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Article

A Study on Influential Factors on Building Damage in Kesennuma, Japan from the 2011 Great East Japan Tsunami

Natt Leelawat[1,a], **Anawat Suppasri**[2], **Ingrid Charvet**[3,4], **Takayuki Kimura**[5], **Daisuke Sugawara**[2], **and Fumihiko Imamura**[2]

1 Department of Industrial Engineering and Management, Graduate School of Decision Science and Technology, Tokyo Institute of Technology, 2-12-1-W9-66 Ookayama, Meguro-ku, Tokyo 152-8552 Japan
2 International Research Institute of Disaster Science, Tohoku University, 468-1 Aramaki, Aoga-ku, Sendai, Miyagi Prefecture 980-8579 Japan
3 Risk Management Solutions, 30 Monument Street, London EC3R 8NB The United Kingdom
4 Earthquake and People Interaction Centre, University College London, Gower Street, London WC1E 6BT The United Kingdom
5 Fukken Co., Ltd., 2-10-11 Hikarimachi, Higashi-ku, Hiroshima 732-0052 Japan
E-mail: [a]leelawat.n.aa@m.titech.ac.jp, n.leelawat@gmail.com (Corresponding author)

Abstract. A number of buildings were damaged by the 2011 Great East Japan tsunami in the Tohoku area. The research objective is to determine the significant predictor variables of the level of building damage. This paper used detailed data on damaged buildings in Kesennuma City, Japan, collected by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT). The tested explanatory parameters included the inundation depth, number of floors, volume of the building, debris flow, structural material, and function of the building. Through multinomial logistic regression, the results found that the number of floors was significantly associated with the damage level; the inundation depth, structural material (reinforced concrete and masonry), and function of the building (commercial facility, transportation/storage facility, and public facility) were partially associated with the damage level. This study can contribute to academic research by assessing the contribution of different variables to observed damage data by applying statistical analysis, as well as the practical contribution of providing an examination of the predominant factors driving tsunami damage to buildings.

Keywords: 2011 great east Japan tsunami, building damage level, multinomial logistic regression, prediction.

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1. Introduction

The 2011 Great East Japan Tsunami created extensive destruction of more than 400,000 buildings in the Tohoku area of Japan [1]. Many parameters were proposed to influence the damage level of buildings from tsunamis, identified by various methods such as the fragility curve and weighed scores, among others. This study was conducted with the purpose of examining the significant factors that appear to correlate with tsunami damage using a statistical method with the detailed building damage data of Kesennuma City, Miyagi Prefecture, Japan. The tested explanatory parameters in this study included the inundation depth, number of floors, volume of the building, debris flow, structural material, and function of the building. The research hypothesis is these explanatory parameters can influence the level of building damage.

In Section 2, a literature review on tsunami damage research is presented. Section 3 describes our research design and methodology. Section 4 presents the data analysis and results of this study. Finally, the findings are discussed and concluded in Section 5.

2. Literature Review

Since the 1990s, Shuto [2] considered the relationship between a range of tsunami inundation depths and building damage using historical tsunami information. One of his examples shows that if the tsunami inundation depth is greater than 2 m, wooden houses may collapse, while reinforced concrete buildings may collapse if the tsunami inundation depth is greater than 8 m [2]. Subsequent studies confirmed such results, such as those by Ruangrassamee et al. [3] and Reese et al. [4]. After the study by Shuto [2], damage criteria for each structural material against a range of tsunami inundation depths were investigated further [5]. A summary of research related to building damage criteria on structural and inundation depth and a summary of research related to building damage criteria on coastal topography and inundation depth are available in [6].

Based on our review focusing on building damage research from tsunamis, this section describes a study on the relationship between tsunami inundation depth with a damage level so-called fragility curve study (Sub-section 2.1), vulnerability of buildings as estimated by the Papathoma tsunami vulnerability assessment method (Sub-section 2.2), and advanced statistical analysis (Sub-section 2.3).

2.1. Fragility Curve Research

"Tsunami fragility" was presented as a new measure for estimating tsunami damage to buildings by Koshimura et al. [7]. Some studies proposed fragility curves for measuring structural destruction from tsunamis for many events such as the 1993 Ohushiri Tsunami in Japan [8-10], the 2004 Indian Ocean Tsunami [11-13], the 2009 American Samoa Tsunami [14], the 2010 Chilean Tsunami [15], and the 2011 Great East Japan Tsunami [16, 17, 18].

2.2. Vulnerability of Buildings (Papathoma Tsunami Vulnerability Assessment Method)

The Papathoma tsunami vulnerability assessment method (PTVA) was developed by Papathoma et al. [19]. Based on the importance of characteristics of buildings identified by previous field surveys of tsunami events and calculations using a multi-criteria evaluation method, the weight factors for various criteria according to their relative importance, in order from high to low, are as follows: (1) "Building material", (2) "Row", (3) "Surrounding", (4) "Condition of ground floor", (5) "Number of floors", (6) "Sea defense", and (7) "Natural environment [19]. Previous studies also demonstrates the importance of building physical parameters and their surroundings in analyzing building damage by tsunamis [20].

2.3. Advanced Statistical Analysis on Building Damage

The new research perspectives on building damage analysis involve applying statistical analysis to examine the influential factors. Leelawat et al. [6] and Charvet et al. [21] applied ordinal regression to analyze the influential parameters influencing the damage level of buildings affected by the 2011 Great East Japan Tsunami. Their study area is Ishinomai City in Japan. The damaged buildings in Sri Lanka from the 2004 Indian Ocean Tsunami were also analyzed by multinomial logistic regression [22].

More information about the tsunami building damage is available at [23].

3. Research Design and Methodology

3.1. Study Area

Kesennuma City is located in the far northeast corner of Miyagi Prefecture, Japan. A pin in Figure 1 indicates the location of Kesennuma City. The right hand side of the city is Kesennuma Bay. The highest elevation of 711.9 m is located in the Motoyoshi District, while the lowest is at sea level. Kesennuma City is our study area.

According to the Ministry of Land, Infrastructure, Tourism and Transport (MLIT) surveys, 251,301 buildings were surveyed by MLIT after the 2011 Great East Japan Earthquake and Tsunami. Among them, 19,815 buildings (7.89%) were in Kesennuma City. Figure 2 shows an example of the damaged buildings in Kesennuma City.

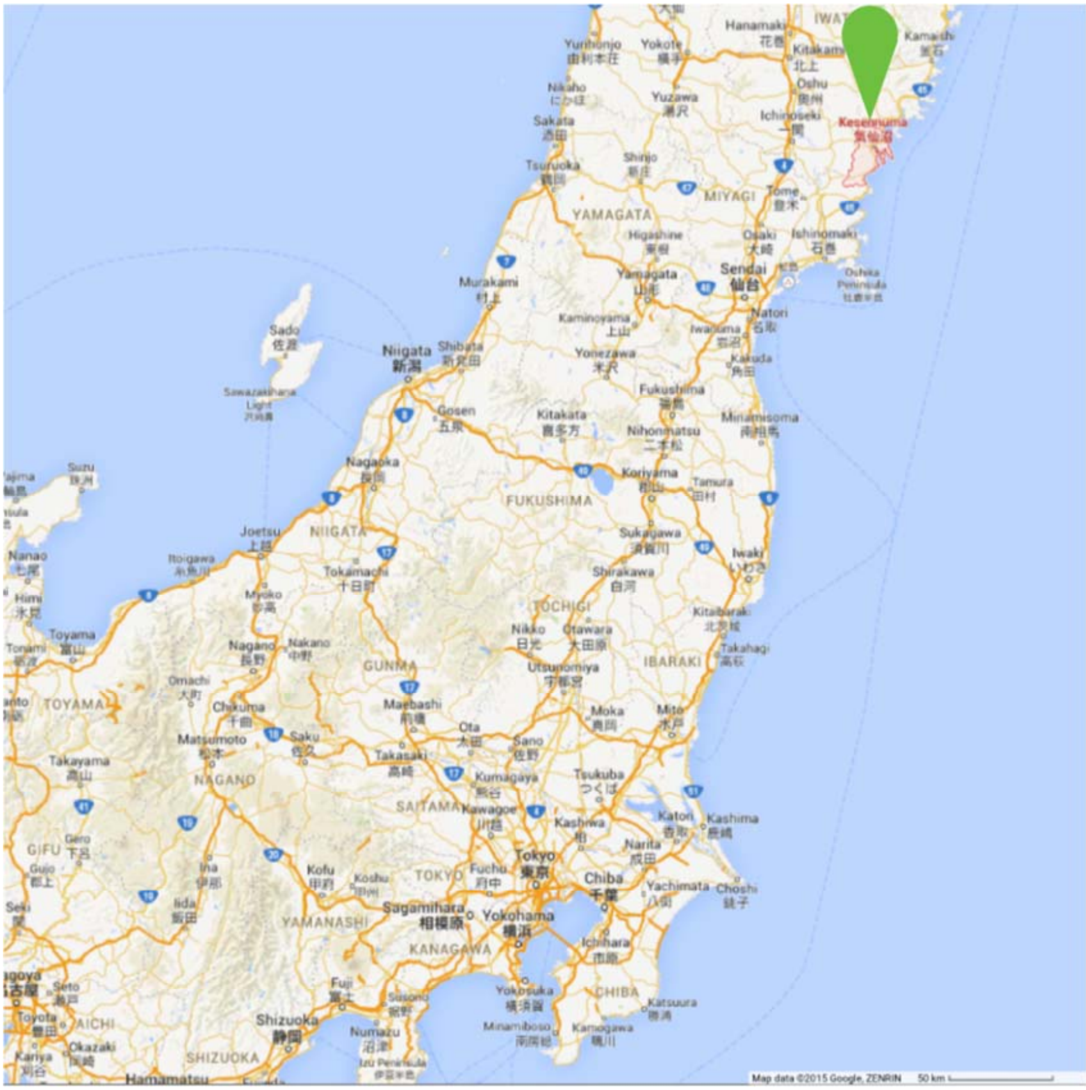

Fig. 1. Kesennuma City, Japan [24].

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Fig. 2. Kesennuma City, Japan taken during a joint survey after the 2011 Great East Japan Earthquake and Tsunami.

3.2. Methodology

Multinomial logistic regression is an extension of binary logistic regression used for multiple dependent categorical outcomes [25-26]. The concept involves comparing the probability between the focus group and the reference group [25].

Based on previous studies and the current available data, the assumed predictor parameters consist of (1) the inundation depth [2-3,6-7,17,27-29]; (2) the number of floors [19]; (3) the building volume; (4) the structural material [6,17-20]; (5) the function of the building [6,17-18]; and (6) the debris impact to the building [21]; the dependent variable is the damage level. The hypothesis is that these predictor parameters can influence the damage level.

According to Japan's Ministry of Land, Infrastructure, Transport and Tourism (MLIT) classification of damage, there are six levels of damage degree: DS1 "minor damage", DS2 "moderate damage", DS3 "major damage", DS4 "complete damage", DS5 "collapsed", and DS6 "washed away". Table 1 provides more details on each damage level.

This paper uses the metric system (e.g., m for the inundation depth, m^3 for the volume of a building). Following previous studies [6,18], the structural material has been categorized into four groups: (1) Wood, (2) Reinforced concrete, (3) Steel, and (4) Masonry. Table 2 provides the definition of the function of the building. Based on MLIT's classification system, the buildings are categorized into six groups (similar to [18]): (1) Residential house, (2) Shared accommodation, (3) Commercial facility, (4) Transportation/storage facility, (5) Public facility, and (6) Agriculture-forestry-aquaculture facility. The debris flow was considered by assuming an area within a radius of 10 m around each washed-away building.

The analysis was performed using IBM SPSS Version 19.0. The method used throughout this study was multinomial logistic regression, for a multi-categorical dependent outcome [25]. Instead of applying the assigned weight scores or linear regression calculation as many previous studies have, this study applied the multi-variable statistical approach to the tsunami vulnerability research.

Table 1. Damage levels, classification descriptions, and conditions of buildings categorized by MLIT.

Damage level and Classification	Description	Condition
No damage	There is no damage.	The building can be used immediately.
DS1 Minor damage	There is no significant structural or non-structural damage, possibly only minor flooding.	The building can be used immediately after minor floor and wall clean up
DS2 Moderate damage	There is slight damage to some walls but no damage in columns.	The building can be used after moderate reparation.
DS3 Major damage	There is heavy damage to several walls and some columns.	The building can be used after major reparations.
DS4 Complete damage	There is heavy damage to several walls and some columns.	The building can be used after complete reparation and retrofitting.
DS5 Collapsed	There is destructive damage to walls (i.e., more than half of wall density) and several columns (i.e., bent or destroyed)	The building has lost its functionality (i.e., system collapse). It is non-reparable or will consume a great cost for retrofitting.
DS6 Washed away	The building was washed away. Only the foundation remains, totally overturned	The building is non-repairable/requires total reconstruction.

Table 2. Function of the building based on MLIT's classifyion system.

Building Type	Group	Definition
11	Residential house	Residential house
12-19	Shared accommodation	Shared accommodation, accommodation with shop or factory facility included
21-29	Commercial facility	Commercial facility or operation/service facility
31-39	Transportation/storage facility	Transportation/storage
41-49	Public facility	Multi-purpose or official workplace
51-59	Agriculture-forestry-aquaculture facility	Agriculture, forestry, or aquaculture facility

4. Data Analysis and Results

4.1. Descriptive Statistics

The data used in this study were collected by MLIT. In total, there are 19,815 buildings. After inspection of the data, 9,066 buildings were determined to have complete data for the analysis.

Table 3 shows the descriptive statistics of the damage level. More than 50% of the buildings (N = 4,785; 52.8%) were washed away. Table 4 describes the descriptive statistics of the function of the buildings. The largest group is residential houses (N = 5,956; 65.7%), while the smallest group is agriculture, forest, and aquaculture facilities (N = 18; 0.2%).

Table 3. Descriptive statistics of the damage level.

Damage level	***N***	**Percent**	**Cumulative percent**
No damage	0	0.0	0.0
DS1 Minor damage	342	3.8	3.8
DS2 Moderate damage	312	3.4	7.2
DS3 Major damage	959	10.6	17.8
DS4 Complete damage	366	4.0	21.8
DS5 Collapsed	2,302	25.4	47.2
DS6 Washed away	4,785	52.8	100.0
Total	9,066	100.0	

Table 4. Descriptive statistics of the function of buildings.

Function of building	***N***	**Percent**
Residential house	5,956	65.7
Shared accommodation	513	5.7
Commercial facility	1,826	20.1
Transportation/storage facility	556	6.1
Public facility	197	2.2
Agriculture, forestry, aquaculture facility	18	0.2
Total	9,066	100.0

Descriptive statistics of structural materials are shown in Table 5. Wooden buildings form the largest group (N = 7,530; 83.1%), while the smallest group is steel (N = 10; 0.1%).

Table 5. Descriptive statistics of structural materials.

Structural material	***N***	**Percent**
Reinforced concrete	180	2.0
Steel	10	0.1
Masonry	1,346	5.8
Wood	7,530	83.1
Total	9,066	100.0

Debris flow parameters were assigned according to the 10-m area around the washed-away buildings. Table 6 provides the descriptive statistics of the debris flow. Approximately 65.4% of the buildings were within the debris flow area. Table 7 shows the descriptive statistics of inundation depth, number of floors, and volume of the building.

Table 6. Descriptive statistics of debris flow.

Debris flow	***N***	**Percent**
Within 10 m area	5,925	65.4
Outside 10 m area	3,141	34.6
Total	9,066	100.0

Table 7. Descriptive statistics of inundation depth, number of floors, and volume of the building

Item	*N*	Min	Max	Mean	SD
Inundation depth (m)	9,066	1	6	1.70	0.590
Number of floors (floor)	9,066	0.0	15.3	4.670	2.7832
Volume of the building (m^3)	9,066	14	58,427	1,329.74	2,514.117

4.2. Testing for Correlated Predictors

It is necessary to check that all predictor variables are independent in order to prevent the multicollinearity problem, which can strongly affect the coefficient estimates of the regression model [30-32]. A Pearson product-moment correlation coefficient was calculated to assess the relationship between each predictor variable [33-34]. As shown in Table 8, based on the criteria of 0.6 [33], the correlation coefficient value showed a moderately strong relationship only between the inundation depth and the debris impact. In addition to the 10-m debris flow area, we also did a further analysis for a 50-m area of debris flow, but the correlation coefficient value still showed a moderately strong relationship with the inundation depth. Thus, the debris influence was eliminated from the regression analysis.

Table 8. Correlation analysis results.

	Number of floors	Inundation depth	Volume of the building	Debris impact (10 m)	Function of the building	Material of the building
Number of floors: Pearson corr.	1					
Inundation depth: Pearson corr.	-0.072**	1				
Volume of the building: Pearson corr.	0.255**	0.007	1			
Debris impact (10 m): Pearson corr.	-0.070**	0.684**	-0.013	1		
Function of the building: Pearson corr.	-0.124**	0.046**	-0.266**	0.045**	1	
Material of the building: Pearson corr.	-0.138**	0.009	-0.331**	0.045**	0.320**	1

Note. *Significant at level $p < 0.05$; **significant at level $p < 0.01$; ***significant at level $p < 0.001$

4.3. Multinomial Logistic Regression Analysis

DS1 was set as the reference group because the research interest would focus on at least the damage to non-structural members. We also set wood as the reference group for the structural material and residential house for the function of the building because they are the largest group in each predictor.

The analysis tested for the goodness of fit [25] and found that this method (multinomial logistic regression) appears to provide the best fit with these data compared with other regression techniques. As shown in Table 9, when setting DS1 as the reference group, the primary results show that significant explanatory variables include the number of floors (all levels), the inundation depth (except DS2), the building volume (only DS4), and the building function (commercial facility for DS2, DS4, DS6; transportation/storage facility and public facility for DS4).

Table 9. Explanatory variables associated with the damage level.

Item	Parameter estimate				
	DS2	DS3	DS4	DS5	DS6
Inundation depth	0.037	0.124***	0.633***	0.418***	0.790***
Number of floors	0.313*	0.388***	1.819***	0.674***	0.415***
Volume of the building	0.000	0.000	0.000***	0.000	0.000
Function (shared accommodation)	-0.398	-0.068	-0.441	0.093	-0.004
Function (commercial facility)	0.793***	0.264	1.187***	0.267	0.347*
Function (transportation/ storage facility)	-0.187	-0.110	1.069**	0.514	0.222
Function (public facility)	0.398	0.658	3.199***	0.783	0.637
Function (agriculture facility)	0.002	-0.386	-0.353	0.571	-0.471
Material (reinforces concrete)	0.667	1.215	5.068***	2.325	-1.307
Material (steel)	-0.402	-0.388	10.482	65.195	-0.891
Material (masonry)	0.291	0.206	2.224***	-0.118	-0.398*

Note. *Significant at level p < 0.05; **significant at level p < 0.01; ***significant at level p < 0.001

In summary, because there are six groups of damage levels, there are 5 equations for the probability (i.e., number of equations = number of dependent groups - 1). The general models according to the supported significant parameters estimate (i.e., coefficient) (see Table 9) are shown in Eq. (1), Eq. (2), Eq. (3), Eq. (4), and Eq. (5):

$$\ln[P(DS6)/P(DS1)] = -1.656 + 0.790x_{inundation\_depth} + 0.415x_{number\_floors} + 0.347x_{function\_commercial} - 0.398x_{material\_masonry} \quad \text{---------} (1)$$

$$\ln[P(DS5)/P(DS1)] = -1.187 + 0.418x_{inundation\_depth} + 0.674x_{number\_floors} \quad \text{---------} (2)$$

$$\ln[P(DS4)/P(DS1)] = -7.098 + 0.633x_{inundation\_depth} + 1.819x_{number\_floors} + 1.187x_{function\_sharedaccommodation} + 1.069x_{function\_transportation} + 3.199x_{function\_public} + 5.068x_{material\_reinforcedconcrete} + 2.224x_{material\_masonry} \quad \text{---------} (3)$$

$$\ln[P(DS3)/P(DS1)] = -0.346 + 0.124x_{inundation\_depth} + 0.388x_{number\_floors} \quad \text{---------} (4)$$

$$\ln[P(DS2)/P(DS1)] = -1.025 + 0.313x_{number\_floors} + 0.793x_{function\_commercial} \quad \text{---------} (5)$$

where $P(DSy)$ is the probability of damage level y; $x_{function\_sharedaccommodation}$, $x_{function\_commercial}$, $x_{function\_transportation}$, $x_{function\_public}$, $x_{function\_agriculture}$, $x_{material\_reinforcedconcrete}$, $x_{material\_steel}$, and $x_{material\_masonry}$ are the predictor variables that have binary values; and $x_{inundation\_depth}$, and x_{number_floors} are the continuous predictor variables for the scale of inundation depth and number of floors, respectively.

Based on Norusis [35], the three commonly used *Pseudo-*R^2 formulas (Cox and Snell [36], Nagelkerke [37], and McFadden [38]) were reported to investigate the amount of variation in output that can be explained by the predictor variables. The results are as follows: $R^2_{Cox\ and\ Snell} = 0.444$, $R^2_{Nagelkerke} = 0.480$, and $R^2_{McFadden} = 0.227$.

4.4. Accuracy of the general models

The analysis accuracy was checked using cross-tabulation with the estimated damage (see Table 10). In total, the classification showed that the model could estimate correctly 62.5% on average with the highest accuracy of 94.7% for DS6.

Table 10. Cross-tabulation analysis result.

Actual damage level	Estimated damage level						%Correct
	1	2	3	4	5	6	
1	**0**	0	297	12	25	8	0.0
2	0	**0**	230	30	46	6	0.0
3	0	0	**464**	92	314	89	48.4
4	0	0	3	**260**	8	95	71.0
5	1	0	300	205	**407**	1,389	17.7
6	0	0	40	157	55	**4,533**	94.7
%Overall	0	0	14.7	8.3	9.4	67.5	**62.5**

5. Discussion and Conclusion

This empirical study demonstrated an analysis to investigate the most significant influential parameters in terms of damage levels of buildings. Multinomial logistic regression was applied to examine all available predictor variables to the damage level. The results found that the number of floors was significantly associated with the damage level. The inundation depth, structural material (reinforced concrete and masonry), and function of the building (commercial facility, transportation/storage facility, and public facility) were partially associated with the damage level.

In line with many previous studies [2-3,6-7,17,27-29], our findings confirm that the inundation depth should be considered as one of the parameters associated with building damage as well as the number of floors. Because the results show that the building function and building material are partially supported in this study, there is evidence to support a deeper study of this issue.

In comparison with [22], which applied a similar method to the case of damaged buildings from the 2004 Indian Ocean tsunami in Sri Lanka, we found that both studies show that inundation depth is one of the significant influential parameters. As for the structural material, Leelawat et al. [22] used a different classification, and thus, it is difficult to compare their study with the current one. In comparison with [6], which is a study on building damage in Ishinomaki City, another city in Miyagi Prefecture, both studies found that inundation depth and number of floors are significantly associated with the damage level. In addition, both studies also found a significant association between damage level and reinforced concrete for structural material; damage level and commercial and transportation facilities for the function of the building. However, their results are different for steel building materials (significant association in [6]), a shared accommodation building function (significant association in [6]), and a public facility building function (not significant association in [6]).

It is important to understand the limitations of this study. Because the research analyzed primarily the data from one city, some characteristic settings may not be generalized to other areas. Moreover, this study applied only the available parameters: some other variables might influence the damage levels. If a future study can investigate those variables, the accuracy of estimations is likely to be improved.

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