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Detecting flood inundation information through Twitter: The 2015 Kinu River flood disaster in Japan

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Abstract

For effective responses to flood disasters, it is essential to identify affected areas in real time. Recently, social media (e.g. Twitter) have emerged as new sources of disaster-related information in real time. However, concerns still remain regarding the trustworthiness and the amount of information, especially that issued from a site of crisis. This study investigated a total of 109 tweets sampled based on certain criteria during a flood disaster in the Kinu River Basin, Japan in September 2015. We classified them into five categories depending on the main contents: 1) flood inundation, 2) rescue, 3) emotion, 4) river condition, and 5) damage situation. The analysis suggests that the highest proportion (37%) of tweets were related to flood inundation followed by damage (19%) and 32% of them were posted in near real time with photos. We further compared well-positioned tweets with other inundation extent information based on our field investigations and aerial photos. The results showed good agreement between the inundation information from the posted tweets and the expected locations. Some tweets suggested additional inundated areas, not originally identified by the aerial photos. Overall, the study shows the potential use of social media to collect local details about floods.

Keywords: The Kinu River Flooding; Flood risk; Social media; Twitter

1. Introduction

On September 10, 2015, due to heavy rainfall over three days, an overtopping flood occurred along the Kinu River in Japan around 6:00 AM. At 12:50 PM on the same day, a levee breach also occurred downstream. This disaster left two people dead and several injured with enormous damage to homes and infrastructure in Joso City. For effective countermeasures, real-time information on the local flood situation is indispensable. Real-time flood hazard maps could offer a better view on a crisis, however, the mapping has not yet been realized. The challenge to create them is how to determine the extent of a flood on a real-time basis.

There are currently three ways to evaluate the extent of damage: remote sensing, computer simulations, and collecting details on local flood inundations in affected areas. In the case of the Kinu River flood disaster, Japan's Geospatial Information Authority (GSI) took aerial photos from helicopters several hours after the flood to measure the area of the flood zone.

Although GSI operated a helicopter after the flood occurrence and used the photos to assess how far it had spread, GSI could not pinpoint specific locations of flood inundation during its spread. Regarding computer simulations, it is still difficult to set inundation parameters in real time, moreover, the accuracy of the inundation model is also a challenge for real-time simulation.

Social media is used extensively for sharing crisis information (Keim and Noji 2011; Choi and Bae 2015; Cameron et al. 2012; Sutton et al. 2008). The first example of intensive uses of Social media during a crisis was a coordinated suicide attack in London in the UK on July 7, 2005. People distributed photographs and videos recorded with mobile media across Flicker and Wikipedia to spread the news about the reality on the ground (Lorenzo-Dus and Bryan 2011; Li et al. 2013). Compared to ordinary situations, the amount of tweets increases during disasters: 3.28 million tweets were posted related to the Haiti Earthquake in 2010, 33 million tweets were posted related to the Great East Japan Earthquake in 2011, 20 million tweets were posted in the case of Hurricane Sandy in 2012, and 5.72 million tweets were posted in Typhoon 'Haiyan' in 2013 (Sarcevic et al. 2012; BIGLOBE 2011; Olanoff 2012; Levine 2013; Kongthon et al. 2012; Ntalla et al., 2015).

There are three main methods of social media usage for disaster response. The first usage is disaster occurrence detection, which typically utilizes an online system to monitor the rapid increase of specific keywords on the Internet (Choi and Bae 2015; Bee 2012; Kumar 2011; Emmanouil and Nikolaos 2015). The second usage is to call for rescue during disasters. Although social media has been utilized to post-rescue requests in recent disasters, there are still some intrinsic issues for decision making in rescuing when replying on social media, identifying only critical rescue requests is a particularly significant challenge (Sato 2017). The third usage is to identify hazard and damage situations. The reported examples include an earthquake intensity map (Paul et al. 2010); flood inundation identifications (Smith 2015; Fohringer 2015; Eilander 2016). The applications expect that on-site residents can be active distributors of disaster-related information by posting real-time information on the situations (Spinsanti and Ostermann 2013).

Among the three usages, this study focuses on the third usage by taking the example of the Kinu River flooding in 2015. In particular, the objectives of the study are: 1) to investigate the main messages in tweets posted during the Kinu River Flooding by manually classifying the tweets posted into five categories including flood inundation, rescue, emotion, river condition, and damage information and 2) to verify if flood inundation-related tweets agree on the actual flood situation both in time and space.

2. Methodology

2.1 Data harvesting

We used the following three methods to collect tweets on the Kinu River flood disaster：

a) Twitter's advanced search function, b) Twitter Application Interface (API) and c) DISAster-information ANALyzer (DISAANA) (Ohtake 2015). The general rules on collecting tweets can be summarized as follows: 1) We focus only on the ones tweeted on the same day as the disaster occurred i.e. from 0:00 to 24:00 on September 10, 2015; 2) We used the following keywords for searching the tweets on the flooding: inundation, levee breach, rescue, typhoon, flood and disaster in Japanese words; 3) to identify the specific event, we used each keyword together with "Kinugawa" and we set "news" as an excluding keyword to eliminate Twitter information from mass media; 4) Since there are still too many uninformative tweets, we manually selected tweets based on the following criteria: flood information by Twitter users who observed levee overtopping directly, inundation and structural damage; tweets that call for rescue or offer information on evacuation (e.g. updating information on rescue team activities); information representing the sender's feelings or emotions on the target flood (e.g. fear of a potential flood).

a) Twitter's advanced search function

We used Twitter's advanced search function by employing the above keywords and tweeted time. The advanced search function is the easiest to access from the Internet.

b) Twitter Application Programming Interface (APIs)

Twitter provides search services based on its own API. We utilized Twitter's REST API to search for disaster-related tweets. REST APIs can set both keywords, time, and allow users to detect tweets posted in a specific time (Twitter 2013). We set the time on September 10, 2015, to obtain tweets related to the Kinu River flooding with the same keywords and criteria set as described above. All the programming and usage of Twitter API follow the rules and guidelines of Twitter.

c) DISAster–information ANAlyzer (DISAANA)

DISAANA is an online system that picks up and locates tweets related disasters and accidents in real time (Ohtake 2015). DISAANA instantly extracts and presents answer candidates when a simple question is input. In this research, the DISAANA system prepared particularly for the Kinu River flooding was used to detect tweets. DISAANA provides two modes: problem-listing mode and question-answering mode. In this study, we used the problem-listing mode by setting the same keywords to obtain related tweets.

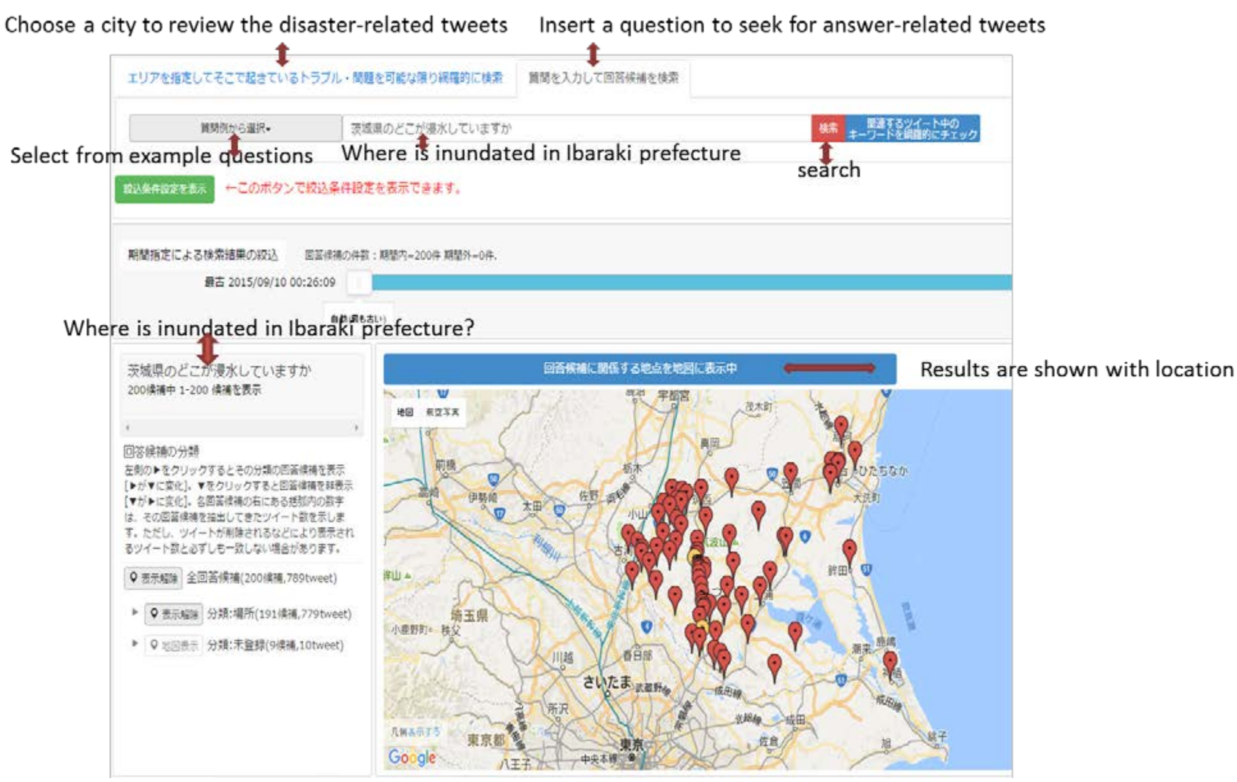

Figure1 Examples of searches when inputting a simple question into DISAANA

As a result, 109 tweets were harvested by those three methods by follwing the rules

2.2 Data analysis
To understand the detailed contents of the 109 selected tweets, we analyzed them from the following viewpoints: 1) the main messages in the content, 2) if the content is related to the user or to others, 3) if tweets were posted in real time, 4) if tweets related to inundation agree with the actual situation centers, shelters and evacuation advice.

3. Results

3.1 Summary of tweets
The collected total of 109 tweets were categorized into the five categories according to the main contents (Fig.2).

1) Flood inundation: tweets contain inundation-related information.
2) Rescue: tweets related to rescue or relief information, such as calling for help, seeking or providing information to an evacuation shelter.
3) Emotion: tweets with personal emotion such as anxiety or fear.
4) River condition: tweets with contents about a river, water levels etc.
5) Damage situation: tweets have information on infrastructure, transportation, damage to daily life etc.

Some tweets are related to more than a single category since the flood situations are tweeted with the expression of fear. In that case, we manually judge the main content of each tweet. If it is related to inundation or damage, we prioritize it because our research is interested in the contents.

The largest category was about the flood inundation (37%), followed by the damage situation (19%). The third largest category was on the river condition (16%). The portion of tweets with some rescue-related information was 12% and 1% contained emotion. The other category (15%) is, for example, landslide information. Table 1 gives examples of each category.

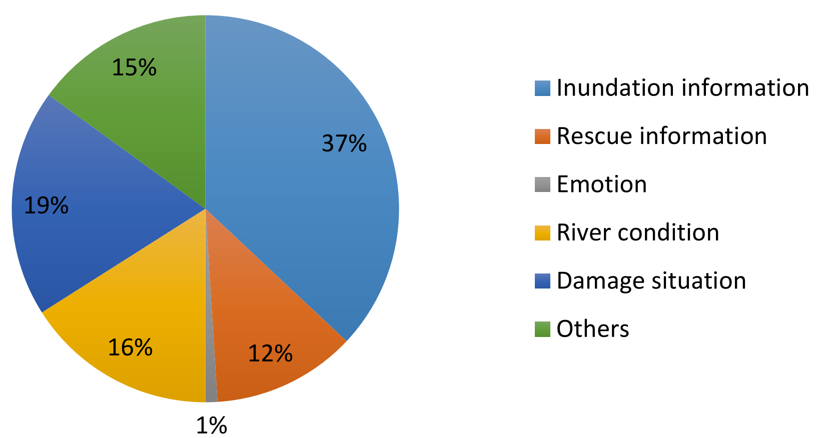

Figure2 Categories and their proportions of the 109 tweet

Table1 Example of tweets of each category

Category	Example
Inundations	✧ Morishita Street was inundated by the Hakkenbori floodgate; the water depth was 1 meter ✧ My house was flooded, with water under the bed ✧ Our farm was inundated
Rescue	✧ Help me, only my mom and I remain in our house. How can I survive this night? # rescue # Kinu River # diffusion ✧ My parents are living in the town of Nakatsuma in the city of Joso. The water depth increased after sunset, and now it seems that the house has been flooded, with water under the floor. What should I do to prevent the water from rising? Who should I contact if something happens at night? # Joso City # Kinu River #Flood'
Emotion	✧ A street 10 kilometers from my house was reported to have suffered flood damage. I got this information from Twitter and the news, but I still don't have a real feeling on it.
River condition	✧ This is the water level situation at Akutsu Bridge (with a photo), it has been a long time since I have seen the water level this high
Disaster situation	✧ National Route 16 was inundated ✧ The Joso Line between Moriya and Shimotsuma Stations was flooded
Other	✧ The water level rose again. Please be careful of landslides. ✧ A levee breach happened at Kinu River, and an alert for landslides was also announced

We also analyzed the other general characteristics of the 109 tweets. Figure 3 shows that 43% of them were posted with photos during the flood. Half of them were related to the senders, while the other 25% tweets related to other people. We could not link the remaining 25% with either the senders or others. In addition, the time intervals between when the event happened and when people posted the tweets are important as disaster information. We compared the time indicated in the tweets' contents or the pictures with the posted time. If the time that related to the facts in the tweets was the same as the post time in several hours, we defined it as a real- time post. For instance, the tweet contents in 'this is the inundation situation in front of the post office now.' The example of a non-real-time post is 'I felt so surprised when I heard about the flood at lunchtime,' but this post was posted in the evening. Other tweets have no clear evidence related to time, so we categorize them as the unknown. As a result, 32% of the posted tweets were real-time posts, while 15% of them were about the non-real-time post, and 53% were unspecified due to the lack of information indicating the time of events.

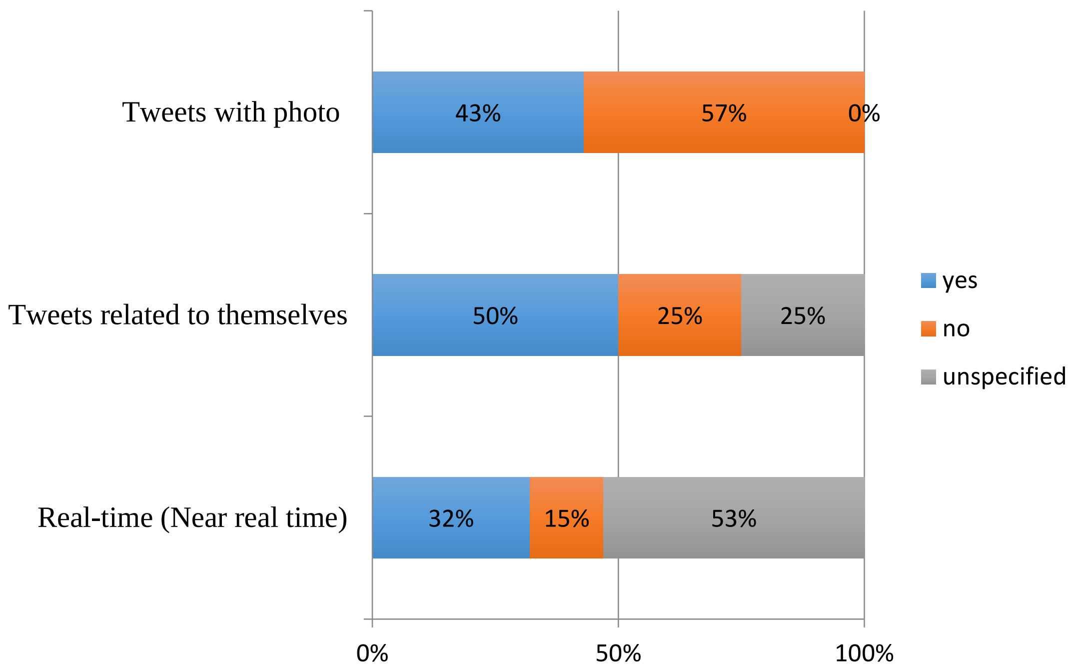

Figure3 General characteristics of the collected tweets

3.2 Inundation information

We further investigated 37% of all 109 tweets (i.e. 41 tweets) categorized as "flood inundation." Table 2 shows the ratios of tweets with or without flood depth and location information. It suggestes that 23% of the flood inundation-related tweets (i.e. out of 41 tweets) were able to estimate both the inundation depth and the location information based on the location name or landmark information shown in the contents of tweets in the pictures. Based on the information, we identified the location and water depth information. With the other 23% it was possible to estimate the tweeted locations but not the inundation depth.

Table2 Characteristics of tweets related to inundation

	Geo-tagged	**Non-geo-tagged**
With depth-related information	23%	17%
Without depth-related information	23%	38%

3.3 Comparison with other inundation information

We compared the geo-tagged inundation-related tweets with the real circumstances of the Kinu River flood disaster. The geo-tagged inundation-related tweets mean tweets with a clear landmark or street name together with inundation-related information in the contents.

Some examples of the extracted information are:

1) What happened in Apita Supermarket and on Ishige Street?
2) Apita supermarket suffered severe damage. It looks like this.
3) Ibaraki Nursing Home was inundated; everyone waited on the second floor to be rescued.
4) Mitsuma Train Station was inundated.
5) Nakatsuma town was inundated with water rising from under the floor.
6) This is the current situation near Joso City Hall.
7) Ainomiya Street was flooded. My neighbor, who come from Brazil, is calling for help.
8) Morishita Street was inundated by the Hakkenbori floodgate; the water depth was 1 meter.

Figure 4 shows a comparison between the extent of the flooding and the information posted in tweets. In this figure, the red line delineates the extent of the inundation at 18:00 on September 10, 2015 (provided by GSI), while the color represents the maximum inundation depths estimated by Sayama and Takara (2016). The figure shows that the content of tweets generally agrees with the estimated areas of flooding. Referring to the flood extent measured by GSI which is shown in the figure with the red circle, tweets No. 1,2 and 3 in Fig. 4 are well located inside the red circles in time and space scales. Moreover, the pictures from Apita Supermarket, taken at 11:10 and 18:59 indicate nearly the same water depths, but show completely different amounts of drift deposits according to the pictures of tweets posted at different timings.

Tweets 4 and 5 (in Fig.4) show the timing of water flowing and the expansion of the flood inundated areas. Tweet 4 was posted 37 minutes after the GSI had measured the extent of the flood zone at 18.00, and 3 hours later, tweet 5 reported an inundation located downstream. Tweets 6, 7, and 8 (in Fig. 4) show some differences in terms of the degree of flooding as measured by the GSI, as shown in the red circle. Tweets 6, 7 and 8 reported severe inundation at 17:00, 22:21 and 22:38, which were not estimated by GSI. Following the crisis, it was confirmed that these areas had been flooded.

Figure 5 shows details on flooding from the early morning in the city of Yuuki, upstream of Joso. Based on the tweets, we can see that the region was severely flooded at 7:50. And the server inundation-related information can give us an early warning on what might happen in the downstream areas.

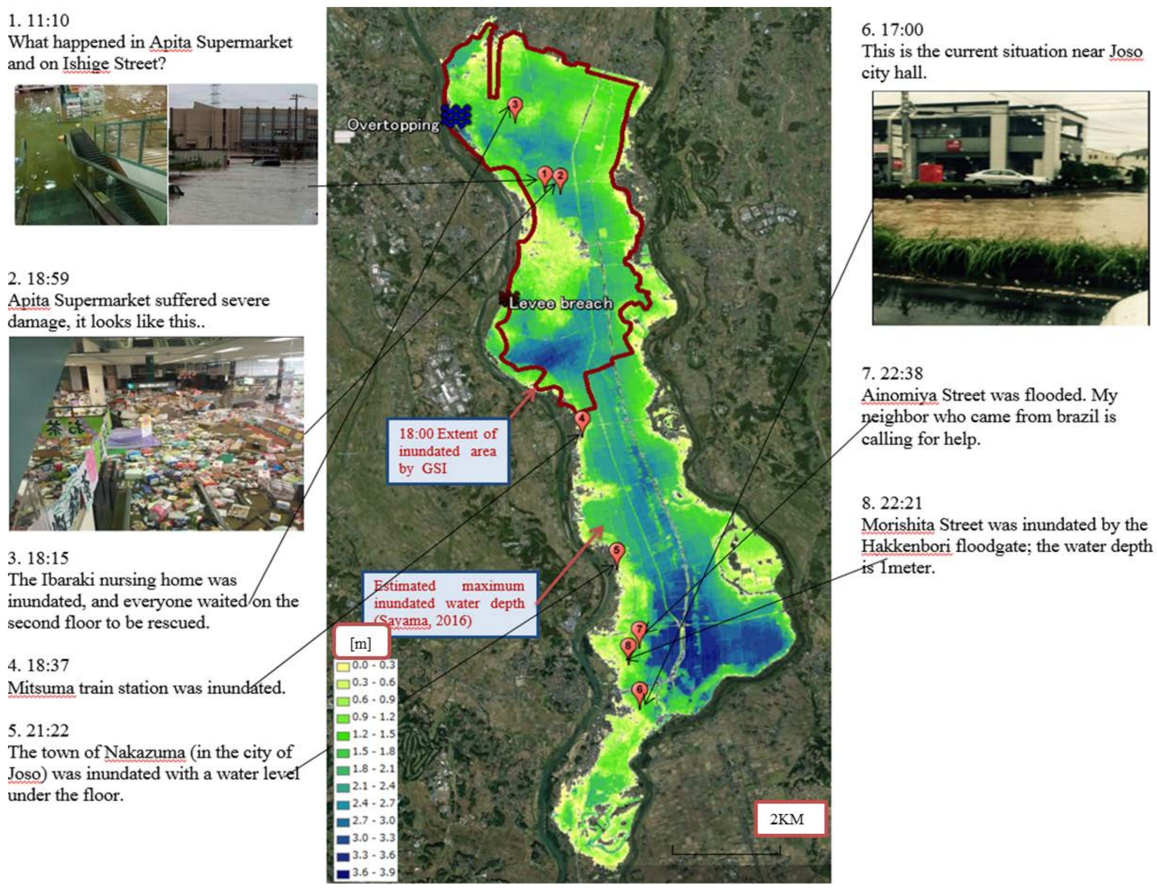

Figure4 Inundation information from tweets

The tweets shown in Fig. 5 reported the following information:

A: ‘Kinu Commercial High School was inundated.’

B: ‘The area in front of Kubota post office was inundated and people cannot pass National Route 15 due to flooding.’

C: ‘This is the current situation of Sakae Bridge between the cities of Chikusei and Yuuki.’

Previous studies indicated that social media users geographically closer to a disaster zone have a higher intention of sharing more accurate knowledge (Thomson and Ito 2012). Furthermore, our study shows many instances of clear data provided by residents inside the crisis area. However, no tweets were posted near the levee breach points. This is possibly due to the location near the levee being one of the most severely damaged zones and residents may not have had time to post anything.

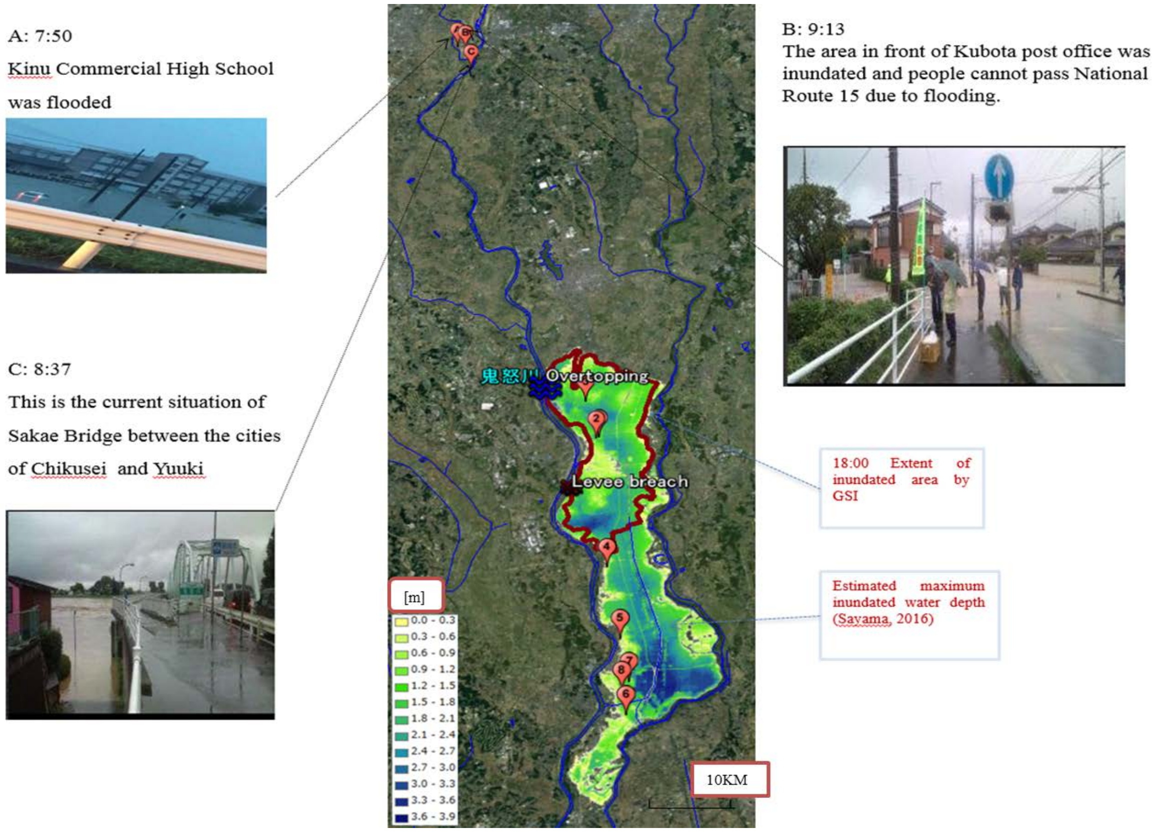

Figure5 Inundation information in the city of Yuuki

4. Discussion

Regarding the reliability of the tweets, several previous studies have tried to categorize Twitter users to investigate the relationship between the reliability of tweets and the categories of users. Li et al. (2013) indicated that well-educated people post more information that is reliable during disasters with geo-tagging and photographs. Meanwhile, tweets posted by volunteers are also considered as highly reliable information sources. Schnebele and Cervone (2013) and their series of studies (Schnebele et al. 2014; Schnebele et al. 2015) developed a method of crisis mapping by combining remote sensing with local information sent by volunteers. They concluded that volunteered information can be a trustworthy source. In this study, we could not divide the posted tweets by users' categories or collect information exclusively from volunteers. Hence, all the collected tweets in this study are posted from the public.

Another factor is on the contents of tweets in this research, Vieweg et al. (2010) investigated how tweets may contribute to increasing the awareness of hazard events based on two case studies. One event is the Oklahoma grass fire, which was an urgent disaster without any alert in advance. The other event is the Red River floods, which was a disaster with lots of alerts and evacuation preparations. The result demonstrated that in a more urgent condition like the grass fire in Oklahoma, tweets were more related to evacuation information, damage and injury situations, and hazard conditions including the wind direction of the fire line. In contrast, for mild flooding with advanced warning, tweets were more related to preparatory activities, flood level, weather and volunteer information (Vieweg et al. 2010). In our study, the Kinu River flood has essentially both characteristics. With three days of heavy rainfall and its alert information, local residents had a certain level of preparedness for the probable impending flooding. However, the levee breach along the main Kinu River happened unexpectedly without any detailed alert in terms of its timing and location. Our finding agrees with that of Vieweg et al. (2010) in the sense that residents intend to report unexpected and sudden hazard situations as well as some damage or relief related information because the situations of a disaster were different depending on the time and area even from a single flood disaster.

From areas that were less affected, the number of tweets decreases. Xiao et al. (2015) called these characteristics as a reverse U-shaped relationship between the distance for the most severely affected disaster area and the number of posted tweets related to the event. This study also agrees with their findings as there was no information from the most severely affected area. In addition, this study suggests that many tweets were posted to report their situations not only from the directly inundated areas by the levee breaching but also from fairly distant areas with local inundation along roads. The hazard information from less severely affected areas may also be useful if it is shared effectively through a system like DISAANA (Ohtake 2015) since conventional mass media tend to report only on the most severely affected areas as long as they are accessible. Moreover, our result in Fig. 5 emphasizes that a grasp of information on an upstream area may contribute to the evacuation activities in a downstream area.

Finally, not all the tweets are reliable. Here we discuss how to check the reliability of social media information for each usage that was identified in the introduction. For the first usage, disaster occurrence detection as big data, generally a rapid increase of keywords in a short time from a particular location is difficult to occur just by fake news, so it is the most promising usage with a number of previous case studies. In the second usage, how to identify critical rescue requests has been difficult. To eliminate the necessary information, some organizations propose adding particular hashtags; however, this has not been so successful as more and more people use social media during disasters (Sato 2017). The same issue remains for the third usage, which is disaster identification even though the selection of the information is not as critical for rescuing. The following approaches can complement the selection of a limited number of reliable items of disaster information.

1) Automatic categorization or elimination of tweets to detect only first-hand information (e.g. Abbasi and Liu 2013).
2) Effective use of tweets with location information and photos. Our study suggestes that these tweets describe realistic flood conditions. A system like DISAANA to automatically map such tweets is helpful for grasping a global view on what is happening in an area.
3) Crosscheck with other information sources such as mass media or government information. Multiple information about social media itself also helps to improve the reliability (e.g. Takahashi and Igata 2012).

If we check the social media information with the above methods before further utilization, the reliability of social media information may be improved.

5. Conclusion

We detected and analyzed 109 tweets posted from disaster-affected area by the flood in the Kinu River Basin.

We manually examined them to interpret their main messages. The greatest proportion (37%) contained details on flooding, followed by information on damage (19%). The third highest number of users posted was about water level (16%). Rescue information was also collected (12%). In addition, emotions accounted for 1%, while other types of data comprised 15%. This demonstrates that many people intend to report on their local flood situation.

Regarding the timing of tweets, we identified 32% as being posted in or near real-time; 15% show clear evidence of not having been posted in real time, while the rest (54%) do not reveal whether they were posted in real time among the 46% tweets containing inundation-related information, and 23% were posted with a clear indication of the flood zone and water depth. From this 23%, in the future, residents could develop a very clear image of risky areas and can provide early warnings to others. The other 23% contained exact site information but water depth was uncertain; thus, the second 23% only provided residents with knowledge of places where they should exert caution.

Comparing well-positioned inundation-related tweets with the degree of how far the flood spread as estimated by GSI, the well-positioned inundation-related tweets show good agreement with the estimated inundation extent at different timings. Furthermore, some tweets suggested additional inundated sites, which were not originally identified by the GSI, but later confirmed by field investigation.

The outcome shows that many people posted information during a disaster, and the well-positioned first-hand tweets display reliability with the advantage of having wide coverage.

However, this study did not detect and analyze tweets automatically; the main messages, location, and water depth were estimated manually. Further work on the automatic detection and analysis of tweets is required. At the same time, as the available tweets with references of location and water depth are limited, the contribution of social media in flood mapping will be improved if we can obtain multiple social media information sources in real time.

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