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Paper:

Time-Cost Estimation for Early Disaster Damage Assessment Methods, Depending on Affected Area

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In recent years, various types of disasters have occurred frequently in Japan. Such incidents require a rapid response. It is necessary to grasp the full extent of the disaster at an early stage. Research and development of effective methods to achieve this are in progress. Although each method has its own characteristics, from a business perspective it is necessary to know when and which method should be used to obtain the full extent of the damage. As of yet, there is no comparison among methods to answer this question. Therefore, the purpose of this study is to position the time-cost per unit area as one of the evaluation criteria to understand or estimate damage. To achieve this objective, the procedure of each method is clarified, the area to be analyzed by each method is identified, and the time-cost of each procedure is estimated. The time-cost per unit area is calculated by dividing the time-cost by the area of interest. Particularly, the time required for the preparation of each method, which is independent on the area, is positioned as the initial time-cost that is also derived and added. Based on the above, a linear function with the area of damage as a variable is determined. Simulations are performed to derive the estimated time-cost. Depending on the assumed area of damage, results are obtained when each method is applied.

Keywords: early damage detection, time-cost simulation, artificial intelligence, satellite image, unmanned aerial vehicle

1. Introduction

Since the Great East Japan Earthquake in 2011, large-scale wide-area disasters have frequently occurred in Japan. Examples include the Kumamoto Earthquake in 2016, the torrential rains in western Japan in 2018, Typhoon No. 15 and Typhoon No. 19 in 2019, and the torrential rains in July 2020. With each incident, the damage tends to intensify. After a disaster occurs, a rapid and effective disaster response is launched to respond to the situation. In disaster response, it is necessary to maximize the power of the organizations involved. For this purpose, unification of situational awareness is essential [1]. Developing Common Operating Picture, that is unification of situational awareness, requires the understanding and sharing of two types of information: the status of damage and the status of available resources.

With the recent progress of information and communication technology (ICT), various methods have been studied to understand damage occurrence. Methods include crowdsourcing from aerial images to hasten labor distribution [2], deep learning from satellite image data to identify the disaster area [3], and deep learning from drone images to understand roof damage [4]. In addition, some of the research results have been applied to disaster areas. Some of the research results have been implemented in disasters. In each research study, accuracy is pursued, but the time-cost is not sufficiently assessed. From the first responder's point of view, it is possible to strategically respond by estimating which method can be used to assess the damage, by when, and with what level of accuracy. This study aimed to evaluate the time-cost per unit area as one of the evaluation items in the phase of damage assessment. To verify the feasibility of this evaluation item, this study focused on five methods that are currently being implemented or are undergoing empirical research. Each method was considered using the time-cost per unit area as the evaluation axis, and simulations were conducted assuming a damaged area. In addition, the characteristics of each method and effective measures for grasping early damage will be discussed.

2. Methods for Grasping Damage to Dwellings

Disasters include both human casualties and infrastructure damage. It is difficult to estimate the human damage because it is highly individualized. It can be determined by medical institutions, disaster response organizations,

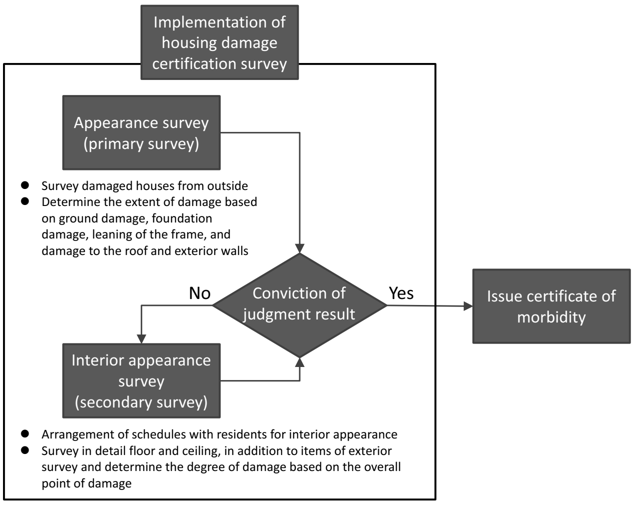

Fig. 1. Overview of housing damage certification survey work.

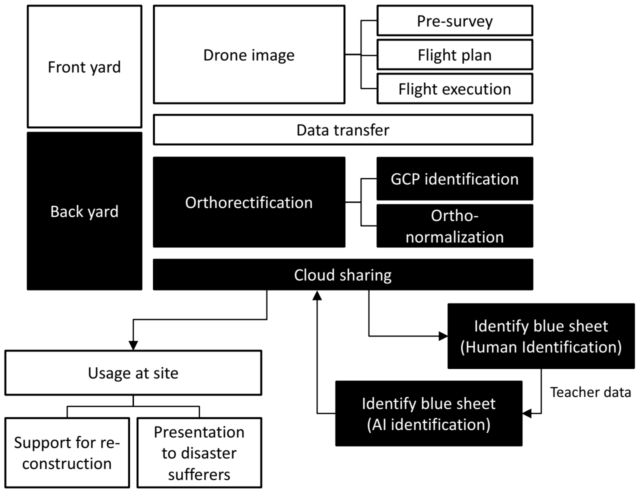

Fig. 2. Flow of blue sheet determination using drone aerial images and classification of front and backyard [7].

and the victims themselves. Therefore, this study used five methods to focus on building damage. In this chapter, an overview of each method, its characteristics, and the specific flow are shown.

2.1. Determination of Damage Level by Residential Damage Assessment Survey

The residential damage assessment survey is a survey conducted by the affected municipalities to determine the extent of damage to dwellings based on the guidelines established by the Cabinet Office [5]. Specifically, the level of damage is classified into five categories: total destruction, major partial destruction, partial destruction, quasi-partial destruction, and damage that does not reach quasi-partial destruction (partial destruction). Prior to the March 2020 guidelines, there were four damage categories: total destruction, major partial destruction, half-partial destruction, and partial destruction. In the case of earthquake disasters and floods with large external forces, in response to a complaint from the victim the extent of damage is determined by an exterior survey (primary survey), followed by an interior survey (secondary survey) (**Fig. 1**). Once a disaster strikes, various disaster relief measures are applied to help victims rebuild their lives. A disaster victim certificate is issued as a basis for such decisions. To determine the extent of the damage, a damage assessment survey is conducted. The survey that determines the degree of damage is called the damage assessment survey. In other words, the survey is indispensable for providing various kinds of support to affected victims.

In this survey method, the occurrence of damage is surveyed mainly on the foundation, roof, and walls. According to the percentage of damage, the damage is classified into five levels. Therefore, it is possible to obtain detailed information on the damage to each house. However, after the occurrence of a disaster, the affected municipalities are required to carry out a variety of related tasks, such as procurement of materials and equipment, securing personnel, establishment of systems, establishment of administrative offices, and data management [6]. These activities require time. This survey is conducted for the purpose of issuing a disaster victim certificate, one of the requirements for receiving aid and reconstruction assistance for disaster victims. The survey is not designed to quickly reveal the full extent of damage. In addition to being a single building survey, there is a limit to the number of personnel that can be secured to conduct these surveys. Although efficiency has improved, these surveys are considered time-consuming in large-scale disasters.

2.2. Roof Damage Identification Using Aerial Imagery

In recent years, drones have become more affordable and easier to operate; they are now in general circulation. In the 2019 Yamagata-ken-oki Earthquake, deep learning was used to identify roof damage based on aerial images taken by a drone in Murakami City, Niigata Prefecture [7].

Specifically, after designating the area where damage is expected, a flight plan is made, aerial photography is conducted, orthoimages are generated from the captured images, and deep learning is used to identify roofs covered with blue sheets in order to detect exact location. In our previous research, the survey roles were separated to improve the efficiency of the work (**Fig. 2**). However, many challenges are also identified, such as the large amount of time required for data transfer and the large number of Ground Control Points (GCPs) that must be manually set when generating orthoimages over a wide area.

While the ease of drone use has increased, data processing after aerial photography has become time-consuming. In the case of a widespread disaster, there will be challenges in procuring drone equipment and materials. Also, the data processing time will be enormous.

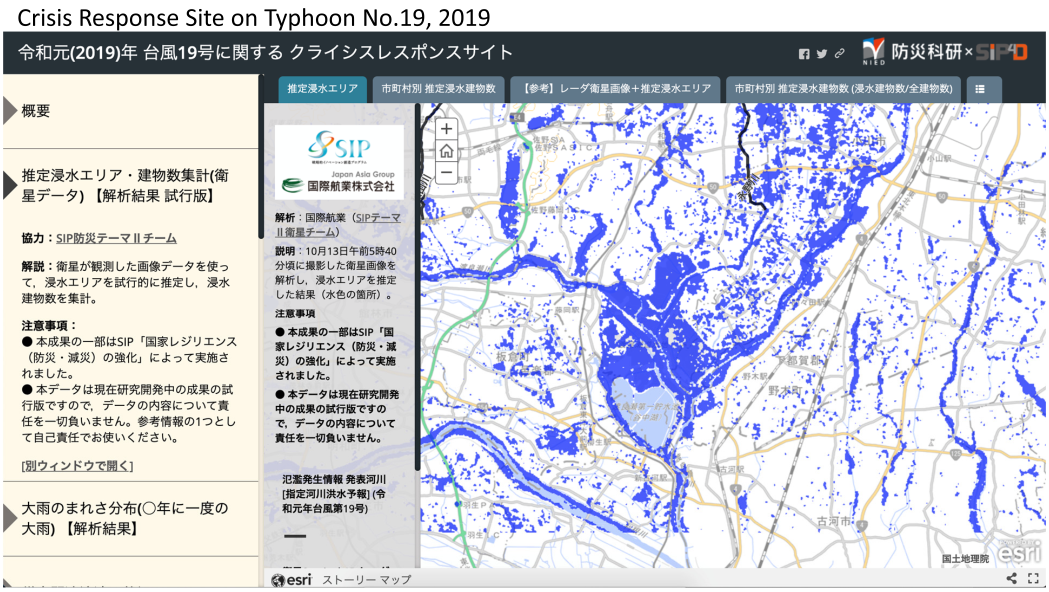

Fig. 3. Crisis Response Site [11].

2.3. Estimating the Number of Damaged Building Using Satellite Image

In recent years, "International Disasters Charter" [8] have been established as international frameworks for sharing satellite data. The 2019 Typhoon No. 19 also triggered the International Disasters Charter that promoted the utilization of aggregated satellite data observation [9].

There are two types of satellite images: Synthetic Aperture Radar (SAR) images are observed by radar and optical images using visible light. The advantage of SAR imagery is that it can be used for a wide range of observation and survey data during nighttime and in bad weather [10].

To identify flooded areas using SAR images, the assumption is that the irradiated microwaves cause specular reflection, which is shown as a region with very low backscatter intensity. SAR images before and after flooding are compared, taking advantage of the fact that the backscatter coefficient decreases in the area that changed from land to water. After a certain threshold is set, the area with a backscatter coefficient that exceeds the threshold is extracted as the flooded area. If SAR images before the inundation are not available, the inundation area can be identified by temporarily setting the threshold value of the backscatter coefficient and using optical satellite images or aerial photographs to identify the area by visual reading. This method is less accurate [11].

During the Typhoon No. 19 in 2019, the National Research Institute for Earth Science and Disaster Resilience (NIED) conducted inundation area identification using the above method, extracted buildings located within the inundation area, and published municipality results on the Crisis Response Site [12]. **Fig. 3** shows the status of disclosure on the crisis response website. Identification of the flooded area using SAR images requires specialized knowledge and skills. Identifying the flooded area using only SAR images involves a certain amount of time and cost because it involves visual inspection.

2.4. Identification of Roof Damage Using High Resolution Satellite Image and Deep Learning

Research on object detection and image classification using deep learning from supervised data and artificial intelligence (AI) has progressed. Research is also being conducted on the application of these techniques for disaster damage assessment. This study uses the transfer learning of the VGG-16 (Visual Geometry Group-16) model developed by the Massachusetts Institute of Technology (MIT) on high-resolution optical satellite images, from a previous study conducted by the authors, to identify roof damage covered by blue sheets [13].

Using this method, high-resolution optical satellite imagery from World View-3 is used as a case study of the 2018 Northern Osaka Earthquake. This satellite image has a resolution of 30 cm/pixel. In this method, an image taken on August 4, 2018 is prepared, about two months after the 2018 Northern Osaka Earthquake. For this satellite image, 32-pixel segments were created, each is 10 m squared and is assumed to contain a house. Each segment is classified into three categories: "blue sheet roof images," "blue roof images," and "other images." Teacher data and validation data are constructed. The VGG-16 model developed by MIT is used to identify the roof damage covered with blue sheets. This model is a convolutional neural network consisting of 16 layers. It was ranked fourth in the Large Scale Image Recognition Competition (ILSVRC) in 2014. It is also famous for its features of simple retraining by transfer learning, which can be applied to various cases. Although the model is capable of 1,000 classifications, this case study deals with three image classifications.

To prevent overtraining from degrading the accuracy of image discrimination, the number of epochs is set to 60

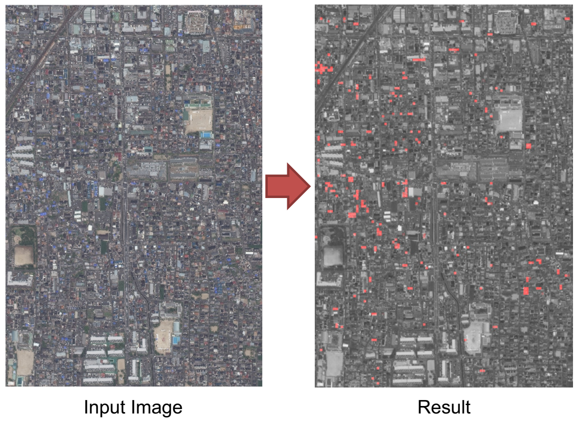

Fig. 4. Result of identifying blue sheet with AI.

Table 1. Results of applying the VGG-16 model to satellite images [13].

Result of Object Detection using VGG-16

Correct Answer		Blue Sheet	Blue Colored Roof	Other	Recall Ratio*	F value***
Correct Answer	Blue Sheet	90	4	1	94.74%	0.9424
Correct Answer	Blue Colored Roof	3	191	11	93.17%	0.9249
Correct Answer	Other	3	13	137	89.54%	0.9073
	Precision Ratio**	93.75%	91.83%	91.95%		

* Recall Ratio: How much can be detected from the correct data?
** Precision Ratio: How many correct answers are actually found in the detected result?
*** F value: Harmonic mean of recall ratio and precision ratio.

based on a preliminary survey, and verification is conducted. As shown in **Fig. 4** and **Table 1**, the accuracy of the blue sheet discrimination is 93.75%. The reproduction rate is 94.74%, and the F-value, which represents the rate of fit, is 0.94. In other words, in this case, the VGG-16 model is shown to be a useful method for blue sheet identification.

2.5. Identification of the Number of Damaged Buildings Using CyborgCrowd

The authors have been studying the rapid identification of affected areas during large-scale floods by using crowdsourcing, a method to link resources with artificial intelligence (AI) by treating them as supervisory data. This method solves problems through the division of labor. In this study, "CyborgCrowd" is the name of the problem-solving method based on the collaboration of crowdsourcing and AI [14].

In a previous case study on the 2018 torrential rains in western Japan, inundation areas were identified from aerial images released by the Geospatial Information Authority of Japan (GSI) [15, 16]. **Fig. 5** shows a schematic of the flow of this method. The aerial images are a set of images taken at regular intervals. Each image is crowdsourced for inundation determination. In the crowdsourcing process, the respondents select one of the following four options: "Not flooded," "All flooded," "Partially flooded or covered by clouds," or "All covered by clouds." The images that are answered as "not flooded," "all flooded," or "all covered by clouds" are used as supervised data for the AI to learn. Then, the AI can make decisions for the entire area. On the other hand, for images that are answered as "partially flooded or covered with clouds," the image are divided into four parts. The same questions are asked.

Publicly solicited AI is trained and judged. The specific model is unknown. The accuracy of AI is not required in this method. It is assumed that the AI can learn the teacher data obtained through real time crowdsourcing, and that the learned AI can determine the entire area of interest. In addition, it is believed that integrated crowdsourced results and the AI's judgment results can determine the areas that are considered the most affected areas at each point in time.

This case study focused on Mabi-cho, Kurashiki City, Okayama Prefecture, which suffered extensive damage from the 2018 torrential rains in western Japan. Crowdsourcing was requested worldwide, and about 600 people from 11 countries participated in the study. The crowdsourced results were obtained in real time, and the AI was trained in two hours, making inundation judgments for the entire area at each phase. The results are shown in **Fig. 6**. The crowdsourced results and the AI results were verified separately, and the results are integrated and visualized as a single map (**Fig. 7**). By assuming a disaster response scene, practitioners can unify their situational awareness based on the results and contribute to decision-making in the initial response. This verification started at 10:00 a.m. and, after about four hours, the changes were small and the results were stable. The number of buildings damaged by flooding is estimated by overlaying building information using GIS on the flooded areas. Since the results of this case study show a certain level of accuracy, this method was best positioned for early damage assessment.

2.6. Organizing the Characteristics of Five Methods and Granularity of Understanding

The five methods described above may be applied in different ways depending on the type of disaster; they may not be applicable in some cases. For example, in the case of dwelling damage assessments for earthquake and windstorms, an exterior survey is conducted, followed by an interior survey (as necessary). However, in the case of wind and flood damage, a lump-sum certification method may be applied, depending on the inundation situation. On the other hand, the method for estimating the number of damaged houses based on the identification of inundation areas may not be applicable to earthquake disasters because the precondition for the estimation is that the inundation area directly affects the houses and is a surface trigger for damage. In this paper, the methods applicable to earthquake disasters and those applicable to wind and flood disasters are analyzed and evaluated together. Considering the current state of disaster prevention measures, it is

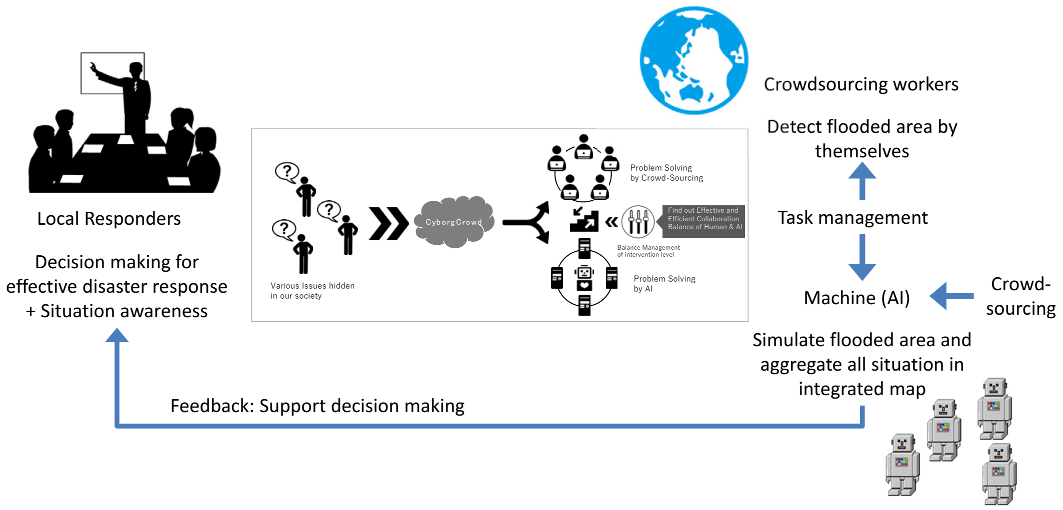

Fig. 5. Flow of identifying inundation area using CyborgCrowd.

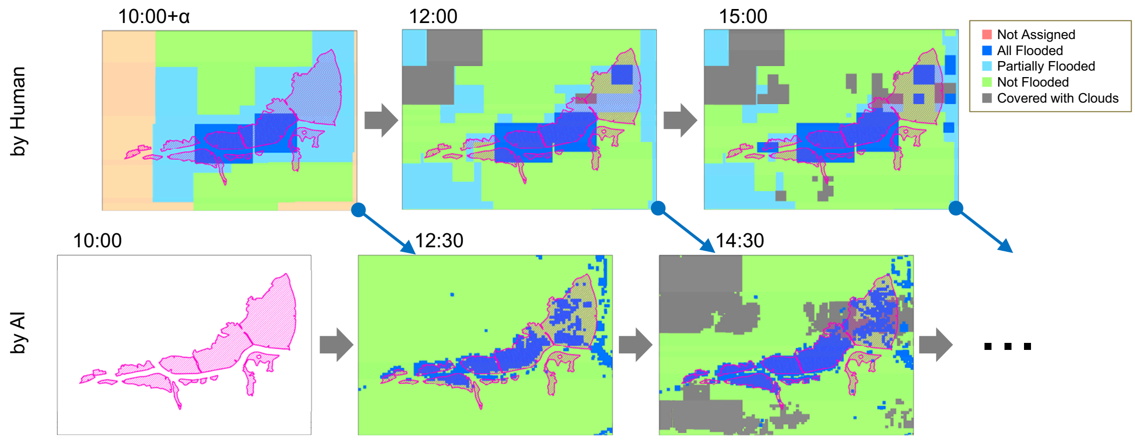

Fig. 6. Learning process of AI from the result of human answers as teacher data [16].

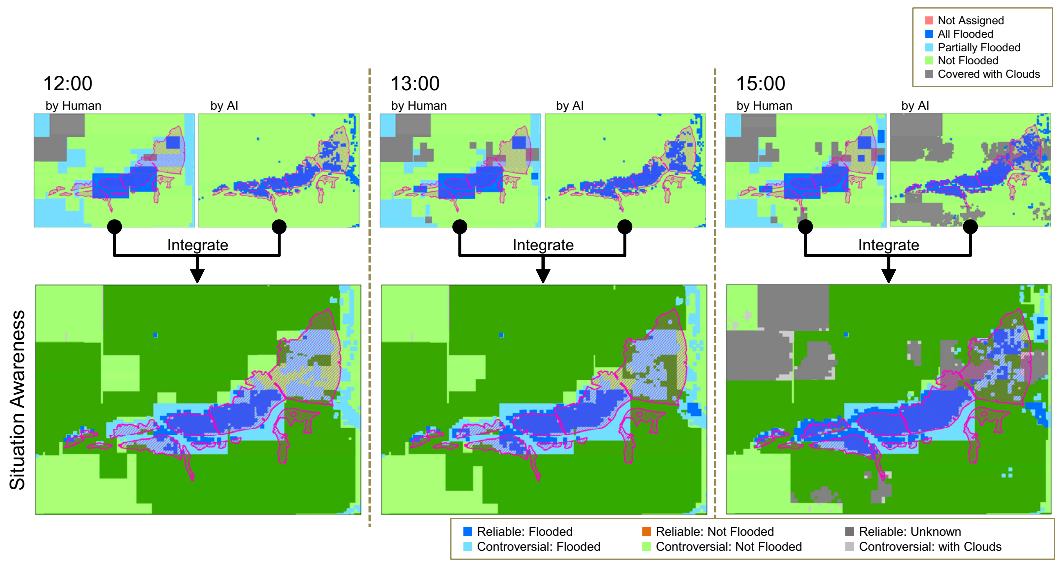

Fig. 7. Transition of detecting flooded area by human and AI [16].

Table 2. Disasters, purposes, and granularity of each method.

	Earthquake disaster	Disaster due to wind and water	Grasping Granularity
(1) Survey to identify residential victim	Exterior survey	Batch certification method*	Per building
(2) Identify damaged houses (roof damage) using drone	Identify roof damage		
(4) Identify roof damage using deep learning with satellite image with high resolution	Identify roof damage		
(3) Identify inundation area and estimate the number of suffered houses based on satellite images		Identify inundation area Presume number of inundated structures	Aggregate value by municipality
(5) Identify inundation area using CyborgCrowd		Identify inundation area Presume number of inundated structures	Aggregate value by unit of inundation area

*The batch certification method refers to the "simple identification method based on the depth of inundation" shown by the Cabinet Office at the time of Typhoon No. 19 in the first year of Reiwa for the purpose of increasing the efficiency and speed of damage certification surveys for houses [17].

necessary to analyze them separately. However, damage assessment and response forecasting are tasks that must be carried out for any disaster. Therefore, this paper does not distinguish between disaster types, but intentionally uses the same indicators for evaluation.

In addition, each of the five methods described above has a different purpose of implementation. The granularity of the understanding of the situation obtained by these surveys (hereinafter referred to as "the understanding granularity") differs. In the case of residential damage assessment surveys and roof damage identification using drones, the damage status is assessed on a building-by-building basis. In the estimation of the number of damaged houses based on satellite images, the total number of damaged houses is obtained by identifying the flooded area. The granularity of understanding is based on the municipality or the flooded area. This is because, the degree of damage cannot be determined based on the judgment of inside or outside the inundation area. In other words, the number of damaged houses derived by applying these methods is useful for estimating the volume of work to be handled.

It should be noted that the damage assessment is a practical task. The survey is used to determine the extent of damage to houses that will be given the damage certificate. The other methods compared in this study are not necessarily essential for governmental agencies to grasp the extent of the damage. However, when the authors interviewed representatives from disaster-affected municipalities, they found that although representatives knew that a dwelling damage assessment survey was necessary, they do not know how to estimate the time required to conduct such a survey. If the area to be surveyed is small, it is possible to obtain detailed and reliable information using the damage assessment method as a general survey. In the case of a local government with little experience in disaster response, it is not possible to make accurate estimates for determining the strategy.

Based on these perspectives, **Table 2** shows the results of organizing the characteristics, positioning, and granularity of the five methods discussed in this paper. In addition, as explained in this section, this study does not intend to evaluate all the methods equally or to select a preferred method. It intends to examine whether various methods can be evaluated using the "time-cost per unit area" as an index. It should be noted that, when utilizing the results of this study, it is necessary to select a method by comparing each objective with the characteristics of the disaster. Thereafter, it is possible to make a forecast of the damage assessment by evaluating among the selected methods. However, it is necessary to organize the methods according to the type of disaster for disaster responders to utilize these methods in an actual disaster response. It is assumed that various methods will be proposed by ICT and technological innovation in the future, but it is necessary to compile these methods for each type of disaster and organize them as a package that can be used in the field.

In this paper, only the "time-cost per unit area" is used for analysis. When applying various methods, it is necessary to evaluate the introduction and operation costs of related systems. Even if the same method is used, the system and the target data are not necessarily uniquely determined. The cost varies depending on the scale of the municipality and the functions installed. In light of these circumstances, this study does not analyze the economic cost, but only the "time-cost per unit area," focusing on "how much damage can be assessed by when," which is needed to determine the response strategy. Future issues will discuss other costs and points to be considered for each type of disaster, which are necessary as countermeasures and preparation.

3. Calculation of Time-Cost per Unit Area for Each Method

In this chapter, the time-cost per unit area for each method presented in the previous chapter is calculated. However, since the time required for each method for the same disaster has not been reliably recorded, estimated values are assigned to some of the methods. The average value differs by case to examine the possibility of using time-cost per unit area as an evaluation item.

3.1. Outline of Calculation Method

As mentioned above, each method differs in terms of prerequisite timing of information acquisition, differences in post-processing steps, and so on. The application of each method differs from disaster to disaster, as applications cannot be started simultaneously for the same disaster. In addition, dwelling damage certification surveys are conducted on a building-by-building basis; drones cover a small area and satellite images cover a wide area. In this study, the number of damaged dwelling units cannot be compared because the time-cost is evaluated without regard to accuracy. Because of the difference in coverage, it is necessary to consider the size of each target area in the analysis.

Therefore, in this study, the time-cost considering the size of the target area is derived. Once the target dwelling is clarified in each method, the area is divided into meshes of 250 m square. The total value of the meshes containing the target is considered as the area of the target. The mesh is based on the "Standard Area Mesh" based on the Administrative Management Agency Notification No. 143 of July 12, 1973. The "Quarter Area Mesh (Sixth Standard Area Mesh)" [18], which is a 250 m mesh, is adopted. This study develops its analysis based on disaster cases. Regarding its applicability to other regions, the standard regional mesh, which can be used in any region of Japan, was chosen as the basis.

The sixth standard regional mesh containing the target is aggregated; the area of the region is calculated. The time-cost per unit area (hours/km^2) is calculated by dividing the time required by each method by the area of the area. On the other hand, if the specific area is known, the time-cost (hours/km^2) is calculated based on the area. The time-cost per unit area is compared and simulated using the area as a variable.

3.2. Calculation of Time-Cost per Unit Area

Based on the aforementioned calculation method, the time-cost per unit area for a total of five methods applied to three purposes is calculated: "residential damage certification survey," "identification of damaged houses using drones (limited to roof damage)," and "identification of flooded areas and estimation of the number of damaged houses based on satellite images." The details are as follows.

3.2.1. Determination of the Degree of Damage to Houses by Residential Damage Assessment Survey

Information about the location of houses and the activity time of the residential damage assessment is not available to the public. Therefore, analysis is implemented regarding the information obtained by the "Livelihood Reconstruction Support Collaborative," in which two of authors participated, during its past support of disaster-stricken areas. In this study, two recent disasters are treated as case studies: the response of Abira Town to the 2018 Hokkaido Iburi East Earthquake and the response of Murakami City to the 2019 Yamagata-ken-oki Earthquake. This selection was made because the efficiency of the survey method for recognizing damage to dwellings has been improved. In the survey of dwelling damage, several teams formed and surveyed the field, but the specific departure time of each team was not recorded. In this study, the number of surveyed households was not recorded.

In response to the 2018 earthquake in Abira Town, Hokkaido, 2,666 buildings were surveyed by 117 teams/day, with an average of 22.79 buildings/group/day. To calculate the size of the area where the surveyed buildings are located, 219 meshes were extracted by superimposing the surveyed points and the sixth mesh using spatial processing with GIS; the size of the area is 13.69 km^2. From this result, the density of buildings in the area is 194.74 buildings/km^2, and 8.54 teams/day/km^2 is derived as the coefficient for the damage assessment in the field.

The response to the 2019 Yamagata-ken-oki earthquake in Murakami City, Niigata Prefecture was conducted for 644 damaged houses by 10 teams in three days (small-scale disaster). In other words, the average number of houses surveyed was 21.47 houses/team/day, which is not much different from the rate in Abira Town. Similarly, the area calculated based on the sixth-time mesh is 5.69 km^2 (91 meshes), and the number of buildings surveyed is 644, giving a building density of 113.18 buildings/km^2. This value is smaller than that of Abira Town.

In averaging the results of these two cases, the average building density of 153.98 buildings/km^2 and the average surveyable buildings number of 22.13 buildings/group/day were obtained. From these values, 6.96 groups/day/km^2 is derived and divided by average actual working hours of 7.75 hours (7 hours 45 minutes), which were calculated subtracting one hour for a lunch break during an 8:30 a.m. to 5:15 p.m. shift. As a result, an average time-cost per unit area of 0.90 teams/hour/km^2 was derived.

This time-cost does not include the time-cost of system maintenance. In the case of Abira Town, the survey started on September 14, 2018, one week after the disaster occurred on September 7. The delay was due to the establishment of a support and relief system and training implementation. In the case of Murakami City, the survey started on June 23, five days after June 18, 2019, the date of the disaster. The local government officials had experience in providing support and quickly established the initial response system. Although the gap of number of the days between the two cases was just two days, it is necessary to average the number of days and account for six days as the initial time-cost for establishing the initial response system.

3.2.2. Roof Damage Identification Using Aerial Images

In this study, the authors focused on the response to the 2019 Yamagata-ken-oki earthquake in Murakami City, Niigata Prefecture, by using a drone to identify damaged houses. This case study was conducted by two of authors in the field. Two aerial photographs were taken. In this paper, the time from aerial photography to orthoimaging is analyzed, but the data transfer to the backyard that occurs during the process is estimated rather than measured.

The first round of aerial photography took about eight hours and the area covered was 5.69 km^2 (91 meshes), and the second round of aerial photography took four hours for the same area. The average time was 0.95 hours/km^2.

Next, the data transfer time was derived. The total data volume was 25,014 MB that is divided by the area of the area to obtain 4398.07 MB/km^2. It is estimated that the transmission time-cost is 0.98 hours/km^2 on the assumption that, for a 10 Mbps bandwidth network in a local city, the transmission efficiency is 100% and the transmission speed is 1.25 MB/s.

In orthoimaging, it is necessary to set up about 20 Ground Control Points (GCPs) within the image area to provide accurate location information and to eliminate distortions. In this case, the area was divided into six parts and 20 GCPs were set in each part; 10.79 hours were needed to identify GCPs. The area is 5.69 km^2, so the average time is 1.90 hours/km^2. In addition, machine processing is required to generate orthorectified images that take a total of 5.79 hours, resulting in an average of 1.02 hours/km^2.

Although one of authors identified 77 incidents of roof damage from the orthoimages, this covered all 644 houses, regardless of whether they are damaged or not. This took 4.43 hours, or 0.78 hours/km^2 when dividing by the same area.

In summary, the average time required to identify houses (roofs) damage using aerial drone images was 5.63 hours/km^2: 0.95 hours/km^2 for aerial photography, 0.98 hours/km^2 for data transfer, 1.90 hours/km^2 for GCP identification, 1.02 hours/km^2 for machine processing for orthorectification, and 0.78 hours/km^2 for roof damage identification. Without data transfer, the average time was 4.65 hours/km^2. However, it is necessary to consider that, since the time required for orthorectification depends on the computer processing power, data processing in the later stage takes more time.

The aerial survey by drone can be conducted on the day of the disaster. Yet, that may depend on the weather conditions on that day. Therefore, the initial time-cost for establishing the initial response system is zero if drone is prepared in the affected area.

3.2.3. Estimation of the Number of Damaged Buildings Using Satellite Images

The authors have not conducted any case studies on the identification of disaster areas and the number of damaged buildings using satellite images. As a case study, the NIED efforts were identified in response to Typhoon No. 19 in 2019. In this case study, although the author did not perform crisis response work or analysis, he was privy to the mailing list for the project progress. The time-cost for the analysis was extracted using the time stamp of the mailing list under their permission. The time stamps of the mailing list are used to extract the time-cost of the analysis. Although the detailed report of the analysis work is not shared, the important events are. The needs of this study were achieved using the time stamps.

According to the efforts of the NIED, the following flow is used to identify the inundation area and estimate the number of damaged buildings.

(1) October 12: Typhoon No. 19 hits Japan, causing heavy rainfall and flood damage in many areas.

(2) October 13, 05:41: Sentinel-1, a radar satellite of European Space Agency (ESA), observed a wide area from Kanto to Tohoku.

Subsequently, inundation is estimated by radar images [Tohoku and Kanto] (analyzed by Kokusai Kogyo, excluding the sea area).

(3) October 16, 07:22: Inundation estimation area is released.

(4) October 19, 12:28: Estimated number of inundated buildings completed.

(5) October 21, 10:00: Calculation of inundation area by municipality completed.

(6) October 21, 10:00: Calculation of inundation area by municipality completed.

(7) October 21, 17:00: Coordination within the institute and among related organizations conducted, and release of the data began.

(8) October 22, 15:00: The final form is released.

In this situation, the radar satellite captured images the day after the disaster. It took three days to obtain data and identify the flooded area. It took about five days to calculate the number of damaged or flooded buildings and to compile that data by municipality. The final release of the data is conducted on the 10th day after the disaster.

Table 3. Machine specification for AI processing.

CPU	Intel® Core™ i7-6800K CPU @ 3.40 GHz
GPU	Geoforce GTX1080 x 2
Memory6	64 GB
OS	Ubuntu 16.04

Because of the emergency, 12 hours of work were allocated per day. As a result, the time after the disaster was 120 hours. The time after the radar satellite observation was 108 hours, and the cost of this study was 108 hours from the time of observation.

The area captured by the radar image was calculated from the resolution of the radar image and the number of pixels in the matrix. The data used in this case study is the radar image of Sentinel-1 with a resolution of 5 $\times$ 5 m. The area used for the analysis was 35,763 $\times$ 57,309 pixels. From this information, the area analyzed at the NIED was 51,238.54 km^2. This means that the time-cost per unit area in this case was 2.11 $\times$ 10^{-3} hours/km^2. However, it should be noted that the time required to obtain satellite images was difficult to reduce. The time required to take images may be longer depending on the satellite orbit. In this case study, the satellite images were obtained in one day, the shortest time possible. Therefore, this was used as the initial time-cost.

3.2.4. Roof Damage Identification Using High-Resolution Satellite Images and Deep Learning

As mentioned above, there are three tasks that incur time-costs: "mask creation," "AI training," and "blue sheet identification by AI."

In the case of "mask creation," one person was assigned to each area; it took 20 hours. On the other hand, the use of AI depends on the machine specifications used. The machine used in this study has the specifications shown in **Table 3**.

The re-training of the AI on the VGG-16 model takes 30 minutes because of the foundation of the model. It also takes three minutes for the AI to identify the blue sheets.

The above time-cost depends on the area. In this case, an area of 2.1 km^2 is used for training and an area of 1.4 km^2 is for verification. Of the 3.5 km^2, 2.1 km^2 is used for AI training and 1.4 km^2 for AI evaluation. The time-cost per unit area is 3.57 $\times$ 10^{-2} hours/ km^2 because it takes three minutes for the AI to evaluate 1.4 km^2.

On the other hand, due to the characteristics of disasters and regions, the accuracy of the existing AI model is not always high. It is necessary to set the ratio of training data to validation data to calibrate each type of data. In the CyborgCrowd case, the result is stable because the AI learns the correct answer data at 12:00. The correct answer data created by humans at that time accounted for 30% of the total. In other words, if it is assumed that relearning is conducted after a disaster occurs, it is possible to obtain results with a certain level of accuracy if about 30% of the correct answer data is created by humans and the remaining 70% is conducted by AI.

Based on the previous information, it is estimated that the time-cost for mask image creation is 5.71 hours/km^2, and the time-cost for AI relearning is 0.24 hours/km^2. In this case, 0.30 km^2 per 1 is used for training and 0.70 km^2 per 1 is used for AI. In addition, mask images were prepared for training of AI. The time-cost per unit area is calculated to be 1.81 hours/km^2. However, the initial time-cost for obtaining satellite images is not clear. Since commercial satellite images are used, the initial time-cost of four days is tentatively estimated, because the images are taken when the victims covered their roofs with blue sheets in three days and the images are available the next day.

3.2.5. Identifying the Number of Damaged Buildings Using CyborgCrowd

This case study focused on flooding in Mabi-cho, Kurashiki City, Okayama Prefecture. The GSI released aerial images of areas other than Kurashiki City in Okayama Prefecture, but it limited images to Mabi Town in Kurashiki City.

The area covered by the aerial images is 19.5 km from east to west and 13 km from north to south; the total area is 253.5 km^2. According to the GSI, the aerial photographs of the area were taken on July 9 in 2018, the day after July 8, when the torrential rain hits western Japan. Images were released the next day. CyborgCrowd automates the image placement and image segmentation for crowdsourcing, and the work was complete in one hour. For the release of the aerial images, the initial time-cost was two days: one day for the aerial shooting and one day for the release of the images. The shooting range is limited and the orthorectification process to vertical images is required. Since there is no time data for this, it is assumed that the initial time-cost is proportional to the area of the image, as there is a time basis for developing images for crowdsourcing. However, since it is proportional to the area, that time for preparation is excluded from the initial time-cost in the calculation.

It takes two hours to obtain stable results by crowdsourcing. Two hours are needed to train the results as teacher data and perform the flooding assessment on all images. In other words, it can be concluded that the entire flooded area could be grasped in four hours after the images are prepared. Based on this time and the aforementioned area, the time-cost per unit area for this method is calculated to be 1.58 $\times$ 10^{-2} hours/km^2. However, this depends on the number of crowdsourced workers. If the number of assigned workers is proportional to the area, the work can be carried out in parallel. In the calculation of the time-cost per area in this study, it is assumed that the number of participants in the case is fixed.

Table 4. Comparison results of time cost per unit area by method.

	α [hour/km^2]	C [hour]
Identification survey of residential victim	0.90 (Assume single team system)	144
Identify damaged houses (roof damage) using drone	5.63 (With data transfer) 4.65 (Without data transfer)	0
Identify inundation area and estimate the number of suffered houses based on satellite images	2.11×10^{-3}	24
Identify roof damage using deep learning with satellite image with high resolution	1.81	96
(Refer) Identify roof damage using deep learning with satellite image with high resolution (No relearning)	3.57×10^{-2}	96
Identify inundation area using CyborgCrowd	1.58×10^{-2} (Presume 600 workers)	48

Derived formula: $E(x) = ax + C$

$E(x)$: Time-cost presumed with methods (hour)
x: Size of disaster area (km^2)
a: Time-cost per unit area (hour/km^2)
C: Initial time-cost required for establishing initial moving body (hour)

4. Comparison of Time-Cost Estimation and Discussion

Table 4 shows the primary equation of the time-cost per unit area for each method calculated in the previous section. As shown in **Table 4**, although the methods and the accuracy of the results are different, the efficiency of each method can be grasped by comparing the time-cost per unit area. By comparing the time-cost per unit area, the efficiency of each method can be understood. Using this result as a basis, it will be possible to compare and verify various methods using the same evaluation items in the future. However, it should be noted that the initial conditions are different. This should be carefully examined in future studies.

Using the results in **Table 4**, **Fig. 8** is obtained when the results are simulated in terms of area. The slope in **Fig. 8** is smaller for the method with lower time-cost per unit area. In other words, even if the initial time-cost is high, if the area to be assessed is large, the total time-cost can be reversed depending on the method. By using **Fig. 8**, the final time-cost changes can be seen. Therefore, method must be selected according to the target area. Based on this graph, the following conclusions were made:

1) Overall, the method of "identification of flooded areas and estimation of the number of damaged houses based on radar satellite images" is overwhelmingly quick in dealing with a wide area of damage. This can be attributed to the fact that radar satellite images can be taken over a wide area and that the method is already established to some extent in the subsequent processing process. The initial time-cost of 24 hours is reversed in the case of using a drone and the case of using radar satellite images in about five. In this case study, the total time-cost per unit area for the method using radar satellite imagery is smaller when the area is larger than five, while the total time-cost per unit area for the method using drones is smaller when the area is smaller than five. However, the accuracy of radar satellite imagery is not as high as that of other methods. Yet, it can be useful for obtaining an overview of the extent of flooded areas and the approximate number of damaged buildings. In addition, it should be noted that the use of multiple drones changes the speed of the survey, but also changes both the initial time-cost and the time-cost of the survey (because of the need for coordination among the drones).

2) The next quickest method is to use CyborgCrowd to identify the flooded area and estimate the number of damaged buildings. As shown in **Table 3**, the coefficient proportional to the area is larger than that of the method using radar satellite images, but smaller than that of other methods on the order of 100. Therefore, as the area to be assessed becomes larger, the total time-cost will be reversed, even if the initial time-cost is different. In the case of the survey in this study, the total time-cost becomes smaller than that of the drone method at the threshold of about 10 km^2 (strictly speaking, nine). In other words, about 10 km^2 is a guideline for using CyborgCrowd in the same scale. However, the method using CyborgCrowd is based on the premise that the GSI releases vertical photographs taken by aerial photography. However, in the case of Typhoons No. 15 and No. 19 in 2019, the vertical images are not released.

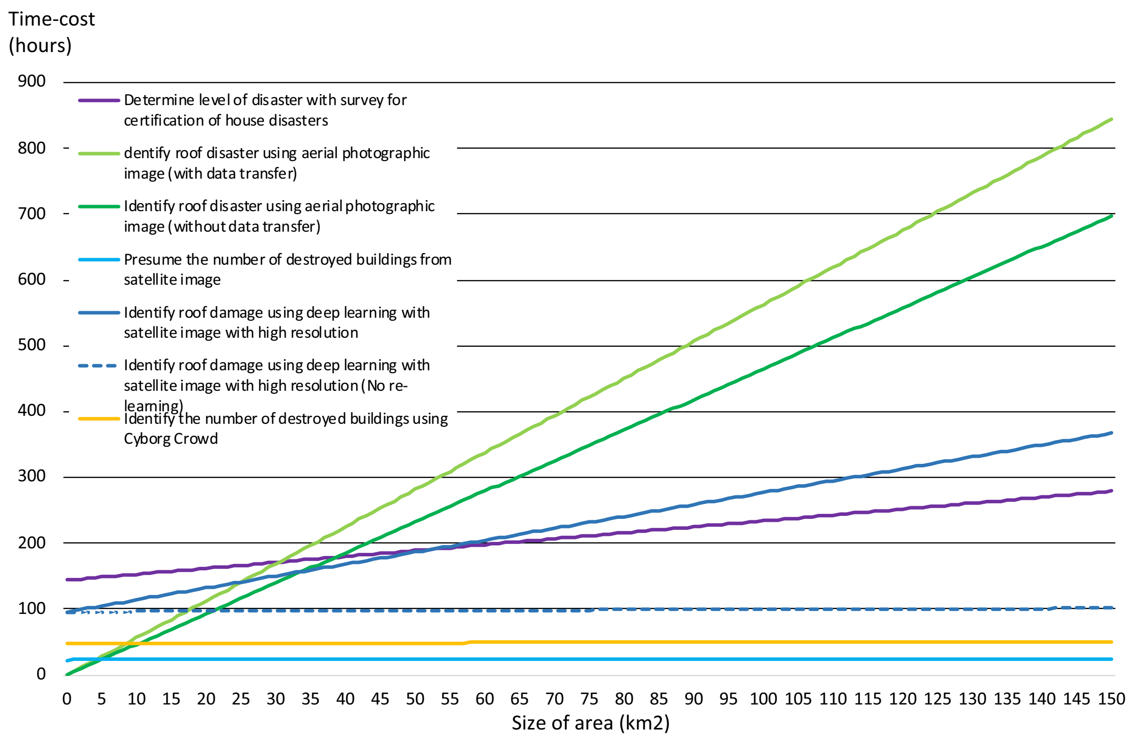

Fig. 8. Time-cost simulation results per unit area depending on methods.

The oblique images have been released. However, in the case of Typhoons No. 15 and No. 19 in 2019, oblique photographs are made public, but vertical photographs are not yet available. When aerial photographs are available and input data can be obtained, the accuracy and granularity of the method is higher than that of the method using radar satellite images. It can be concluded that the method is useful for wide-scale disasters.

3) The method using high-resolution optical satellite images has a large initial time-cost, but the total time-cost can be kept small even for a relatively small area. The method using high-resolution optical satellite images has a large initial time-cost, but the total time-cost is small even in a relatively small area. In the case of the method using high-resolution optical satellite images, the time-cost of creating supervisory data for deep learning is significant. The total time-cost increases as the target area becomes larger for more precise results. For example, **Fig. 8** shows that the damage assessment method is more reliable and faster when the target area is larger than 53 km^2. On the contrary, if the area is less than 53 km^2, high-resolution optical satellite images can be used to understand the damage, although it is limited to roof damage. Particularly, since it takes time to establish a system for a survey method to recognize dwelling damage, it is considered effective to utilize this time to capture the whole picture using high-resolution optical satellite images and to use them to determine a survey policy. The case with no relearning is shown by the dashed line in **Fig. 8**. In the case where sufficient learning is conducted in advance, the survey method is faster than the dwelling damage recognition method, regardless of the area. This is true, although it is limited to roof damage. However, it should be noted that the results of this study use an average of 6.96 teams/day/km^2, because the survey speed varies depending on the size of the team mobilized when using the residential damage certification survey method.

4) Finally, the drone method used in this study has 4K resolution, which enabled us to capture high quality aerial images of the damage of each building. However, due to the drone characteristics, the aerial photography range is narrow, the flight time is limited, and post-processing is required at this point. Therefore the time-cost tends to be high. However, compared to satellite images and aerial images, drone image quality is more granular. For example, even a single roof tile of a building can be identified. In other words, even minor damage can be extracted. Practitioners who are responsible for on-site response can survey with the same quality and accuracy from the air as from the ground. In other words, this method highly complements the ground survey. Since this method is highly dependent on the area, it is considered effective to identify the target areas using other methods and then use the drone (with the ground survey) to conduct a detailed survey.

5) One of the findings obtained through the above discussion is that it is important to select the correct

method according to the situation and purpose. Additionally, it is important to pay attention to the accuracy and granularity of the results obtained and the degree of accuracy of each method. In the period immediately after a disaster strikes, there is an information gap about damage. Despite its accuracy or granularity, satellite imagery is an effective method for surveying the initial damage. After a certain period, various types of response will be required. Each will have its own requirements for accuracy and granularity. In addition to selecting a method based on these requirements, time should be used to determine which method is needed to give a strategic response. In particular, the initial dwelling damage survey is needed to support disaster victims rebuild. It must be conducted at the granular level of each building. In this case, satellite imagery is insufficient. It is necessary to combine ground-based surveys with aerial photography or drone surveys to assess the damage. In this way, the optimal combination of the two methods according to the situation and purpose can be ascertained.

5. Conclusion

The purpose of this study is to estimate the time-cost of damage assessments to execute disaster response efficiently and effectively. In addition to the damage assessment survey based on the guidelines of the Cabinet Office and conducted by the affected municipalities, research and implementation of the following methods are being conducted: identifying the number of damaged houses from drone and satellite images using ICT, and estimating the flooded area and the number of flooded buildings using CyborgCrowd. Although the accuracy of the methods studied has been compared in terms of their reproducibility and suitability, the comparison in terms of time and cost has not. For practitioners who will use these methods, it is important to know in advance the accuracy of the available methods and when the methods will provide the results needed for a damage assessment or estimation.

In this study, the time-cost is calculated per unit area for five methods that can determine the area of interest and the time-cost required for processing. Specifically, the area of the target area and the time required for the work based on actual data from past disasters are surveyed. It is modeled after the time required for preparation for the work, as the initial time-cost. The other work time is proportional to the area. This model is taken as a simple linear equation. The estimated area of damage is used as a variable to estimate the time required to achieve the results of each method.

The time-cost per unit area is calculated to be 0.90 teams/hour/km^2 for residential damage assessment and 5.53 hours/km^2 for the drone survey, including data transfer and 4.55 hours/km^2 without data transfer. In the case of satellite images, two cases are investigated and clarified. The time required for radar satellite images is 2.11 $\times$ 10^{-3} hours/km^2, while the time required for high-resolution optical satellite images is 1.81 hours/km^2, including deep retraining. In the case of high-resolution optical satellite images, the time without relearning is 3.57 $\times$ 10 -2 hours/km^2, which is extremely efficient. On the other hand, the latest method based on crowdsourcing and AI is 1.58 $\times$ 10^{-2}, which is not as fast as radar satellite images but is the second fastest among the five methods. However, each method has its own initial time-cost, which must be taken into account. In terms of the granularity and accuracy of the survey, the survey of damage to dwellings is the most detailed and accurate. However, satellite images have rough granularity and the accuracy is not high. In this study, only the time-cost is analyzed, but it is necessary to verify the accuracy as well.

Each of the methods used in this study has its own purpose and position, as shown in **Table 2**. Based on the characteristics of the disaster, it is necessary to use the available methods appropriately. In addition, to implement each method, the use of information systems, additional personnel, and materials and equipment may be required for data management and operational efficiency. In addition, not only the time-cost but also the economic costs should be analyzed, such as the introduction cost and operation cost of the system and materials, etc. In practice, it is necessary to include these economic costs in the selection of work implementation methods. The results of this study are analyzed only by evaluating time. Future, studies should analyze other types of costs. In addition, the data on time used in this study are not completely recorded in minutes; some are estimated. Through this study, new knowledge is obtained by analyzing time. To obtain more precise results, the recording method of time data and developing a tool to support it are reviewed. Depending on the scale of the disaster, it is necessary to estimate the initial time-cost for environmental preparation, even if the time-cost for implementation remains the same. Knowledge of future disasters is accumulated and research on how to estimate the initial time-cost for various disaster scales is conducted.

Soon, Japan is expected to experience a widespread national disaster. this study prioritizes methods according to efficiency, when the disaster area is large. Future studies plan to improve the accuracy of the time-cost estimation based on the results of this research, and to conduct analysis to match the granularity and accuracy of the assessed damage.

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References:

[1] H. Hayashi and M. Inoguchi, "What Should Be Considered to Realize ICT Support for Effective Disaster Response and Recovery?," IEICE Trans. on Fundamentals of Electronics, Communications and Computer Sciences, Vol.E98-A, No.08, pp. 1594-1601, 2015.

[2] K. Abe et al., "Support for disaster situation awareness by collaboration of image processing and crowdsourcing," Proc. of the 77th National Convention of Information Processing Society of Japan (DVD-ROM), p. 2, 2015 (in Japanese).

[3] M. Inoguchi, S. Hara, K. Shirai, and A. Imai, "Challenge of Roof Damage Housings Detection from Satellite Images by Applying Deep Learning Methodology –A Case Study of Ibaraki City at 2018 Osaka Earthquake–," Proc. of the 35th Int. Technical Conf. on Circuits/Systems, Computers and Communications (ITC-CSCC2020), 2020.

[4] M. Inoguchi, K. Tamura, and R. Hamamoto, "Establishment of Work-Flow for Roof Damage Detection Utilizing Drones, Human and AI based on Human-in-the-Loop Framework," Proc. of IEEE Int. Conf. on Big Data 2019, pp. 4618-4623, 2019.

[5] Cabinet Office of Japan, "Guideline for building damage certification standard operation at disaster," 2020, http://www.bousai.go.jp/taisaku/pdf/r203shishin_all.pdf (in Japanese) [accessed June 24, 2020]

[6] M. Inoguchi, K. Tanyra, K. Hirue, and H. Hayashi, "Implementation of Web-based System for Building Damage Assessment on Online Network: Case studies of Typhoon MAN-YI (1318) and Typhoon WIPHA (1326) in Japan," 2014 IEEE Asia Pacific Conf. on Circuits and Systems (APCCAS), pp. 395-398, 2014.

[7] M. Inoguchi et al., "Utilization of Aerial Photos Taken by Drone for Capturing Roof Damage and Survivors Support –A Case Study of Response in Murakami City at 2019 Yamagata-oki Earthquake–," Proc. on the 60th Conf. of Civil Engineering Planning Research (CD-ROM), Vol.60, p. 6, 2019.

[8] International Disasters Charter, "Disaster Relief Organisations," https://disasterscharter.org/web/guest/about-the-charter [accessed March 8, 2021]

[9] National Research Institute for Earth Science and Disaster Resilience (NIED), "Response in theme-2 to Typhoon No.19 in 2019," 2020, https://www.bosai.go.jp/nr/result/result_detail_02.html (in Japanese) [accessed June 24, 2020]

[10] Water and Disaster Management Bureau, Ministry of Land, Infrastructure, Transport and Tourism, "Guidebook for utilization of satellite at disaster –Flood version–," p. 16, 2018, https://www.mlit.go.jp/common/001227723.pdf (in Japanese) [accessed June 24, 2020]

[11] The Remote Sensing Society of Japan, "Guideline for utilization of satellite data at disaster," 2017, http://rssj-kokudo.civil.ibaraki.ac.jp/file/saigai-guide.pdf (in Japanese) [accessed June 24, 2020]

[12] National Research Institute for Earth Science and Disaster Resilience (NIED), "Crisis Response Site on Typhoon No.19, 2019," 2019, http://crs.bosai.go.jp/DynamicCRS/index.html?appid=9424c7b32d784b60a9b70d59ff32ac96 (in Japanese) [accessed June 24, 2020]

[13] M. Inoguchi, S. Hara, K. Shirai, and A. Imai, "Challenge of Roof Damage Housings Detection from Satellite Images by Applying Deep Learning Methodology –A Case Study of Ibaraki City at 2018 Osaka Earthquake–," Proc. of the 35th Int. Technical Conf. on Circuits/Systems, Computers and Communications, pp. 172-176, 2020.

[14] A. Morishima, M. Inoguchi, K. Tajima, and I. Kitahara, "Digital Knowledge Era and the Future of Work: Challenges and the Current Status of JST Cyborg Crowd Project," Workshop on Addressing SDGs Through Data Analytics and AI, Int. Conf. on Digital Landscape 2019, pp. 68-78, 2019.

[15] Geospatial Information Authority of Japan, "Information on July rainfall disaster in 2018," 2018, https://www.gsi.go.jp/BOUSAI/H30.taihuu7gou.html (in Japanese) [accessed Septemer 11, 2020]

[16] M. Inoguchi, K. Tamura, K. Uo, and M. Kobayashi, "Validation of CyborgCrowd Implementation Possibility for Situation Awareness in Urgent Disaster Response –Case study of International Disaster Response in 2019–," Proc. of 2020 IEEE Int. Conf. on BigData, 2020.

[17] Cabinet Office of Japan, "About points to note regarding the efficiency and speeding up the damage certification investigations of housings at Typhoon No.19 in 2019," October 2019, http://www.bousai.go.jp/oyakudachi/pdf/siryo_26.pdf (in Japanese) [accessed September 11, 2020]

[18] Ministry of Internal Affairs and Communications (Statistics Bureau), "Chapter1: Characteristics and history of regional mesh statistics," http://www.stat.go.jp/data/mesh/pdf/gaiyo1.pdf (in Japanese) [accessed June 24, 2020]

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- "Structure of Web-Based Victims Master Database of the Life Rebuilding Process –A Study of the Great East Japan Earthquake of 2011–," Proc. of the 15th World Conf. on Earthquake Engineering (CD-ROM), 8pp., 2012.
- "Visualization Methods and Associated Challenges of Disaster Data for Common Operational Picture –A Case Study of the 2011 Great East Japan Earthquake based on the Activities of Emergency Mapping Team of the Cabinet Office–," J. of i-Society 2012 (CD-ROM), 5pp., 2012.
- ISBN: 978-4-864-43100-2, March, 2016.
- ISBN: 978-4-864-43089-0, December, 2015.
- ISBN: 978-4-621-07951-5, January, 2008.

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• K. Tamura and M. Inoguchi, "Proposal of Elements for Creating Scenarios for Those Needing Support During National Disasters," J. Disaster Res., Vol.11, No.5, pp. 870-880, 2016.

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• M. Kobayashi, H. Morita, M. Matsubara, N. Shimizu, and A. Morishima, "An Empirical Study on Short- and Long-term Effects of Self-Correction in Crowdsourced Microtasks," Proc. of the AAAI Conf. on Human Computation and Crowdsourcing (HCOMP 2018), pp. 79-87, 2018.

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• D. Gross-Amblard, A. Morishima, S. Thirumuruganathan, M. Tommasi, and K. Yoshida, "Platform Design for Crowdsourcing and Future of Work," IEEE Data Eng. Bull., Vol.42, No.4, pp. 35-45, 2019.
• M. Hayashi, M. Kobayashi, M. Matsubara, T. Amagasa, and A. Morishima, "Incentive Design for Crowdsourced Development of Selective AI for Human and Machine Data Processing: A Case Study," 2019 IEEE Int. Conf. on Big Data, pp. 4596-4601, 2019.
• E. Iwamoto, M. Matsubara, C. Ota, S. Nakamura, T. Terada, H. Kitagawa, and A. Morishima, "Passerby Crowdsourcing: Workers' Behavior and Data Quality Management," Proc. ACM Interact, Mobile, Wearable and Ubiquitous Technologies, Vol.2, No.4, pp. 169:1-169:20, 2018.
• ISBN: 978-3-319-49304-6, December, 2016

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