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► **To cite this version:**

Makoto Kitsuya, Jun Sasaki. Proposed Evacuation Behavior Model Using Open-Source Data: Flood Disaster Case Study. 6th International Conference on Information Technology in Disaster Risk Reduction (ITDRR), Oct 2021, Morioka, Japan. pp.51-62, 10.1007/978-3-031-04170-9_4. hal-04082629

HAL Id: hal-04082629

<https://inria.hal.science/hal-04082629v1>

Submitted on 26 Apr 2023

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Proposed Evacuation Behavior Model Using Open-Source Data: Flood Disaster Case Study

Makoto Kitsuya¹ and Jun Sasaki²

Graduate School of Software and Information Science, Iwate Prefectural University,
Takizawa, Iwate, Japan
g231s008@s.iwate-pu.ac.jp, jsasaki@iwate-pu.ac.jp

Abstract. In a flood disaster, safe evacuation is essential to save lives. However, there have been problems such as low capacity or biases in evacuation centers for some flood disasters in Japan. Therefore, estimating the number of evacuees in each evacuation center during a disaster is vital for a safe evacuation. Consequently, it is necessary to develop highly accurate evacuation behavior simulation models. This paper proposes an evacuation behavior model using open-source data that are readily available from the internet. As a case study, the evacuation behavior model parameters and coefficients were obtained for a flood in Kuji City, Iwate Prefecture in Japan, where many people were affected by Typhoon Hagibis in 2019. By comparing the actual number of evacuees with the predicted number from the proposed evacuation behavior model and conducting a field survey of the actual evacuation shelters, we measured the validity of the evacuation behavior model and identified possible improvements.

Keywords: Evacuation, Behavior Model, Flood Disaster, Simulation

1 Introduction

Japan has experienced many natural disasters in recent years. As a disaster strikes, the meteorological agency issues weather warnings and advisories, and local governments announce evacuation-related information to encourage residents to take safety actions. However, there is a concern that information sharing, especially after a disaster occurs, may result in delays in responding to the changing disaster situation. As a result of those delays, the capacity of evacuation shelters may be exceeded. For example, 13 evacuation shelters in Iwaki City, Fukushima Prefecture, were overcrowded after Typhoon Hagibis in 2019. In another example, in 2020, 383 evacuation shelters nationwide in Japan were overcrowded after Typhoon Haishen hit Kyushu during the COVID-19 pandemic [1].

It is necessary to predict congestion in shelters to prevent such overcrowding, and an evacuation behavior model can predict the crowdedness of evacuation shelters by computer simulation. In conventional research, evacuation behavior models have been

proposed, some using questionnaires and some using person trip (PT) data, but those data are difficult to obtain.

In this study, we propose an evacuation model using open-source data readily available from the internet and attempt to identify the parameters influencing shelter overcrowding. As a case study, the parameters of the evacuation behavior model in Kuji City, Iwate Prefecture in Japan during Typhoon Hagibis in 2019 are estimated, and the coefficients for each parameter are obtained. By comparing the actual number of evacuees with the number predicted by the evacuation behavior model and conducting a field survey of evacuation shelters, we measured the validity of the proposed model and identified possible improvements.

2 Related Studies

There have been many studies of disaster evacuation behavior models. Yamada et al. [2] modeled the selection of tsunami evacuation buildings (shelters), and a decision-making model for choosing an evacuation site during an earthquake and fire was developed by Nishino et al. [3]. Mancheva et al. [4] presented a multi-agent geospatial simulation of human social interactions and behavior in bush fires. These three studies used decision-making models for different disasters (tsunamis, earthquakes, and fires), but none addressed evacuation behavior modeling for a flood disaster. Flood disaster recovery of small businesses using agent-based modeling and simulation was studied by Alhabi et al. [5]. However, their simulation model was for flood disaster recovery rather than before or during the flood.

In references [2–5], behavioral model parameter estimation was based on questionnaires or PT data from a hypothetical disaster. Generally, the questionnaire does not include the characteristics of actual disasters and is therefore not true data. The PT data requires subjects to carry GPS loggers, which has the disadvantages of low data availability and high cost. In addition, these studies assume one-time decision-making for the evacuation. In the case of an actual flood disaster, multiple decisions may be made as the disaster occurs. Our study aims to build an evacuation behavior model using open-source data available from the internet that permits multiple decisions depending on the flood disaster situation.

In our previous research [6], an evacuation support system was proposed to rescue required support people, and the effect of the proposed system was reported using a multi-agent simulation. Additionally, a real-time mapping system of shelter conditions was introduced and developed to contribute to safer evacuations [7]. If the number of evacuees can be estimated before an actual flood disaster, the effectiveness of disaster response systems will increase. This potential flood disaster response improvement motivates the development of the proposed evacuation behavior model discussed in this paper.

3 Evacuation Model Concept

Figure 1 shows the concept of our evacuation model as a precondition of the proposal. In this concept, many factors were considered, including time, the population of a residential area (grid), the distance to shelters, the distance to a river, shelter capacity and facilities, and precipitation radar echo intensity. As the first step in the evacuation behavior model construction, we have identified three processes to be modeled: the decision to evacuate, the probability of an evacuation shelter being chosen, and the number of evacuees per unit time. We adopt the repeated binary logit model proposed by Fu et al. [8] for the decision-making model. The parameters for calculating the probability and the number of evacuees are determined using open-source data because it is actual data that can be easily obtained from the internet.

To use the time-series open-source data for the number of evacuees at each evacuation shelter, we assume that residents evacuate based on general decisions such as the distance to the shelter from their homes and river conditions. We set the grid to obtain the number of evacuees per unit time by population and the evacuation probability in each grid. The grid size is scaled to 250 by 250 meters, which is the highest resolution available in the data.

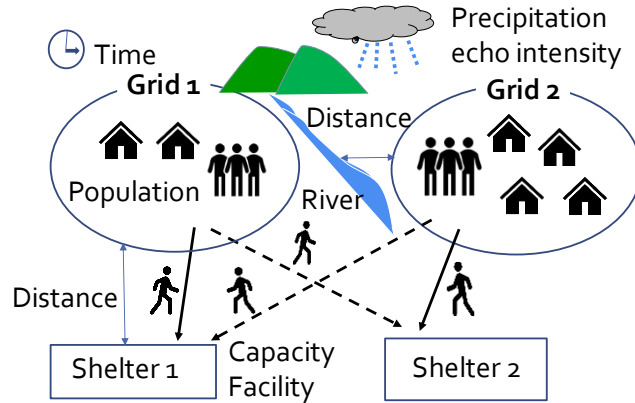


Fig. 1. Evacuation model concept

3.1 Evacuation Decision Process Model

The decision to evacuate is made using the repeated binary logit model, representing multiple decisions during the evacuation. Figure 2 shows the state transition diagram of the repeated binary logit model. It starts from the non-evacuated state, and at a time t_j , if the probability of transitions to the evacuated state is given as probability $\Pr(t_j)$, then the probability of the non-evacuated state is given as $1 - \Pr(t_j)$.

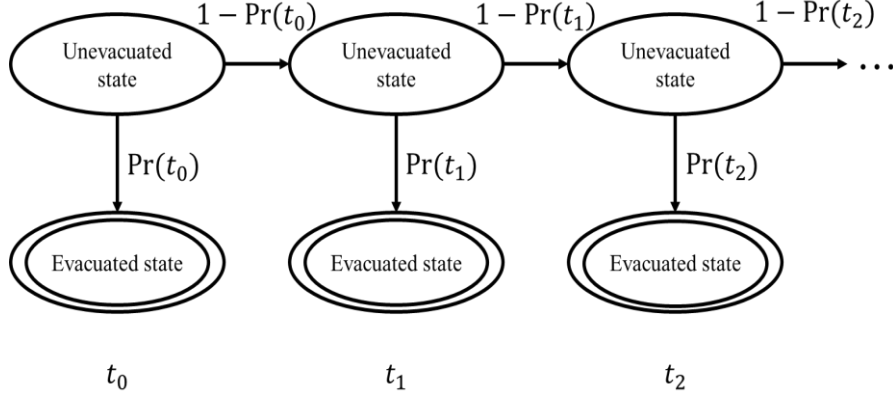


Fig 2. State transition diagram of the repeated binary logit model to evacuate

3.2 Calculation of Evacuation Shelter Choice Probability

The multinomial logit model numerically determines the utility of multiple evacuation site candidates and calculates the probability of residents choosing an evacuation site. The probability $\Pr(t, i, n)$ that subject (resident) n chooses option (evacuation shelter) i at time t , is given by equation (1), where $V_{t,i,n}$ is the utility function of subject n for option i at time t , and C is the total number of candidates.

$$\Pr(t, i, n) = \frac{\exp(V_{t,i,n})}{\sum_{i=0}^C \exp(V_{t,i,n})} \quad (1)$$

The utility function $V_{t,i,n}$, where $x_{k,t,i,n}$ are the explanatory variables and β_k are the coefficients, is given by equation (2):

$$V_{t,i,n} = \sum_{k=1}^D x_{k,t,i,n} \beta_k \quad (2)$$

where D is the total number of explanatory variables.

3.3 Evacuee Rate Calculation

The rate of evacuees per unit time is obtained by multiplying the probability of an evacuation shelter choice, calculated in section 3.2, by the number of people staying in the 250 by 250 meter grid. The initial number of people staying in the grid is equal to the population of the grid at the time, t_0 , and is thereafter updated to the number of people who have not yet evacuated at each time.

4 Simulation

4.1 Algorithm Overview

We estimated the evacuation behavior model parameters by comparing the proposed model's simulation results with open-source data for the actual number of evacuees. Specifically, the error between the number of evacuees predicted by the model with a unit time of 10 minutes and the actual number of evacuees is calculated as the root mean square error (RMSE). The parameters and coefficients are determined to minimize the RMSE using a genetic algorithm (GA).

4.2 Target Area and Data

Open-source data were used for the selected simulation site of Kuji City, Iwate Prefecture, Japan, which experienced a flood disaster from Typhoon Hagibis in 2019. During that time, the Koyahata River overflowed through a residential area, causing 455 houses to flood above ground and 561 houses to flood below ground [9]. The simulation was conducted for the period from 3:40 p.m. to 11:40 p.m. on October 12. This period was from the beginning of the evacuation by government-announced advisory and order to the end when no more evacuees were confirmed.

Figure 3 shows the distribution of the population on the 250 by 250 meter grid. In total, there are 1,255 grids in the city.

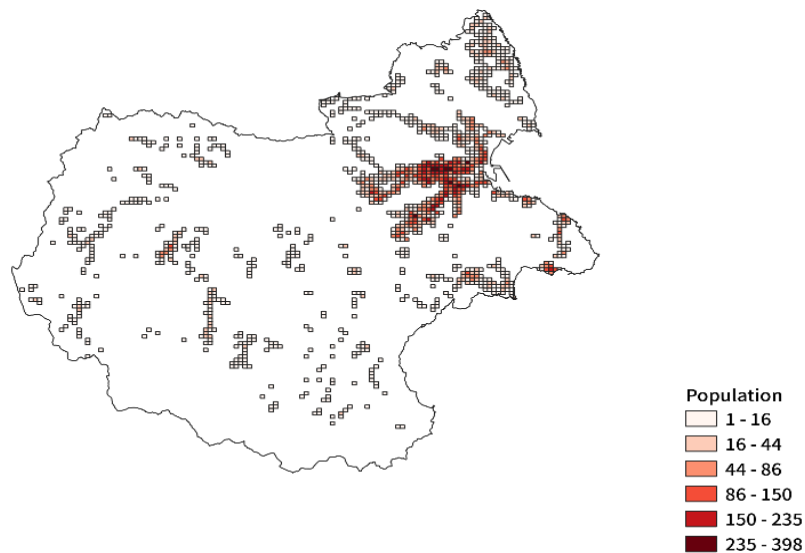


Fig. 3. Location and population of grids in Kuji City



Fig. 4. Evacuation shelters in Kuji City opened during Typhoon No. 19
(Japanese characters indicate the names of shelters)

Figure 4 shows the locations of 22 evacuation centers opened in Kuji City during Typhoon Hagibis. It was confirmed that the evacuation shelters were established according to the population distribution shown in Figure 3. The accessibility of the evacuation shelters is unclear because the topography and road conditions are not available from these maps.

4.3 Data Used in the Simulation

The data used in the simulation are shown in Table 1. All data are open-source and can be obtained from the internet.

Table 1. List of data used in the experiment

Name	Description
Iwate disaster prevention information portal (evacuation shelter information) [10].	Time-series data on the number of evacuees in each evacuation center at the time of the disaster
Designated emergency evacuation shelter data [11].	Latitude and longitude information of evacuation shelters
2015 Census, the 5th grid (250 by 250 meters grid) [12].	Population per 250 by 250 meters grid
2015 Census, subregions [12].	Polygon data (Shapefile) for 250 by 250 meters grid
GPV precipitation echo intensity [13].	Precipitation intensity data every 10 minutes

4.4 Explanatory Variables

The explanatory variables used in the utility function $V_{t,i,n}$ are shown in Table 2. Different explanatory variables are used for the cases of evacuation and non-evacuation. These parameters are selected based on the criteria of objective indicators for evacuation decisions and data availability.

Table 2. List of explanatory variables

Name	When evacuated	When not evacuated
Elapsed time	✓	✓
Time of day	✓	✓
Distance between the grid and the nearest river	✓	✓
Distance between the shelter and the nearest river	✓	
Precipitation echo intensity	✓	✓

4.5 Scenarios

Three explanatory variable combinations were selected as scenarios for the simulation, as shown in Table 3. Scenario A is the simplest combination, using only elapsed time and time of day. Scenario B uses all explanatory variables except for precipitation radar echo intensity. In scenario C, all explanatory variables are used.

Table 3. Correspondence between scenarios and explanatory variables

Name	A	B	C
Elapsed time	✓	✓	✓
Time of day	✓	✓	✓
Distance between the grid and the nearest river		✓	✓
Distance between the shelter and the nearest river		✓	✓
Precipitation echo intensity			✓

4.6 Optimization Method

The R programming language was used for data preprocessing, and C++ was used for the evacuation simulation modeling. A real-valued genetic algorithm (GA) with a population of 50 and 2000 iterations is used to optimize the coefficients.

4.7 Comparison between Actual and Predicted Number of Evacuees

Comparisons between the actual number of evacuees and the proposed evacuation behavior model results are shown in Figure 5 for scenario A, Figure 6 for scenario B, and Figure 7 for scenario C. In each figure, there are 22 evacuation shelters, and for each shelter, the actual number of evacuees is shown as a red line, and the simulation prediction is shown as a blue line. The numbers in the bold typeface are the RMSE values for each shelter, and the different orange background shades correspond to the RMSE magnitudes. The evacuation center numbers are 1–5 from left to right in the top row, 6–10 in the second row, and so on, ending in numbers 21–22 in the bottom row. These shelter numbers correspond to those shown in Figure 4. The average RMSE for each scenario is listed in Table 4.

From these comparisons, we found that scenario A had the largest error. The error was especially large for shelter numbers 20 and 21, where the number of evacuees was large. Scenario B showed an improvement in RMSE compared with scenario A. However, the number of evacuees at evacuation center number 7 is overestimated. Scenario C has the lowest RMSE, especially when the actual number of evacuees was small, although when the actual number of evacuees is large, the RMSE is large in some cases, such as in shelter number 18.

These results indicate some general directions for improving the overall accuracy of the model. Still, we could not find the cause for the RMSE change for each evacuation center, so we conducted a field survey to obtain additional information.

Table 4. Average RMSE for each scenario

Scenario	Average RMSE
A	21.48326
B	13.33299
C	10.02989

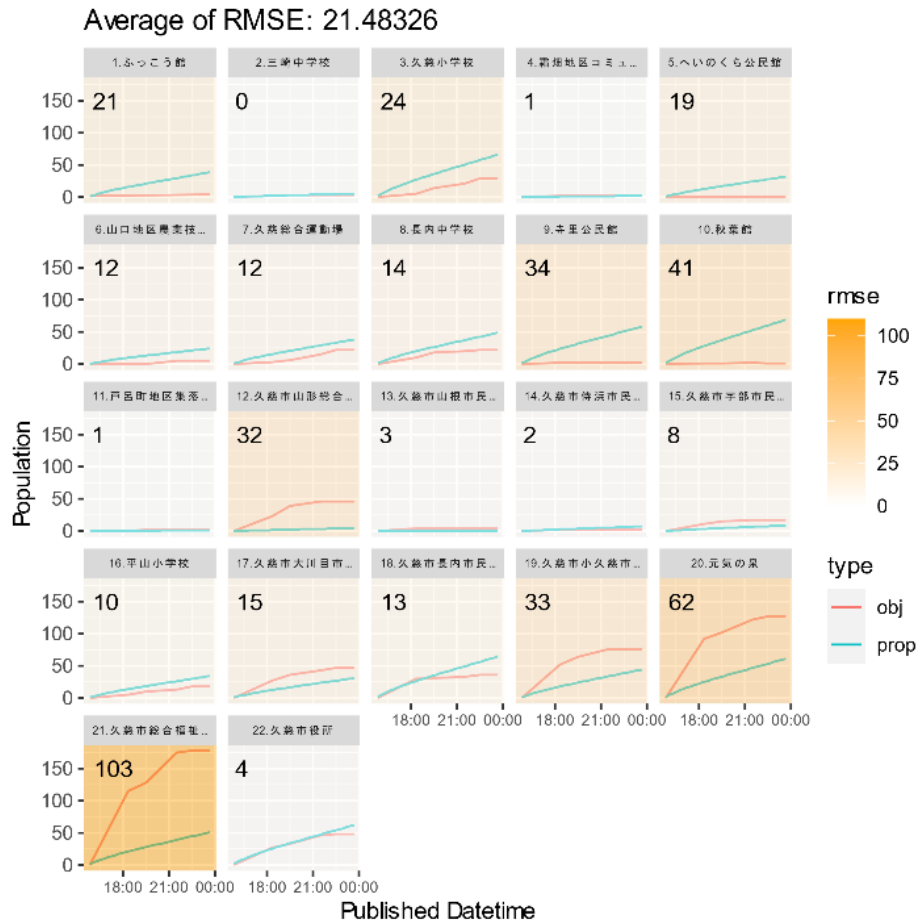


Fig. 5. Number of evacuees and root-mean square error (RMSE) at each shelter in Scenario A. The number on each graph is the RMSE for that shelter.

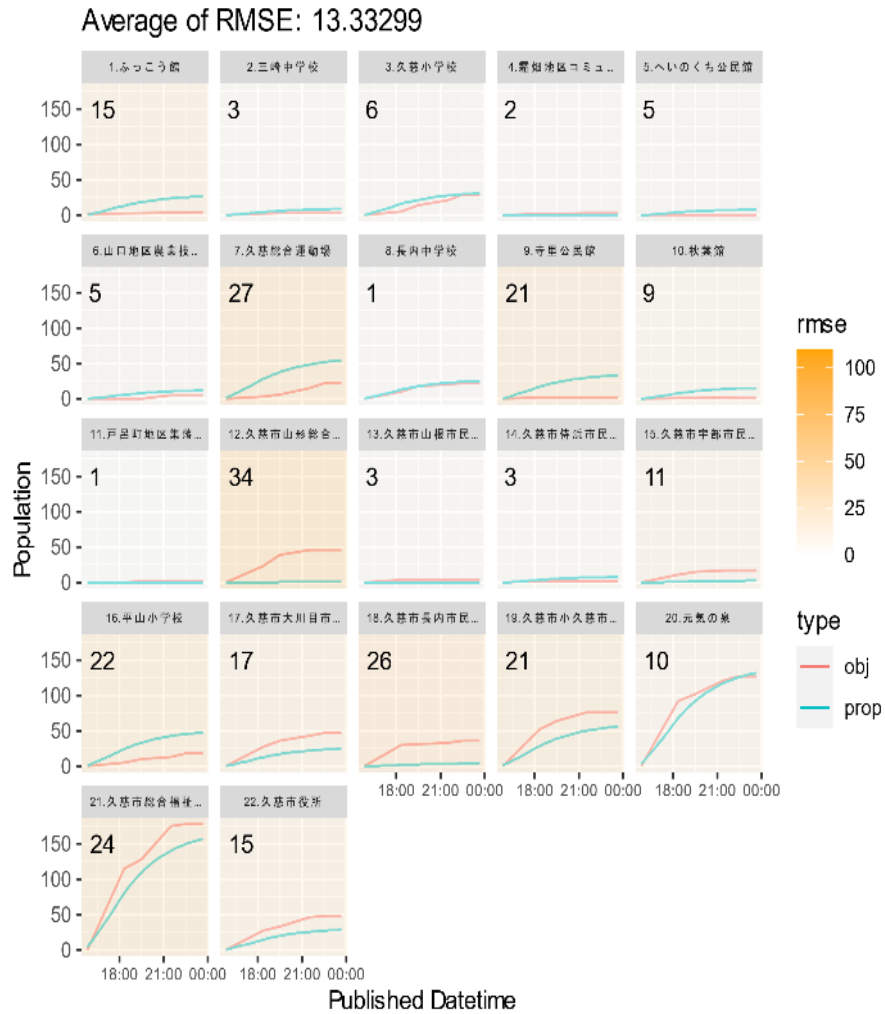


Fig. 6. Number of evacuees and root-mean square error (RMSE) at each shelter in Scenario B. The number on each graph is the RMSE for that shelter.

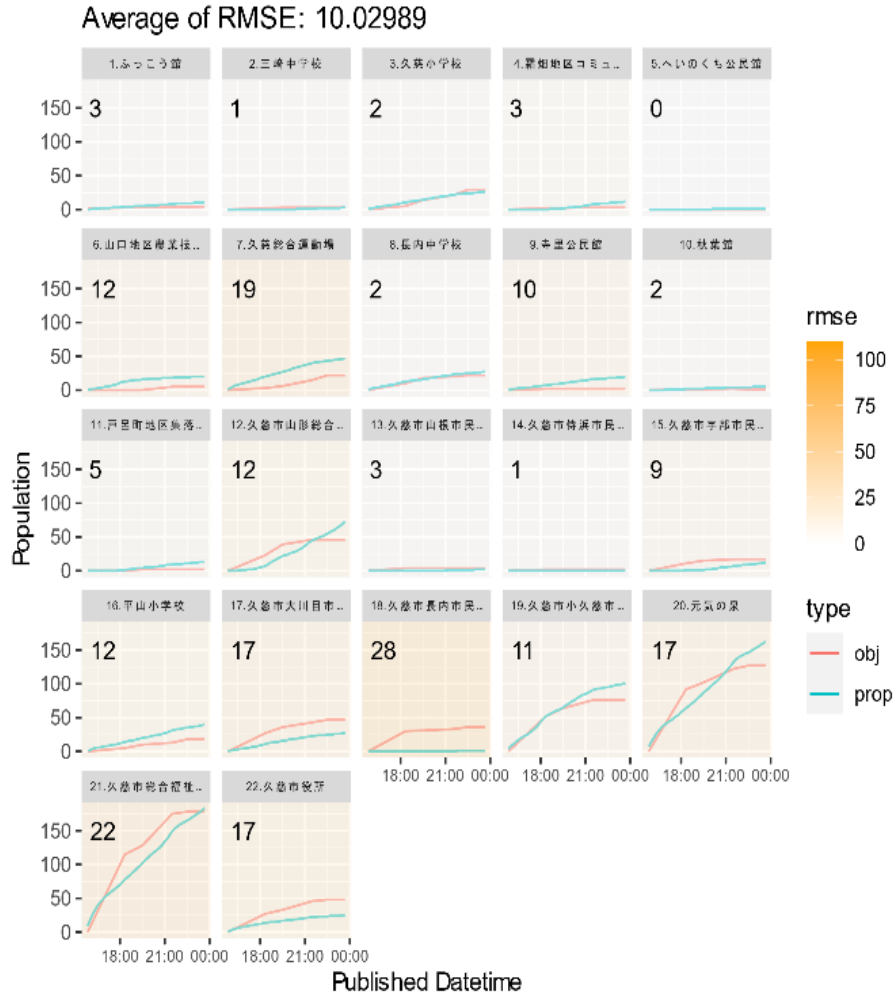


Fig. 7. Number of evacuees and root-mean square error (RMSE) at each shelter in Scenario C. The number on each graph is the RMSE for that shelter.

4.8 Field Survey

A field survey was conducted on May 26, 2021, in Kuji City, Iwate Prefecture, Japan, to understand the differences between the actual and predicted numbers of evacuees. In the field survey, we visited 14 evacuation centers located in urban areas and observed the surrounding environment. The survey was limited to the 14 urban area shelters because evacuation centers in the suburbs do not have other nearby evacuation centers, so residents do not have a choice. Figure 8 shows photographs of some of the shelters surveyed.

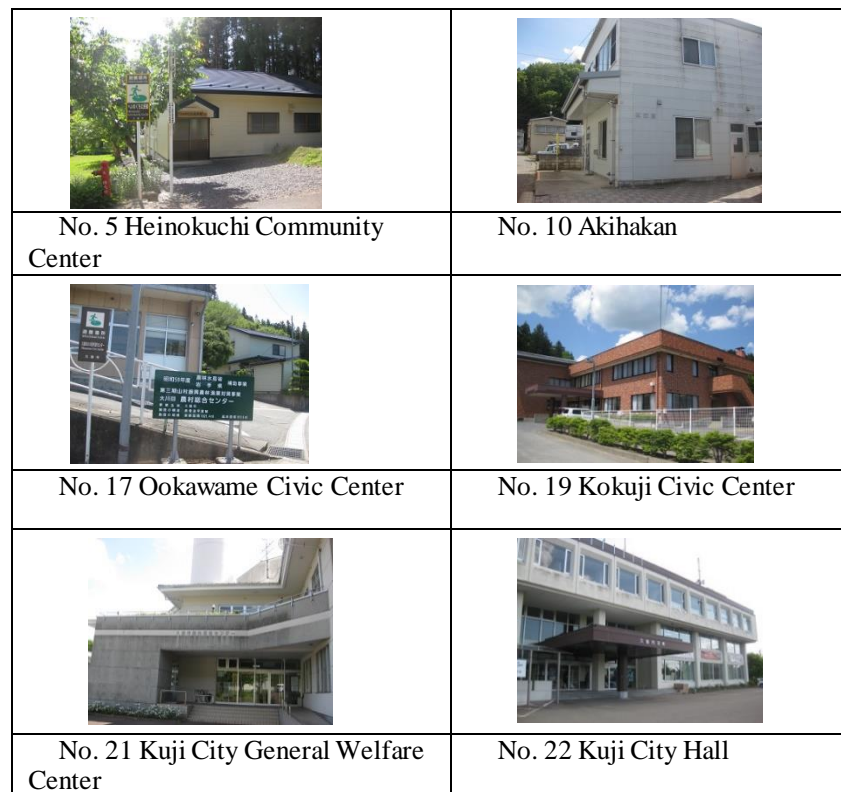


Fig. 8. Examples of shelters surveyed

During Typhoon Hagibis in 2019, there were almost no evacuees in shelter numbers 5 and 10. In the case of shelter 5, there were few residents in the vicinity, and the shelter was inaccessible to evacuees on foot. Shelter 10 was easily accessible in the city center, but the building was small, and other larger evacuation centers such as the city hall and the joint government building were nearby.

For shelter numbers 17 and 19, we were able to conduct interviews with the staff. These shelters were similar because voluntary disaster prevention organizations encouraged residents to evacuate to them. They have Japanese-style rooms and other facilities and resident staff to assist the residents. We found that while some people evacuated voluntarily, many older adults were brought to the shelter by disaster prevention organization volunteers. These factors may explain why the actual numbers of evacuees are more than the model-estimated values.

Shelter numbers 21 and 22 are public institutions that accepted many evacuees. In particular, shelter 21 is located on a hill with a large parking lot and has substantial

resident staff, medical staff, and facilities. This sense of security is thought to have attracted many evacuees.

In general, the evacuation centers with the fewest evacuees had inconvenient access in common, such as being located in alleys or crowded areas with small parking lots. In addition, they were relatively small, unpopular, and did not appear to be used regularly. However, evacuation centers with many evacuees were superior in terms of accessibility, and it was confirmed that they were frequently used. We plan to incorporate the results of this survey into our model, including shelter accessibility, frequency of use, and the existence of voluntary disaster prevention organizations. We also intend to consider the availability of shelter facilities and staff and that some people may evacuate after a disaster has occurred.

5 Conclusion

This paper has described an evacuation behavior model for estimating the number of evacuees moving to shelters during floods. It proposes a method for estimating the parameters of the evacuation behavior model using open-source data. We confirmed that the model's accuracy could be improved by identifying and adding simulation parameters using actual disaster data from Kuji City, Iwate Prefecture, Japan, during Typhoon Hagibis in 2019. We also conducted a field survey to ascertain the cause of the error between the actual and predicted values for the number of evacuees and discussed possible missing elements in the model. In the future, we plan to develop a more practical evacuation behavior model and parameter estimation method based on the results of the data and field surveys.

Acknowledgments. This research is supported by the Telecommunications Advancement Foundation. We thank Robert A. Brewster, PhD, from Edanz (<https://www.edanz.com/ac>) for editing a draft of this manuscript.

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