]

Simulation-based evacuation planning models predict travel demand, usually as a function of people's decisions to evacuate. The results of empirical analysis by evacuation choice models[(14),(15),(16)] provide the parameters for evacuation simulation. However, these modeling studies excluded the risk-recognition phase, and tended to understate the factors related to disaster mitigation. Some theoretical[(17),(18)] and analytical[(19),(20)] studies have shown that, apart from factors pertaining to the level of danger, emergency warnings, and the evacuation order, the most important factor in people's evacuation decisions is their recognition that they are at risk. However, these studies cannot quantify risk recognition for disaster mitigation measures owing to methodological constraints. To evaluate these measures, we need a framework that can evaluate risk recognition quantitatively. An empirical study using this framework can also clarify the effects of spatiotemporal factors. Spatiotemporal factors are clearly related to risk recognition, but previous studies have provided only a rough analysis[(21)] or no analysis at all.

In short, the least understood issues are: (1) what determines a person's risk recognition; (2) how can risk recognition be captured in evacuation-demand models; and (3) how should it be considered in evacuation planning. These three issues are addressed in this paper. To this end, (1) we analyze empirical data based on survey responses from the 2011 Great East Japan earthquake; (2) we formulate and estimate an ordered logit model to predict people's level of risk recognition; and (3) we use the estimated model to evaluate the role of risk recognition including aspects of risk education, disaster information provision, and emergency warning. The paper is structured as follows. Section 2 reviews earlier studies that addressed risk recognition and related factors. Section 3 discusses the 2011 Great East Japan earthquake and the dataset that was collected. Section 4 analyzes this data to identify what determines risk recognition, statistically. Section 5 formulates an ordered logit model to describe risk recognition. Section 6 estimates several forms of this model, discusses the estimated results, and evaluates the risk-related measures in a high-risk area using the estimated model with respect to evacuation departure time. Section 7 discusses the risk recognition approach to evaluate the risk-related measures. Section 8 presents the conclusions of this study.

2. EARLIER STUDIES ON RISK RECOGNITION

A number of earlier studies have looked into factors that influence risk recognition and its influence on evacuation departure choice. Starting with the former, risk recognition has been studied by analyzing statistical correlations between self-reported subjective risk recognition and objective actual risk, where the actual risk is defined by, for example, disaster scales and spatial characteristics.[(21),(22),(23),(24),(25)] In these studies, factors that are often reported include the individual's socio-demographic characteristics, risk knowledge or education, and prior experience with hazardous situations or disasters. Other studies[(17),(18),(19)] have hypothesized the influence of disaster information on risk recognition. A review paper[(18)] emphasized that people should perceive risk before evacuation, and a warning alone is not sufficient. Expectancy valence approaches[26],[27],[28] have focused on a series of influences from threat and recognition, to response and behavior, theoretically. In particular, the Protective Acton Decision Model (PADM) model[19],[28],[29],[30] adopted a wide range of factors such as social context and social information. Originally, this model was presented as a framework for behaviors in an acute emergency. Some empirical studies[25],[31] analyzed people's risk recognition and behavior on the basis of the PADM model by performing a simple statistical test using stated preference data. Further, the impact on risk recognition was evaluated by multiple regression analysis using stated preference data.[32] A part of their results show the influence from actual risk to risk recognition, and from risk recognition to evacuation. However, the results from this approach cannot be used to evaluate the quantitative impact of mitigation measures on evacuation behavior because they employ simple statistical tests, such as the chi-squared test. Another problem is that these studies did not consider the dynamics of risk recognition. Review studies[33],[34] report that empirical studies that focus on the influence of risk recognition and risk-related measures on evacuation behavior remain insufficient. One of the reasons is the difficulty in capturing these influences, which involve dynamic conditions in real-life situation.[24],[35]

Risk recognition is typically conceptualized by the notion of thresholds beyond which a certain level of risk is recognized.[13],[21],[36] Hence, in the study,[21] an ordered response model was estimated to analyze these risk-recognition levels and how they influenced evacuation choices. In the study,[37] in addition to socio-demographics, hurricane characteristics were also included. Furthermore, the risk recognition of individuals will have a strong heterogeneous characteristic because people have to make decisions under time constraints and with uncertainty. Hence, it is advisable to take a probabilistic approach when designing appropriate policy and management measures.[38]

These discrete-choice models describe individual evacuation choices as a function of their risk recognition, which in turn is a function of various characteristics of the individual in combination with available disaster information. The discrete choice model can be applied to analyze evacuees' behaviors, namely evacuation choice,[14],[15],[16],[39],[40],[41],[42] destination choice,[42],[43],[44],[45] transport mode choice,[46] and route choice.[47],[48] Incorporating factors such as risk education and risk information into these models enables us to evaluate the impact on parameters such as the evacuation response rate. However, a few papers[16],[42],[44],[47] have shown the significance of risk information, which is related to risk-mitigation measures. Moreover, these studies that employed the discrete-choice model did not explicitly consider the relationship between the actual risk, risk measures, risk recognition, and behavioral responses, as in the case of the PADM model. This risk-recognition phase between the actual risk and the behavioral response may have an important role in evaluating risk-mitigation measures. The framework of the PADM model shows that a combination of actual risk and individuals' risk-related knowledge influence their risk recognition, and the risk recognition, in turn, influences their behavioral response. To evaluate the significance of risk measures precisely, an analysis using the discrete-choice model is employed this stepwise framework. These factors, including example risk information and actual risk, will change over time and space. Therefore, it is expected that an evacuation choice model should be evaluated based on a timeline and the evacuees' location.[14],[49] While risk recognition should be evaluated as spatiotemporal variables, few of the previous studies focused on the influence of time and space. Therefore, in this study, we estimated a sequential and dynamic choice model that specifically accounts for these risk recognition-related factors.

For disaster mitigation, planners have to understand the impact of risk education and risk information on evacuees. For example, a theoretical framework provides clarity on issues ranging from risk-related measures to behavioral responses, but these measures are not always significant in simple discrete-choice models. This means that these measures cannot be evaluated quantitatively using a behavior choice model. Our approach applies the sequence from actual risk to risk recognition and behavior to the departure time choice. In particular, risk recognition is required to evaluate risk-related measures, and it is evaluated as a discrete class for the departure time choice. For the risk-recognition model, the actual risk should be described accurately as a time-space related factor. Thus, we can begin to understand risk management in time and space by describing the actual risk as a spatiotemporal-related factor.

3. DESCRIPTION OF THE 2011 GREAT EAST JAPAN EARTHQUAKE

3.1. General Impact and Evacuation Problems

This section shows the casualties and damages caused by the 2011 Great East Japan earthquake. These casualties and damages were reported by the national government[(50),(51)] and local governments.[(52)] The earthquake occurred underwater off the Pacific coast of Tohoku, Japan, at 14:46 JST on Friday, March 11, 2011, and had a magnitude of 9.0. This was the strongest recorded earthquake in Japanese history. The earthquake triggered powerful tsunamis that reached maximum heights of 30 m in Miyako, Iwate Prefecture. These tsunamis were substantially higher than initial expectations, and impacted coastal zones leading to embankment failures, which caused devastating damage.

The initial tsunami warning estimated a tsunami height of 3 m, and was issued 3 min after the quake in Iwate Prefecture. A second warning estimated a tsunami height of 6 m, and was issued 28 min after the quake. A third warning estimated a tsunami height in excess of 10 m, and was issued 45 min after the quake. The first tsunami with height 8 m arrived at Iwate Prefecture 32 min after the quake.

Overall, the earthquake and subsequent tsunamis caused 19,325 deaths and 2,600 people were reported missing. A total of 535 km^2 of land was inundated, of which 119 km^2 was urban. Deaths caused by drowning accounted for 90% of total deaths. With regard to damage to real estate, 129,896 houses were completely destroyed, while 258,348 houses were severely damaged.

Previous studies[(10),(53),(54)] state the following observations regarding evacuation behavior and problems that were encountered. First, the extreme height of the tsunami, which exceeded the wave heights that people had previously experienced, created a situation in which some people did not realize the pressing need to evacuate or were evacuated to a location that was later damaged by the tsunami. Secondly, some deaths were attributed to the inability of people to evacuate themselves owing to their old age or physical disability, as well as because of their delay in commencing evacuations. Others were hit by the waves en route as they were stuck in traffic while either evacuating, picking up family members, or assisting others. These two observations are related to the behavior of both survivors and casualties of the disaster. Overall, the number of casualties was less than 5% of the entire population of the affected area, as the vast majority of inhabitants managed to evacuate on time.

3.2. Impact on Rikuzentakata City

The remainder of this paper focuses on the evacuation behavior observed in Rikuzentakata city, as shown in Figure 1. The higher-than-expected tsunamis caused problems to this city in particular. In 2011, Rikuzentakata had a population of 24,246. The main tsunami reached the coastline of the city 37 min after the earthquake, and it reached the most inland part of the city 45 min after the earthquake. Locally, the disaster resulted in 1,757 casualties and 7,912 destroyed buildings. In Figure 1, the destroyed houses and non-residential buildings are shown in red and orange, respectively. The inundated area, shown in aqua in the figure, extended more than 1 km inland from the coast, and was approximately 13 km^2. In Figure 1, the black shaded area shows the number of casualties who lived in each district. Note that these were their home neighborhoods and not necessarily where they were struck. Twenty percent of the victims were harmed after they had evacuated to the public shelters. Finally, approximately 10% of the casualties assumed a leading role in evacuations, such as local officers or rescue crew members. The extensive destruction was related to the strongest recorded earthquake in Japanese history for this affected area. Some survivors believe that their homes were safe because of their respective locations, which were far from the sea and had never been affected by tsunamis. Therefore, they began evacuating too late, and some people who did not recognize their risk began to evacuate only after watching the tsunami unfold.[(10),(55)] Some people were harmed by the tsunami because of the delay in starting their evacuation.

3.3. Description of the Dataset

The following analysis is based on the responses obtained from a large-scale survey conducted by the Japanese Ministry of Land, Infrastructure, and Transport (MILT) among survivors of the Great East Japan earthquake in 2011. The survey was undertaken via interviews; the total number of respondents was 10,603 people across 49 cities that were impacted by the tsunami. The respondents, who lived in the tsunami-affected areas, were sampled randomly. The survey focused on individuals and not households. The interviewers assigned by MILT went to the respondents' living spaces, which included their houses, temporary houses, or shelters. The respondents were informed in advance that the

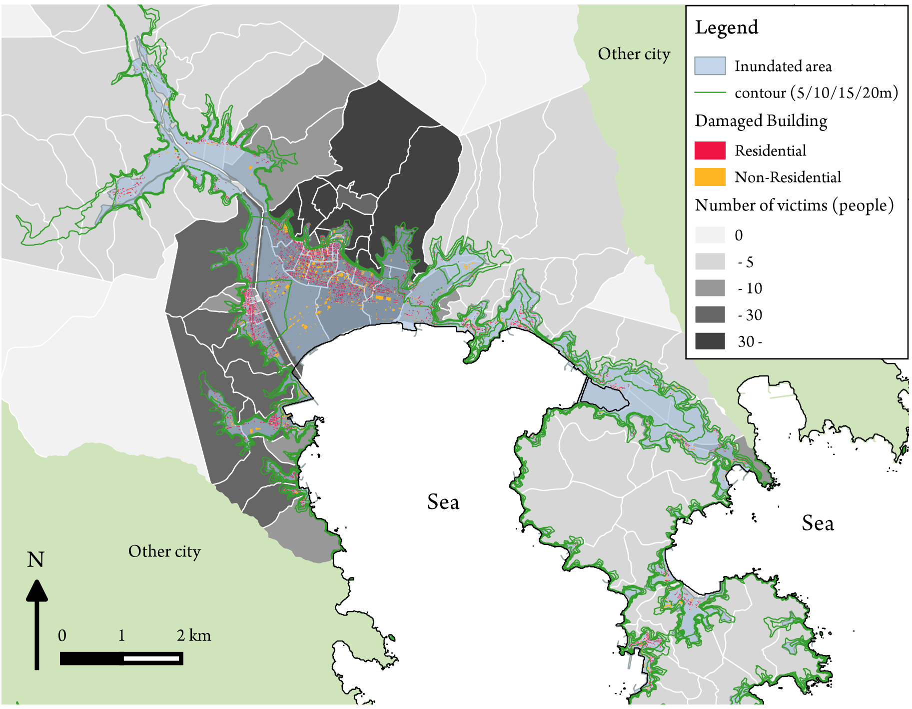


Figure 1: Damaged buildings and number of victims in Rikuzentakata city

interviewers would be visiting them. This door-to-door survey was conducted from September 2011 to December 2011. The survey data contains information on the respondents' activities and location at various points in time (e.g., at the time of the earthquake, the tsunami emergency alert, and the tsunami impact), the warning they received, the information they had access to, their emergency preparations and prior experience with evacuation training, and their socio-demographics and that their households. Furthermore, two questions sought to determine people's perceptions about being at risk, both directly after the earthquake and during the time between the earthquake and the tsunami impact. The respondents were allowed to answer "Not sure." This dataset has been made available as an open-source resource for researchers.[56] In this study, we considered the 510 respondents who lived in the city of Rikuzentakata, and who were evacuated from the tsunami.

4. ANALYSIS OF REPORTED RISK RECOGNITION AND EVACUATION TIMING

4.1. Risk Recognition and Evacuation Timing

Table I presents the relationship between people's self-reported risk recognition and evacuation time. Here, risk recognition was measured by people's responses to two survey questions regarding their prior perceptions about being in danger, directly after the earthquake, and during the time between the earthquake and the tsunami impact. The table shows the mean values of evacuation timing for all respondents in each of the risk-recognition levels. The results were obtained by performing one-way ANOVA analyses, where the Bartlett's test confirmed that each class of risk recognition had equal variance. The results show that the timing of the start of the evacuation was sooner for people with a higher risk-recognition level; this difference is statistically significant, both

Table I: Influence of risk recognition on evacuation timing.

Factors	Evacuation Timing mean	p-values	Observations
Q3: Just after the earthquake, did you think that the tsunami would reach your place?			
Level 3: Will absolutely come	19.8		170
Level 2: Will probably come	22.6	0.00	90
Level 1: Will not come or did not think about it	28.6		162
Q9: Before the tsunami impacted, did you think that you had to evacuate?			
Level 2: Will have to evacuate	22.2	0.00	346
Level 1: Will not have to evacuate or did not think about it	32.2		73

just after the earthquake and later when the tsunami was approaching. With respect to the number of observations for Questions 3 (Q3) and 9 (Q9), the number of people with higher risk recognition increased over time. Q3 reads, "Just after the earthquake, did you think that the tsunami would reach your place?" The answer to Q3 was related to risk recognition immediately after the earthquake, and may be influenced by risk education. Q9 reads, "Before the tsunami impacted, did you think that you had to evacuate?" The answer to Q9 was related to risk recognition before the tsunami, which arrived 37 min after the earthquake, and may have been influenced by risk information.

The results obtained show that the evacuation timing varied based on people's risk recognition. Table II presents the results obtained from the same statistical tests on how risk recognition and evacuation times are influenced by socio-demographic characteristics, risk education and information, and a person's location. This test used the answers to Q3 as respondents' risk recognition, with the exception of the statistical tests on information factors. The statistical tests on information factors used the answers to Q9 as their risk recognition.

The results related to socio-demographics in Table II show that gender, age, and the presence of a child or elderly person in the household were not related to risk recognition and evacuation timing. All of the variables that describe risk education and the official tsunami alert were correlated with risk recognition, and these relationships were statistically significant at 1% confidence level. These relationships reflect the expected trend that risk-recognition levels are higher when there is familiarity with the hazard map, previous evacuation preparedness, receipt of the official tsunami alert, and receipt of the evacuation order. For evacuation timing, only evacuation preparedness and the receipt of an evacuation order had a statistically significant influence on evacuation timing. The evacuation order was given by the local government via a wireless broadcast system and oral communication. The observations that the mean evacuation times of people who received the tsunami alert and evacuation order were higher than those of people who did not can be attributed to the fact that early evacuees started to evacuate before the alert was issued. In addition, knowledge of the hazard map and shelters did not significantly influence evacuation timing despite it being significant for risk recognition.

The distance from the sea and the altitude of each location were statistically significant at 1% confidence level for both risk-recognition and evacuation timing. Both relationships reflect the expected trend of people closer to the sea or at lower altitudes reporting higher risk and earlier evacuation times. The only other statistically significant correlation noted is the influence of the number of stories of a building at the location at the time of evacuation. The survey only asked about these two factors just after the earthquake, and we did not include these factors in the following model analysis.

4.2. Risk Recognition in Space and Time

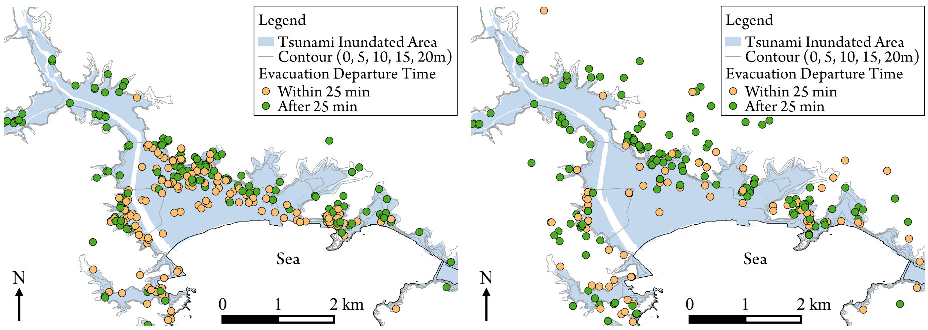
The analyses already show how people's evacuation timing varied widely depending on their risk recognition, and that risk-recognition levels were correlated with the factors of risk education, information measures, and location of the individual. In this section, we show how risk recognition may change over time and space.

First, Figure 2(a) presents the points of origin of people who decided to

Table II: Influence on risk recognition and evacuation timing.

Factors	Risk recognition mean	Risk recognition p-values	Evacuation Timing mean	Evacuation Timing p-values	Observations
Socio-demographics					
Gender					
Male	1.98	0.50	24.9	0.16	162
Female	2.04		23.1		260
Age					
Non-elderly	1.99	0.38	23.1	0.13	286
Elderly (60+ years)	2.07		25.1		136
Job					
Office worker	2.01	0.24	25.9	0.08	138
Self-employed	2.18		23.7		49
Fishery and Agriculture	2.23		20.9		31
Other	1.96		22.5		193
Presence of child in family					
Yes	1.95	0.31	23.3	0.63	125
No	2.05		24.0		297
Presence of elderly in family					
Yes	1.98	0.36	23.8	0.94	230
No	2.06		23.7		192
Risk education					
Hazard Map or Shelter					
Have Known	2.14	0.00	23.4	0.36	281
Have not	1.77		24.6		141
Prepare for evacuation before the day					
Have done	2.09	0.00	22.6	0.00	322
Have not	1.79		27.5		100
Information					
Official Tsunami Alert just after the quake[1]					
Receive	1.88	0.00	24.2	0.41	245
Not Receive	1.75		23.1		177
Evacuation order from local goverment[1]					
Receive	1.85	0.09	25.4	0.01	205
Not Receive	1.80		22.2		217
Location when the quake occurred					
Place					
Home	1.95	0.17	23.3	0.68	231
Working place	2.06		24.5		83
Other	2.14		24.3		108
Number of stories of the building					
1	1.99	0.84	25.0	0.01	90
2	2.01		21.4		213
3+	1.92		27.8		38
Distance from sea [km]					
- 0.4	2.26	0.00	19.8	0.00	144
0.4 - 1.0	2.25		23.2		95
1.0 - 1.5	1.88		24.7		110
1.5 -	1.44		31.0		73
Altitude [m]					
- 5	2.19	0.00	21.3	0.00	189
5 - 10	1.99		22.7		117
10 - 15	1.80		28.3		56
15 - 20	1.71		28.1		49
20 -	1.82		35.7		11

Notes: [1] Answer to Q9 with respect to risk recognition.



(a) origins (b) destinations

Figure 2: Mapping origins and destinations of evacuation trips and its departure and arrival time.

evacuate within a certain time period. Similarly, Figure 2(b) presents the destination of these people. These figures illustrate how the origins and destinations of evacuees change over time. Both the origin and destination locations tended to be farther away from the sea, over time. Assuming that people evacuate from a perceived unsafe location toward a perceived safe location, this general trend of moving further inland over time is expected. It means that an evacuee assumes her/his point of origin as unsafe and her/his destination as safe. The dynamic changes in origins and destinations in these figures show that people's recognized risk change over time. Thus, information on evacuation trip can shed light the dynamical and spatial changes in risk recognition.

5. RISK-RECOGNITION MODEL FORMULATION

5.1. Conceptual Framework

To clarify the concept of risk recognition, consider Figure 3. Risk recognition is defined as the degree to which a person recognizes that he/she is at risk. In our questionnaire, this degree is defined by the fact that the tsunami would absolutely/probably/not reach an evacuee's location. In other words, an

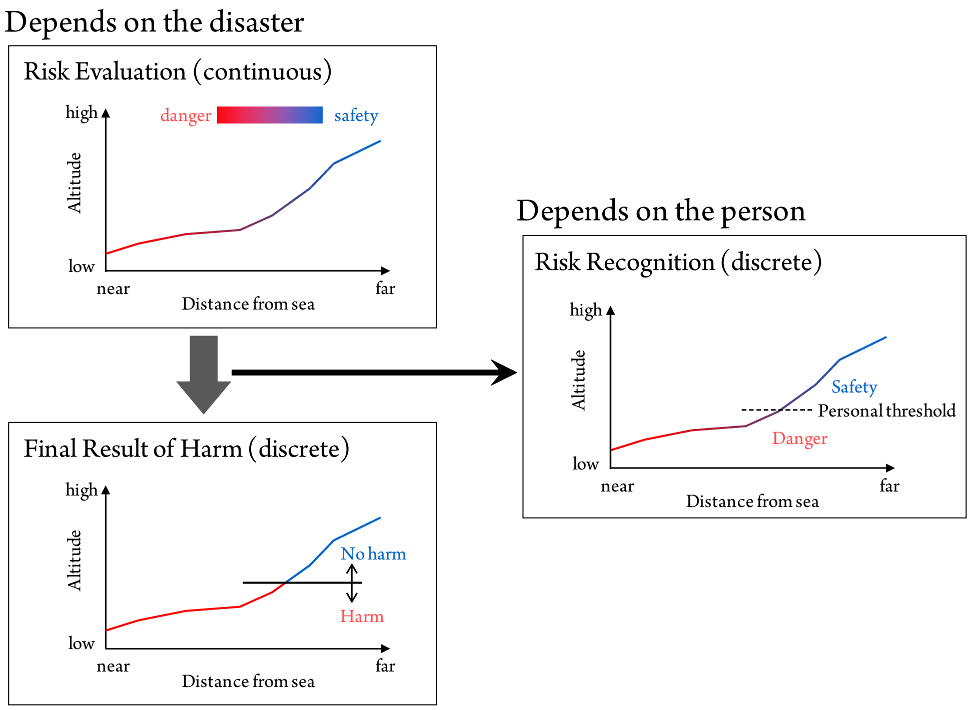


Figure 3: Discrete risk recognition in space.

individual's risk recognition is influenced by her/his exposure to danger and her/his comprehension hereof. The left upper box represents the objective risk exposure as a function of disaster characteristics. The left lower box indicates that the risk needs to exceed a specific threshold in order to be recognized as such, and this threshold is hypothesized to depend on personal characteristics. In this way, people recognize their discrete levels of risk and make decisions about whether or not to evacuate.

The analyses results discussed in the previous section show the influence of various factors on risk recognition and evacuation timing. These findings were used to develop the conceptual framework, as presented in Figure 4. This figure simplifies the PADM model to illustrate our focus, which ranges from disaster mitigation to evacuation choice. We apply repeated decision-making at each

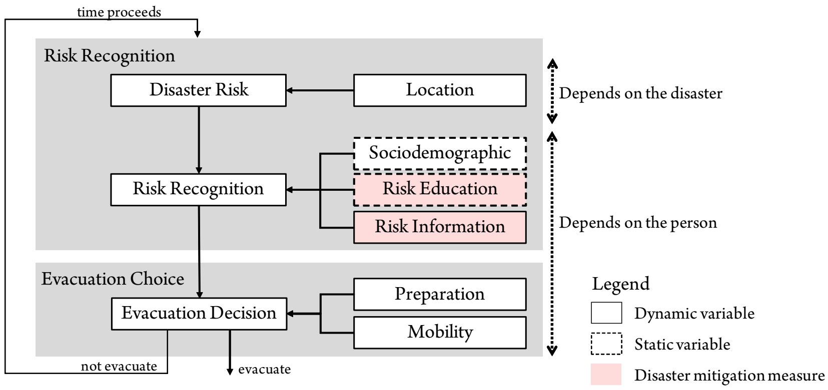


Figure 4: Framework of evacuation decision with risk recognition.

time period.

The framework states that the disaster risk is a function of a person's location, while risk recognition is a function of the disaster risk as well as personal characteristics related to socio-demographics, risk education, and risk information. Risk recognition, together with a person's preparedness and mobility, then determines the decision to evacuate. Subsequently, a person's evacuation time and intermediate activities, such as picking up family members and important documents or personal items, may depend on aspects of their mobility and the time window available to perform these tasks. The decision to evacuate is thus a repeated choice process until the evacuation commences, where the variables that change over time are the location, risk information, preparedness, and mobility.

Our aim is to perform a quantitative evaluation of risk-related measures by introducing risk recognition. Our proposed model will involve two models, the risk-recognition model and evacuation timing model. Risk-related measures, risk information, and risk education, along with the actual risk, will influence an individual's risk recognition. The risk-recognition model evaluates this condition. We can evaluate the impact of risk-related measures on departure time using the evacuation timing model with risk-recognition classes. The effectiveness of choosing to evacuate depends on the risk-recognition levels. It is hypothesized that people recognize their risk discretely and that the level of risk recognition significantly affects evacuation timing. This framework may be applied to a mental and theoretical model, and evaluating the measures quantitatively using departure time should be straightforward.

5.2. Risk-Recognition Model

This conceptual framework can be obtained by developing an ordered logit model that describes the risk recognition, combined with a latent class model that describes evacuation choices. The former is explained in this subsection, while the latter is explained in the next subsection.

Let $R(s_t)$ denote the exposure to danger, which is defined as a function of the location s at time t, and which is referred to as disaster risk. Based on the findings in the previous analyses, risk $R(s_t)$ can be derived from factors such as the distance from the sea and the altitude relative to sea level. Then, let the recognized risk level be denoted by l, and let $H_i^l(t)$ denote for individual i the threshold value at time t, beyond which the risk is recognized as risk level l. Based on the findings in the previous analyses, threshold $H_i^l(t)$ may be derived from factors such as a person's socio-demographics, prior risk education, and the risk information that he/she receives.

This yields the ordered logit model, where the probability of individual i recognizing risk level l or more is given as

$$P_i^{l,t}(R(s_{i,t}) > H_i^l(t)) = \frac{\exp(\sum_j \beta_j s_{i,t}^j)}{\exp(\sum_j \beta_j s_{i,t}^j) + \exp(H_i^l(t))} \tag{1}$$

when expressing risk $R(s_{i,t})$ and threshold $H_i^l(t)$ as

$$R(s_{i,t}) = \sum_j \beta_j s_{i,t}^j + \epsilon_{i,t} \tag{2}$$

$$H_i^l(t) = \sum_k \gamma_k h_{i,t}^k + \sigma_{i,t} \tag{3}$$

where $s_{i,t}$ consists of the location factors of individual i at time t, and $h_{i,t}$ consists of the socio-demographics, risk education, and risk-information factors of individual i at time t. Parameters β and γ can be estimated using the maximum-likelihood method. The error terms ϵ and σ capture the heterogeneous influence of any unobserved factors that are not included in $s_{i,t}$ and $h_{i,t}$, respectively. The ordered logit model holds under the assumption that error terms ϵ are identically and independently Gumbel (i.e., Extreme Value Type I) distributed. We can apply the probit model but the parameters will not be estimated if the number of explanatory parameters is high.

Next, to account for heterogeneity, we extend this model with a mixing distribution of σ, where the risk-recognition probability is defined as $P_{m,i}^{l,t}$, with

$$P_{m,i}^{l,t} = \int P_i^{l,t} f(\sigma|\phi) d\sigma \tag{4}$$

where $f(\sigma|\phi)$ is the density function of σ, with ϕ referring to a vector of parameters of that density function (i.e., mean and variance). The distribution of σ thus accounts for an observable interpersonal heterogeneity of risk recognition. At the same time, we hypothesize the intrapersonal heterogeneity, which is denoted by $\sigma_{i,t}$, to follow Brownian motion.(57) Thus,

$$\sigma_{i,t} - \sigma_{i,t'} \sim \mathcal{N}(0, t - t') \ (t > t') \tag{5}$$

This implies that individual i has her/his perceptional error $\sigma_{i,t}$ at time t, which is correlated with $\sigma_{i,t'}$ owing to its temporal proximity. Such a perceptional error is commonly assumed to follow a normal distribution $\mathcal{N}$; however, here, we apply a truncated normal distribution. We truncate the distribution below 0.1 to incorporate the observation that approximately 10% of the population in Rikuzentakata city did not evacuate successfully.

This model structure is chosen as it addresses both issues of understanding and modeling risk recognition. First, the model allows the identification of the determining factors for risk recognition by estimating the model parameters. At the same time, the influence of exogenous disaster risk is separated from the influence of personal characteristics, which is advantageous for policy evaluation purposes. In addition, the model lets us capture the effect of a person's risk recognition in an evacuation demand model. This is made possible by employing a latent class model, where the proposed ordered logit model predicts class membership (i.e., the risk-level recognition), while the class membership probability is an explanatory variable for predicting an individual's evacuation decisions. The fact that risk recognition is an explanatory variable for predicting evacuation demand has been argued in earlier studies, including those cited in Section 2, and this is supported by the findings explained in the analyses in Section 4.

5.3. Evacuation Choice Model with Risk Recognition Class

The evacuation choice with risk-recognition level can be captured by the latent class model, where the probability of evacuation at time t of individual i is given as

$$P_i^{ev}(t) = \sum_l P_i(ev|l,t) p_{m,i}^{l,t} \tag{6}$$

where the probability $p_{m,i}^{l,t}$ of having a specific risk-recognition level is given by Equation (1) under the assumption of homogeneity and Equation (4) under the assumption of heterogeneity. This evacuation-choice probability function is repeated over time, as depicted in Figure 4, yielding a sequential logit model,[14] The probability $P_i(ev|l,t)$ for risk recognition class l at time t is given by

$$V_{i,l}^{ev}(t) = \sum_j \alpha_l^j x_{i,t}^j + \nu_{i,l,t} \tag{7}$$

$$P_i(ev|l,t) = \frac{\exp(V_{i,l}^{ev}(t))}{1 + \exp(V_{i,l}^{ev}(t))} \tag{8}$$

where the evacuation utility V^{ev} consists of the identified personal factors $x_{i,t}$ at time t. This latent class model holds under the assumption that error terms ν are Gumbel distributed. Given that the choice of whether or not to evacuate is binary, the model can be formulated as a standard binomial logit (as in Equation 8). Finally, parameters α_l for each class l can be estimated using the maximum-likelihood method.

6. MODEL ESTIMATION AND ANALYSIS

6.1. Parameter Estimation for Risk-Recognition Model

Here, we estimate the ordered logit models that describe risk recognition, as formulated in the previous section, based on the dataset presented in Section 3. An individual's risk recognition is obtained by Q3 just after the quake and based on the origin and destination locations of their evacuation from the onset of the earthquake 45 min later. Table III presents the estimation results. Five model specifications are distinguished based on three characteristics: (1) whether an individual's risk recognition is modeled statistically or is dynamically updated (using the sequential logit model); (2) whether interpersonal heterogeneity is included (using the logit mixture formulation); and (3) whether intrapersonal heterogeneity is included (assuming Brownian motion).

The tested variables are based on the analyses in Section 4. All of the variables were found to be statistically significant at the 1% or 5% significance levels. All parameters had the expected signs. The parameters of risk education and risk information were negative. This means that people with risk education and risk information recognized their risk as higher. The risk education factor, as well as the knowledge of hazard maps and shelters, was not significant for the results obtained from the static models (model 1 and model 2). This means that an analysis without a timeline cannot clarify the impact of risk education. In this earthquake-tsunami disaster, some people did not recognize their risk immediately after the earthquake, but for some risk-educated people, it became easy to recognize their risk after some time. The negative parameter of the elapsed time shows that people recognized their risk as increasing over time. The parameters of altitude and distance from the sea were negative and significant in all models. This means that a location that is higher and further away from the sea has a low risk. The tsunami risk varied with location, and this locational risk affected the risk recognition of people who eventually evacuated. In two of the three models that assumed heterogeneity, the standard deviation of the error term σ was statistically significant, thus supporting the hypotheses on interpersonal and intrapersonal heterogeneity. A constant term, which is significant, worked as the mean of σ. However, these heterogeneities were significant only among people located 5– 19 m above sea level. Below 5 m, the altitude risk was almost always recognized as high, while above 19 m, the altitude risk was almost always recognized as low. There is no room for heterogeneity among people who stayed in the lower and higher areas. This means that a planner should broadcast risk information to people who live in these areas so that those who do not recognize their risk are made aware of the danger they are facing.

Table III also shows the leave-one-out cross-validation value of the log likelihood. The test statistics of the log-likelihood ratio show the pairwise comparison of models for their goodness-of fit.[58],[59] We excluded model 4 because a heterogeneity parameter in the model, which is characterized by dynamic and heterogeneity, was not significant. First, as expected, all dynamic and/or heterogeneity models (models 2, 3, and 5) had better predictive power than the static model (model 1), where the improvement was statistically significant at 1% (model 3, 5) and 5% (model 2) significance level. Secondly, the dynamic and heterogeneity model (model 5) had better predictive power than the static heterogeneity model (model 2), where the improvement was statistically significant at 1% significance level. Thirdly, the risk-recognition dynamic model with heterogeneity by the Brown mechanism (model 5) had a better predictive power than the homogeneous dynamic model (model 3), where the improvement was statistically significant at the 1% level. These results indicate that we should describe the dynamical heterogeneity as being cumulative.

Table III: Estimation result for risk-recognition model.

Attributes	1. Static No heterogeneity		2. Static Heterogeneity		3. Dynamic No heterogeneity		4. Dynamic Heterogeneity		5. Dynamic BM Heterogeneity[6]	
	Param.	t-Stat.	Param.	t-Stat.	Param.	t-Stat.	Param.	t-Stat.	Param.	t-Stat.
Threshold variables										
Knowledge of hazard map / shelter[1,2]					-0.35	-1.96†	-0.36	-1.97†	-0.36	-2.00†
Received information[1]	-0.42	-3.30*	-0.42	-3.34*	-0.83	-4.77*	-0.84	-4.81*	-0.83	-4.76*
Elapsed time [h][3]	-	-	-	-	-1.57	-4.10*	-1.59	-4.13*	-1.57	-4.08*
Difference between 2 thresholds	0.36	9.82*	0.36	9.82*	0.36	9.82*	0.36	9.82*	0.37	9.82*
S.d. of σ[4]	-	-	0.10	2.59*	-	-	0.12	1.00	0.18	2.02†
Constant	-2.61	-11.47*	-2.62	-11.50*	-2.42	-9.26*	-2.42	-9.27*	-2.43	-9.29*
Risk variables										
Altitude [m][5]	-1.40	-13.70*	-1.41	-13.82*	-1.50	-13.66*	-1.51	-13.68*	-1.52	-13.75*
Distance from sea [km][5]	-0.25	-4.67*	-0.25	-4.64*	-0.26	-4.79*	-0.26	-4.78*	-0.26	-4.76*
Observations		1246		1246		1246		1246		1246
Log Likelihood at 0		-1368.87		-1368.87		-1368.87		-1368.87		-1368.87
Final Log Likelihood		-984.05		-980.65		-975.68		-975.18		-973.59
Cross Validation Log Likelihood		-987.75		-985.73		-984.60		-		-980.20
Adjusted ρ^2		0.277		0.279		0.282		0.282		0.283

Notes: *=significant at 0.01, †=significant at 0.05, -: no available
[1] Included as dummy variable
[2] Count within 5 min just after earthquake in dynamic model
[3]: Included only for people did not receive information
[4]: Included only for people who stayed between 5 m and 19 m height above sea level
[5]: logarithm
[6]: Introduce a Brown mechanism to dynamic heterogeneity

The estimated risk-recognition model can be used to isolate the impact of risk education and that of risk information. To this end, we define four cases to determine the effect of risk education, risk information, and time by comparing the reference case. The reference case (A) assumes no risk education and no risk information 5 min later after the quake occurred. Case (B) applies the same assumptions, but computes the risk recognition 20 min later, to show the effect of time. Case (C) assumes full risk information to show the associated effect 5 min later. Case (D) assumes full risk education to show the associated effect 5 min later.

In general, it can be observed that risk recognition is limited. However, compared to reference case (A), we observe that risk information (case C) has a higher impact, yielding a risk recognition that is 1.46 higher, followed by time (case B), yielding a risk recognition that is 1.33 higher, and risk education (case D), yielding a risk recognition that is 1.22 higher. Thus, risk information appears to be most effective to ensure that persons recognize their level of risk.

6.2. Parameter Estimation for Evacuation Choice Model

Here, we estimate the latent class models that describe the evacuation choice, as formulated in the previous section. We analyzed the evacuation decisions every 5 min until the respondents started to evacuate. Table IV presents three estimation results. These three model specifications are classified as the proposed latent class model and two no-class models depending on whether disaster characteristics are included or not. The parameters of the former model were estimated jointly using the risk-recognition model. The latter two no-class models functioned as references.

All of the estimated parameters were statistically significant at the 1% or 5% significance level, and had the expected signs. The two-class model provided better goodness-of-fit than the no-class models, where the improvement was statistically significant at the 1% level from the likelihood test using the leave-one-out cross-validation log likelihood. Note that the second no-class model tried to include the explanatory variables that represent knowledge of hazard maps and received information, but these variables were found to be not statistically significant. This means that this evacuation choice model without the risk-recognition class cannot be used to evaluate the disaster mitigation measures. This observation supports the validity of the concept of risk recognition, and the way in which it is based on objective disaster risk, personal socio-demographics, risk education, and risk information (as depicted in Figure 4).

In the two-class model, the parameters of number of trips and companion were positive. These parameters are related to previous behavior at that time. For people who had already traveled many times, and who had remained home after the earthquake, it was easy to choose to evacuate. For people who had companions, it was also easy to choose to evacuate. It was also easy for elderly women to choose to evacuate. People were more likely to choose the evacuation option 35 min after the earthquake, and this was related to the expected arrival of the tsunami. In this city, the tsunami arrived at the coastline 37 min after the earthquake. People were able to observe the effects of the tsunami approximately 35 min after the earthquake. The main difference in the values of the constant terms for people who either did or did not recognize the risk shows that people who did not recognize their risk evacuated late. The parameters in the risk-recognition model are almost same as the parameters of model 5 in Table III.

Table IV: Estimation result for evacuation choice model

Attributes	No-class Param.	No-class t-Stat.	No-class with risk-related factor Param.	No-class with risk-related factor t-Stat.	Two class (joint estimation) Param.	Two class (joint estimation) t-Stat.
Number of trips[1]	0.80	10.07*	0.80	9.71*	0.78	2.95*
Number of trips (high risk class)[2]	-	-	-	-	1.19	6.88*
Companion[2,3]	0.64	5.00*	0.76	5.65*	0.93	5.61*
Had stayed home[2,3]			0.35	2.32†	0.40	2.26†
Elderly female[2,3]	0.40	2.57†	0.44	2.79*	0.62	3.24*
35 min later[2,3]	1.45	6.52*	1.62	7.05*	2.33	5.14*
Constant[1]	-2.33	-21.67*	-2.24	-10.47*	-4.44	-6.30*
Constant (high risk class)[2]	-	-	-	-	-2.27	-13.15*
Knowledge of hazard map / shelter[3,5]	-	-			-	-
Received information[3]	-	-			-	-
Altitude [m][6]	-	-	-0.28	-2.82*	-	-
Distance from sea [km][6]	-	-	-0.24	-4.71*	-	-
Risk-recognition model [7]						
Knowledge of hazard map / shelter	-	-	-	-	-0.38	-2.17†
Received infomation	-	-	-	-	-0.94	-5.81*
Elapsed time [h]	-	-	-	-	-1.58	-4.27*
Difference of 2 thresholds	-	-	-	-	0.36	9.82*
S.d. of σ	-	-	-	-	0.19	2.20†
Constant	-	-	-	-	-2.24	-8.75*
Altitude [m]	-	-	-	-	-1.47	-13.75*
Distance from sea [km]	-	-	-	-	-0.31	-5.98*
Observations		2067		2067		2067
Likelihood at 0		-1432.74		-1432.74		-1432.74
Final likelihood		-876.51		-855.26		-846.33
Cross Validation LL		-882.43		-865.06		-854.57
Adjusted ρ^2		0.384		0.397		0.404
Risk recognition model [8]						
Final likelihood		-		-		-974.54
Cross Validation LL		-		-		-980.72

Notes: *=significant at 0.01, †=significant at 0.05., -: no available
[1]: Param. of low risk recognized in two class model
[2]: Param. of high risk recognized in two class model
[3]: Included as dummy variable
[4]: estimate one parameter in two class
[5]: Count within 5 min just after Earthquake in dynamic model
[6]: Logarithm
[7]: the variables below are the same as in the risk-recognition model
[8]: observations and likelihood at 0 are the same as in the risk-recognition model

6.3. Simulation-based Analysis of Evacuation Choice Model

The evacuation probability curve can be predicted using the estimated parameters. The estimated evacuation choice model can be used to isolate the effect of risk information on evacuation timing. This is presented in Figure 5. The affected area can be artificially divided into three zones depending on the objective disaster risk and the number of observation in each area is approximately equal. The evacuation choice probabilities can then be computed for each of these zones. In this way, the red graph in Figure 5 shows the evacuation probability curve for people in low disaster-risk areas where is far from the sea and at high altitude, the blue graph shows the curve for people in high-risk areas where is near the sea and at low altitude, and the green graph shows the curve for people in an intermediate disaster risk area. For each of these graphs, the dotted line shows the case corresponding to no risk information, while the solid line shows the case for all people who received risk information. Risk information led to a moderate increase in evacuation probabilities in the high disaster-risk zone, a larger increase in the intermediate disaster-risk zone, and a two-fold increase in the low disaster-risk area. This is because risk-recognition levels were already high in the high-risk zone, regardless of risk information. Note that risk education has a similar, but smaller, effect. These results imply that, while the local government may tend to broadcast risk information mainly to people in high-risk areas, it is likely that the average evacuation time for the entire area would have been less had the risk information been broadcast in low-risk areas.

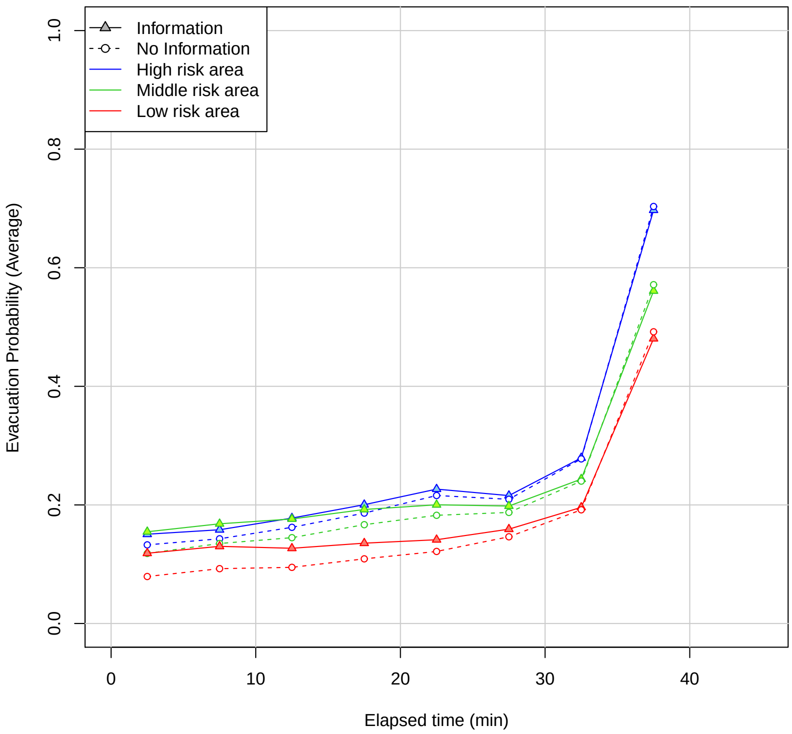


Figure 5: Evaluation of the effect of information about evacuation probability for each location.

7. DISCUSSION

7.1. Availability of Evacuation Trip Data for Understanding Risk Recognition

The need to travel for evacuation purposes enables us to analyze risk recognition in space-time. The locations and timing of evacuation trips provide rich and varied inputs of an individual's risk recognition. An ordinary interview survey after a disaster cannot reveal the risk recognition itself with time and space. This is because people find it difficult to remember and describe their risk recognition within the timeline. The same can be said about locations. In addition, they may give a self-affirming biased recognition. This difficulty may result in less empirical studies of risk recognition. The survey analyzed in this paper also sought to determine evacuees' risk awareness after a warning was issued and before the tsunami's impact, but the survey did not ask about actual times and locations. Therefore, we were unable to utilize these questions for our analysis.

This study used the origin and destination of evacuation trips to analyze an evacuee's risk recognition in addition to the answers to the questionnaire. We hypothesized that there was a recognition of high risk at the origin of the evacuation trip at the time of departure, and low risk at the destination of evacuation trip at the time of arrival. This determination of risk recognition based on the evacuation trip is useful for analysis purposes, although an interview survey performed after a disaster generally has limitations with regard to the accuracy of the time and locations of the trips. Evacuees can more easily recall their trip behavior than their risk recognition itself. Questions about behavior are suitable for survey after a disaster. We should consider that the departure time of evacuation may have a time margin from when she/he recognizes the risk, while the arrival at the location may have a safety margin from where she/he recognizes a low-risk location. However, our analysis can obtain reasonable results that are consistent in time and space. It shows that in our survey, our approach for the evacuation trip is suitable.

7.2. Evaluation of Risk-related Measures Using Risk Recognition

Our proposed model can be used to evaluate risk-related measures by focusing on the sequence of actual risk, risk recognition, and evacuation choice. The model is consistent with the conceptual framework of risk response, for example, the PADM model,[(19), (28), (29), (30)] and we can evaluate risk-related measures quantitatively using the discrete choice model. Previous studies[(21), (22), (23), (24), (25)] that focused on this recognition phase could not evaluate the disaster-mitigation measures quantitatively because of limitations in their statistical approach. Moreover, only a few studies[(23), (24)] have statistical tests using real evacuation data. On the other hand, the evacuation choice model,[(14), (15), (39)] which is based on the discrete choice model, can show the quantitative results using real evacuation data. However, it did not consider the risk-recognition phase because of the lack of interest in the evaluation of disaster mitigation measures. Additionally, the measures cannot be evaluated owing to the omission of the risk-recognition phase in their models.

This study shows the framework used to analyze and evaluate the risk recognition and evacuation choice. The results of our model were obtained using a real dataset. It shows that risk recognition is affected by a combination of the actual risk and risk knowledge. The model parameters of risk education and risk information are not significant in the estimation result (shown in Table IV) if we do not introduce the risk-recognition class. The inclusion of a risk-recognition phase into the proposed model can be used to evaluate risk-related measures quantitatively for the evacuation choice. Our results, which were obtained for one disaster and with a limited number of respondents, definitely require further validation using another dataset.

Our analysis of spatiotemporal risk recognition is related to the measures considered. For example, initially, the results showed that a person who was in a location far from the sea began to evacuate later, whereas people who were in a location near the sea started to evacuate earlier and left the coastal areas. There is a possibility that road congestion will occur because of both early and evacuations. We aim to promote evacuation based on risk information for people who are located far from the sea in order to avoid this congestion. In addition, spatiotemporal risk recognition is useful to clarify the destination choice behavior for both evacuation and pick-up purposes.[(9)] People will choose their destination based on their risk recognition. A model analysis will be more suitable by employing a random-parameter model[(39), (41)] that can show a variety of heterogeneities.

8. CONCLUDING REMARKS

A part of the evacuation planning and management process is to determine the travel demand in the event of a disaster. Simulation-based evacuation models have been used to predict evacuation demand, usually as a function of people's decision to evacuate, which in turn is strongly related to their recognition of being at risk. In this paper, we used an empirical dataset to show (1) the underlying factors that determine people's risk recognition; (2) how risk recognition and evacuation choice can be modeled; and (3) the main drivers of these two processes and how they can be efficiently addressed in evacuation planning.

We have shown how evacuation timing differs according to people's risk recognition, and that risk recognition cannot be solely described by people's location, and is therefore not based only on their exposure. We identified the factors that explain risk recognition, namely risk education and information as well as socio-demographics. In addition, we determined how risk recognition changes dynamically over time.

These results were used to formulate an ordered logit model that describes risk recognition combined with a latent class model that describes evacuation choices. Both models were estimated and evaluated according to their goodness-of-fit and predictive power. For both risk recognition and evacuation timing, we used simulation-based analysis to show the impact of risk education and risk information, and compared these with the impact of socio-demographic characteristics.

The presented analyses and models are expected to be helpful in understanding evacuation behavior. The derived insights will be helpful at the planning and policy levels when considering the aspects of risk education, disaster forecasting and information provision, emergency warning, and anticipated measures for disaster mitigation.

REFERENCES

(1) Wang H, Mostafizi A, Cramer L, Cox D, Park H. An agent-based model of a multimodal near-field tsunami evacuation: Dicision-making and life safety. Transport Research Part C. 2016;64:86-100.

(2) Lu Q, George B, Shekhar S. Capacity constrained routing algorithms for evacuation planning: A summary of results. Advances in Spatial and Temporal Databases Springer Berlin Heidelberg. 2005;3633:291-307.

(3) Xie C, Lin DY,Waller S. A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies. Transportation Research Part E. 2010;46:295-316.

(4) Pel A, Huibregtse O, Hoogendoorn S, Bliemer M. Optimizing evacuation

instructions while anticipating traveler compliance behavior. Proceedings of 13th IEEE ITSC, Madeira, Portugal. 2010; 462-467.

(5) Ben-Akiva ME, Lerman SR. Discrete choice analysis: theory and application to travel demand. MIT press. 1985; 9.

(6) Pel AJ, Bliemer MCJ, Hoogendoorn SP. A review on travel behavior modelling in dynamic traffic simulation models for evacuations. Transportation. 2012;39:97-123.

(7) Murray-Tuite P, Wolshon B. Evacuation transportation modeling: An overview of research, development, and practice. Transportation Research Part C. 2013;27:25-45.

(8) Murray-Tuite P, Mahmassani H. Model of household trip-chain sequencing in emergency evacuation. Transportation Research Record. 2003;1831:21-29.

(9) Liu S, Murray-Tuite P, Schweitzer L. Analysis of child pick-up during daily routines and for daytime no-notice evacuations. Transportation research Part A. 2012;46(1):48-67.

(10) Urata J, Hato E. Modeling the cooperation network formation process for evacuation systems design in disaster areas with a focus on japanese megadisasters. Leadership and Management in Engineering. 2012;12(4):231-246.

(11) Ozbay K, Yazici M. Analysis of network-wide impacts of behavioral response curves for evacuation conditions. In: Intelligent Transportation Systems Conference, ITSC'06 IEEE. 2006;157-162.

(12) Pel A, Bliemer M, Hoogendoorn S. Modelling traveller behaviour under

emergency evacuation conditions. European Journal of Transport and Infrastructure Research. 2011;11(2):166-193.

(13) Hsu Y, Peeta S. An aggregate approach to model evacuee behavior for no-notice evacuation operations. Transportation. 2013;40:671-677.

(14) Fu H, Wilmot C. A sequential logit dynamic travel demand model for hurricane evacuation. Transportation Research Record: Journal of the Transportation Research Board. 2004; 1882: 19-26.

(15) Dixit V, Pande A, Radwan E, Abdel-Aty M. Understanding the impact of a recent hurricane on mobilization time during a subsequent hurricane. Journal of the Transportation Research Board, 2008; 2041: 49-51.

(16) Sadri AM, Ukkusuri SV, Murray-Tuite P. A random parameter ordered probit model to understand the mobilization time during hurricane evacuation. Transportation Research Part C, 2013; 32: 21-30.

(17) Perry RW, Green MR. The role of ethnicity in the emergency decision-making process. Sociological inquiry. 1982;52(4):306-334.

(18) Dash N, Gladwin H. Evacuation decision making and behavioral responses: Individual and household. Natural Hazards Review. 2007;8(3):69-77.

(19) Lindell M, Hwang S. Households' perceived personal risk and responses in a multihazard environment. Risk Analysis. 2008;28(2):539-556.

(20) Lim MBB, Lim HRJ, Piantanakulchai M. Factors of evacuation decision and its implication to transportation planning. Journal of the Eastern Asia Society for Transportation Studies. 2013;10:163-177.

(21) Villegas J, Matyas C, Srinivasan S, Cahyanto I, Thapa B, Pennington-Gray L. Cognitive and affective responses of Florida tourists after exposure to hurricane warning messages. Natural Hazards. 2013;66(1):97-116.

(22) Peacock W, Brody S, Highfield W. Hurricane risk perceptions among Florida's single family homeowners. Landscape and Urban Planning. 2005;73:120-135.

(23) Brommer D, Senkbeil J. Pre-landfall evacuee perception of the meteorological hazards associated with hurricane Gustav. Natural Hazards. 2010;55(2):353-369.

(24) Siebeneck LK, Cova TJ. Spatial and temporal variation in evacuee risk perception throughout the evacuation and return‐ entry process. Risk analysis. 2012;32(9):1468-1480.

(25) Wallace JW, Poole C, Horney JA. The association between actual and perceived flood risk and evacuation from hurricane Irene, beaufort county, North Carolina. Journal of Flood Risk Management. 2014;38(3):610-635.

(26) Rogers RW. Cognitive and physiological processes in fear appeals and attitude change: A revised theory of protection motivation. In J. T. Cacioppo & R. E. Petty (Eds.), Social Psychophysiology: A Sourcebook. NewYork: Guilford Press. 1983;153-176.

(27) Ajzen I, Fishbein, M. Belief, Attitude, Intention and Behavior: An introduction to theory and research. Addison-Wesley, Boston. 1975.

(28) Lindell MK, Perry RW. Behavioral Foundations of Community Emergency Planning. Hemisphere Publishing Corp. Washington, DC. 1992.

(29) Lindell MK, Perry RW. Communicating Environmental Risk in Multiethnic Communities. Thousand Oaks, CA: Sage Publications. 2004.

(30) Lindell MK, Perry RW. The protective action decision model: theoretical modifications and additional evidence. Risk Analysis. 2012; 32(4): 616-632.

(31) Horney JA, MacDonald PD, Van Willigen M, Berke PR, Kaufman JS. Individual actual or perceived property flood risk: Did it predict evacuation from Hurricane Isabel in North Carolina, 2003. Risk Analysis. 2010; 30(3): 501-511.

(32) Kellens Wim, Zaalberg R, Neutens T, Vanneuville W, De Maeyer P. An analysis of the public perception of flood risk on the Belgian coast. Risk Analysis. 2011; 31(7): 1055-1068.

(33) Lindell MK, Prater CS. Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: examples from hurricane research and planning. Journal of Urban Planning and Development. 2007; 133(1): 18-29.

(34) Bubeck P, Botzen WJ, Aerts JC. A review of risk perceptions and other factors that influence flood mitigation behavior. Risk Analysis. 2012; 32(9): 1481-1495.

(35) Rogers G. The dynamics of risk perception: How does perceived risk respond to risk events? Risk Analysis. 1997;17(6):745-757.

(36) Kates R. Natural hazard ecological perspective: Hypotheses and models. Economic Geography. 1971;47(3):438-451.

(37) Matyas C, Srinivasan S, Cahyanto I, Thapa B, Pennington-Gray L, Villegas J. Risk perception and evacuation decisions of Florida tourists under hurricane threats: a stated preference analysis. Natural Hazards. 2011;59(2):871-890.

(38) Kolen B, Helsloot I. Decision-making and evacuation planning for flood risk management in the Netherlands. Disasters. 2014;38(3):610-635.

(39) Hasan S, Ukkusuri S, Gladwin H, Murray-Tuite P. Behavioral model to understand household-level hurricane evacuation decision making. Journal of Transportation Engineering. 2010;137(5):341-348.

(40) Dixit V, Wilmot C, Wolshon B. Modeling risk attitudes in evacuation departure choices. Journal of the Transportation Research Board, 2012; 2312: 159-163.

(41) Hasan S, Mesa-Arango R, Ukkusuri SV. A random-parameter hazard-based model to understand household evacuation timing behavior. Transportation research Part C. 2013;27:108-116.

(42) Yin W, Murray-Tuite P, Ukkusuri SV, Gladwin H. An agent-based modeling system for travel demand simulation for hurricane evacuation. Transportation Research Part C, 2014; 42: 44-59.

(43) Cheng G, Wilmot CG, Baker EJ. A destination choice model for hurricane evacuation. Transportation Research Board 87th Annual Meeting Compendium of Papers DVD, Washington, D.C.. 2008.

(44) Mesa-Arango R, Hasan S, Ukkusuri SV, Murray-Tuite P. A household-level model for hurricane evacuation destination type choice using Hurricane Ivan data. Natural Hazards Review. 2012; 14(1): 11-20.

(45) Troncoso Parady G, Hato E. Accounting for spatial correlation in tsunami evacuation destination choice: A case study of The Great East Japan Earthquake. Natural Hazards. 2016; 82(2): 797-807.

(46) Sadri AM, Ukkusuri SV, Murray-Tuite P, Gladwin H. Analysis of hurricane evacuee mode choice behavior. Transportation Research Part C. 2014; 48: 37-46.

(47) Sadri AM, Ukkusuri SV, Murray-Tuite P, Gladwin H. How to evacuate? A model to understand routing dcisions during hurricane evacuation. ASCE Journal of Transportation Engineering, 2014; 140(1): 61-69.

(48) Sadri AM, Ukkusuri SV, Murray-Tuite P, Gladwin H. Hurricane Evacuation Route Choice of Major Bridges in Miami Beach, Florida. Journal of the Transportation Research Board, 2015; 2532: 164-173.

(49) Gudishala R, Wilmot C. Comparison of time-dependent sequential logit and nested logit for modeling hurricane evacuation demand. Transportation Research Record: Journal of the Transportation Research Board. 2012;2312:134-140.

(50) Fire and Disaster Management Agency. The Great East Japan Earthquake Damage Report, 2017;155. (in Japanese) (Accesed 7^{th} April 2017)
Available at : http://www.fdma.go.jp/bn/higaihou/pdf/jishin/155.pdf

(51) Geospatial Information Authority of Japan. Geospatial Information about The Great East Japan Earthquake Damage. (in Japanese) (Accesed 7^{th} April 2017)
Available at : http://www.gsi.go.jp/BOUSAI/h23_tohoku.html

(52) Rikuzentakata city. The Great East Japan Earthquake Damage Report. (in Japanese) (Accesed 7^{th} April 2017)
Available at : http://www.city.rikuzentakata.iwate.jp/shinsai/shinsai.html

(53) Suppasri A, Shuto N, Imamura F, Koshimura S, Mas E, Yalciner AC. Lessons learned from the 2011 Great East Japan tsunami: Performance of tsunami countermeasures, coastal buildings, and tsunami evacuation in Japan. Pure and Applied Geophysics. 2013;170:993-1018.

(54) Hara Y, Kuwahara M. Traffic monitoring immediately after a major natural disaster as revealed by probe data a case in ishinomaki after the Great East Japan earthquake. Transportation Research Part A. 2015;75:1-15.

(55) Urata J, Pel AJ. Modeling people's risk recognition preceding evacuation, 9th Triennial Symposium on Transportation Analysis (TRISTAN IX), Oranjestad, Aruba, June 12-17, 2016.

(56) Archive of reconstruction supprot survey (in Japanese) (Accesed 7^{th} April 2017) Available at : http://fukkou.csis.u-tokyo.ac.jp/

(57) Williams JT. Capital asset prices with heterogeneous beliefs. Journal of Financial Economics. 1977;5(2):219-239.

(58) Bolt DM, Lall VF. Noncompensatory multidimensional item response models using morkov chain monte carlo. Applied Psychological Measurement. 2003;27(6):395-414.

(59) Ibeas A, Conrdera R, dell'Olio L, Moura JL. Modelling demand in restricted parking zones. Transportation Research Part A. 2011;45:485-498.