Investigating images as indicators for relevant social media messages in disaster management

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ABSTRACT

The use of social media during disasters has received increasing attention in studies of the past few years. Existing research is mostly focused upon analyzing text-based messages from social media platforms such as Twitter, while image-based platforms have not been extensively addressed hitherto. However, pictures taken on-the-ground can offer reliable and valuable information for improving situation awareness and could be used as proxy indicators for relevance. To test this hypothesis, this work explores various social media platforms, including image- and text-based ones in the case of floods in Saxony 2013, Germany. Results show that there is a significant association between disaster-related messages containing images and their proximity to the disaster event. Hence, the existence of an image within a social media message can serve as an indicator for high probability of relevant content, and thus can be used for enhancing information extraction from social media towards improving situation awareness.

Keywords

Social Media, Disaster Management, Volunteered Geographic Information, Flood, Germany

INTRODUCTION

In the last few years, social media has evolved to a new information channel. In the case of disaster events, people exploit social media not only to acquire and share information but also to produce new information (Palen, Vieweg, Liu and Hughes, 2009). A particular advantage arises from local individuals in immediate proximity to the event when they use social media to share their particular perspective of the facts. They are often in a position to provide exclusive information from the ground that is not yet provided by any other source (Landwehr and Carley, 2014).

In the case of social media for disaster management, a major concern of recent research is to identify relevant messages that have the potential to improve situation awareness. Thereby, the main issue is to filter out the most relevant messages within the high volume, variety and velocity of information. For instance, Vieweg, Hughes, Starbird and Palen (2010) explored Twitter messages (tweets) for their usefulness to improve situational awareness and categorized messages of local contributors to different situational features. Regarding to the informational value of social media messages, Imran, Elbassuoni, Castillo, Diaz and Meier (2013) point out that disaster-related messages greatly differ in their usefulness for disaster management. They successfully applied machine-learning algorithms to automatically distinguish between informative messages and noninformative ones within a set of disaster-related tweets. Furthermore, previous research studies have shown that local users are more probable to provide relevant information (Acar and Muraki, 2011; Starbird, Muzny and Palen, 2012; Imran et al., 2013; Landwehr and Carley, 2014). Most of these studies perform a binary classification of the messages into local/non-local, based on hand-analysis of messages and metadata of user profiles (Vieweg et al., 2010; Acar and Muraki, 2011) or using machine learning algorithms upon the content of messages (Starbird et al., 2012; Imran et al., 2013). Furthermore, these approaches use only social media as standalone information source.

However, a number of recent studies exist that rely upon other information sources to take geographic context into account (Spinsanti and Ostermann, 2013; Albuquerque, Herfort, Brenning and Zipf, 2015). Spinsanti and Ostermann (2013) rate the relevance of social media messages related to forest fires based on their distance to well-known forest fire hotspots in France. Albuquerque et al. (2015) investigated the spatial relationship of tweets and flood-affected areas in the case of the Elbe River flood 2013 in Germany. They revealed that flood-related tweets are closer to the disaster event than the remaining tweets.

For the most part of recent research, Twitter is the only source of social media data (Landwehr and Carley, 2014). However, Twitter is of course not the only source of social media and other sources are mentioned as well. Especially image-based social media is seen as a promising source of information retrieval in cases of disaster events (Landwehr and Carley, 2014). A single picture can give promising insights, especially about disaster impacts and other on-the-ground information (Liu, Palen, Sutton, Hughes and Vieweg, 2008). However, until now there is scant research about other social media sources besides Twitter and especially about the differences between image- and text-based social media messages in the context of disaster management.

In this study, we hypothesize that disaster-related messages containing an image are more likely to contain on-the-ground information – for example photos taken and posted by eyewitnesses. Consequently such messages should be closer to the disaster event, i.e. affected areas. This is mainly founded by two findings: On the one hand, relevant messages have been proved to be closer to the disaster event (Albuquerque et al., 2015). On the other hand, on-the-ground information tends to contain highly informative value and is thus very relevant for disaster management (Imran et al., 2013). Therefore, we investigate the following research question: *Does the existence of image content within a social media message indicates on-the-ground information and is thus suited as a proxy for relevance for disaster management?*

For answering this research question, we investigate tweets and messages from Flickr and Instagram (both image-based platforms) in the case of intensive flood events 2013 in Saxony, a federal state of Germany.

This paper is organized as follows: In the next section we present the case study and our used data sets, followed by our methodology and first results. Finally we present our findings and their implications for future work.

CASE STUDY AND DATA SOURCES

In June 2013 almost all river basins in Saxony were affected by intensive floods. For the majority of them the highest alert level, indicating high risk and high damage potential, was reached, including the largest river Elbe. The proclaimed alert level indicates very high flood potential that requires active flood defense. The first signs of a beginning flood situation began at the end of May 2013 and the flood peaks of the river basins were all reached within the first third of June resulting in a 50- to 100-year flood classification for most river basins (LfULG, 2014).

Social Media Data

Our dataset contains 26,713 messages that were posted on Flickr (1,865), Instagram (486) and Twitter (24,362) between the 25th May and 23th June 2013 and are located within the federal state of Saxony. Every message contains a timestamp when it was posted to the corresponding social media platform and a georeference by latitude and longitude coordinates.

All messages were retrieved by their respective public Application Programming Interface (API). The Twitter data was fetched via the public streaming API during the mentioned time period using as filter a bounding box covering Germany.

Through the public streaming API only 1% of all tweets are accessible. Furthermore, only tweets that were georeferenced using a GPS were retrieved, i.e. tweets having a point coordinate with longitude and latitude. To receive the Flickr data the API-method *flickr.photos.search* was applied to collect all messages within a bounding box that covers Germany. The Flickr API allows access to all public photos without time limitations. Nevertheless, the data retrieval for Flickr was performed during the mentioned time period above. The Instagram data was fetched afterwards the mentioned time period. Since a geo-search, based on a bounding box, was no longer available for this time period, we applied a tags-search (API-method *tags/{tag-name}/media/recent*) that allows covering this time period. The used tags for the search are mentioned in the next chapter.

After the data was retrieved, we used official data for the administrative boundary of Saxony[1] to filter all messages located within the state boundaries during the mentioned time period.

Authoritative Data: Hazard Areas and Water Levels

We obtained authoritative data from hazard maps which correspond to flood-prone areas with a probability of occurrence every 100 years, so-called centurial floods (HQ100). This matches the mentioned flood extents. These hazard areas are provided by environmental authority of Saxony and can be accessed via an OGC Web Feature Service[2]. Besides factual flooded areas, these areas are also likely to include areas where temporary flood protection measures such as sandbag dikes occur as well as emergency efforts and volunteer activities. Those are of great interest to improve situational awareness.

Furthermore, we used official water level data of the Elbe River provided by the German Federal Waterways and Shipping Administration. For the other rivers no water level data was available. The water level measurements were provided in a 15-minute resolution for the whole analyzed period. The location of the measurement station with the current water levels is accessible via OGC Web Feature Service[3].

METHODOLOGY

At first, we search for certain keywords within the messages to separate flood-related (on-topic) from the remaining messages (off-topic). A keyword-based filtering is commonly applied in a first step to select disaster-related messages (Landwehr and Carley, 2014). Messages that contain one of the following keywords, regardless of case-sensitivity or mutated vowel (*ä-ae and ü-ue*), were thus marked as on-topic: The German words for flood *Hochwasser*, *Flut*, *Überschwemmung* and the English word *flood* as well as *Deich* (*dike*), *Sandsack* (*sandbag*) and *Sandsäcke* (*sandbags*). The retrieval of Instagram data was also based on the existence of one of these keywords in the tags of messages.

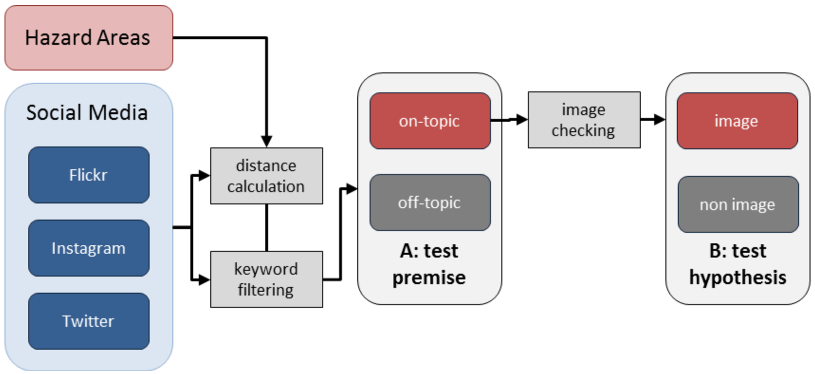

Figure 1. Methodological workflow.

Furthermore, we flagged all messages that contain an image. Since for Flickr and Instagram image content is mandatory, this applies only for tweets. Images within a tweet are embedded by an URL linking to the image. During the streaming the image content was not retrieved. Afterwards we queried every tweet containing an URL via the Twitter API (*/statuses/show/{id}.json*) to check if the tweet contains

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[1]http://sg.geodatenzentrum.de/wfs_vg250?request=GetCapabilities&service=wfs
[2]http://www.umwelt.sachsen.de/umwelt/wasser/11773.htm
[3]http://www.pegelonline.wsv.de/webservice/wfsAktuell

an image. After the classification process (Figure 1), we calculated the Euclidean distance between every message and the hazard area. Then, we first check if on-topic messages tend to be closer to the event (represented by hazard-areas) than off-topic messages. For this reason, we compare the distance values between on- and off-topic messages for each platform (A in Figure 1). After that, we compare the distances particularly for on-topic messages with and without an image to the hazard areas to test if there is a correlation between proximity and existence of image content (B in Figure 1). This refers particularly to tweets where image content is optional. Applying this, we want to test our hypothesis if the existence of image content is a proxy for detecting on-the-ground messages, and thus potentially relevant content. To test the central tendency between the respective groups (on/off-topic for each platform; with/without image for tweets) on statistical significance, we compute the Mann-Whitney's U-Test (U test) since the distance values are not normally distributed.

RESULTS

The descriptive distribution of all social media messages shows that the most on-topic messages were posted in the first third of June (Figure 2). This applies for every social media source and also matches with the flood peaks in Saxony (LfULG, 2014) including for the areas around Dresden where the most messages are located (Figure 3 and 4).

social media platform	messages all	on-topic	off-topic
Flickr	1,865 (100%)	281 (15%)	1,584 (85%)
Instagram	n/a	486	n/a
Twitter	24,362 (100%)	485 (2%)	23,877 (98%)

Table 1. Distribution of on- and off-topic messages.

Regarding the number of on-topic messages, the Instagram and Twitter dataset show a higher absolute quantity compared to Flickr (Table 1). However, the proportion of on-topic to all messages is quite low for Twitter (~2%) compared to Flickr (15%). The proportion of Instagram message is unknown, since only on-topic messages were available. In total, 1,251 on-topic messages could be identified.

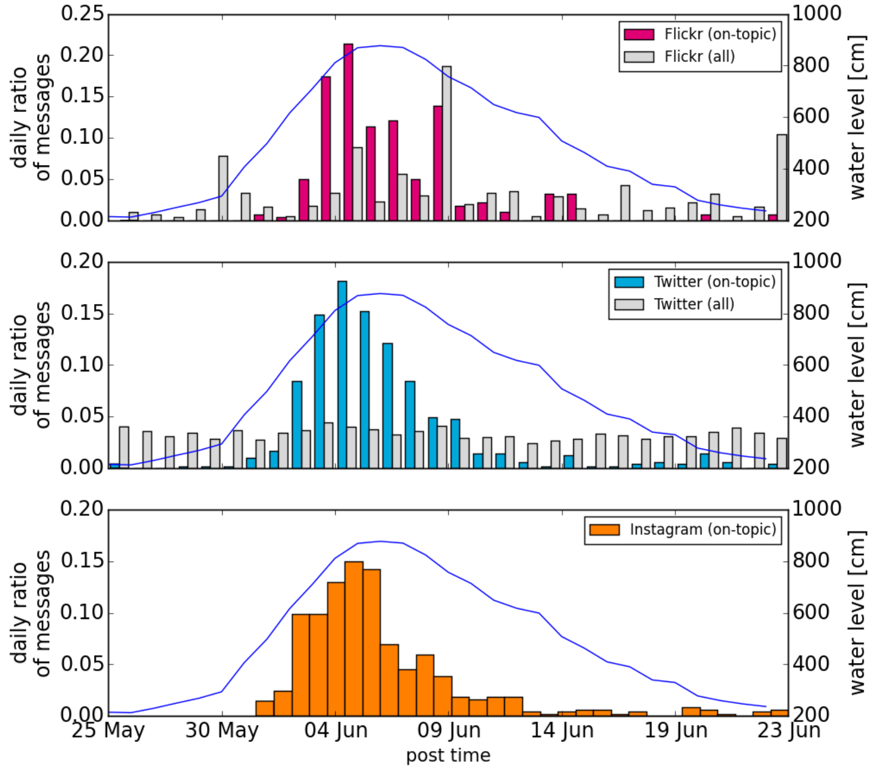

Figure 2. Temporal distribution of on- and off-topic messages for all platforms. The blue line shows the water-gauge (daily maximum) of the Elbe at Dresden.

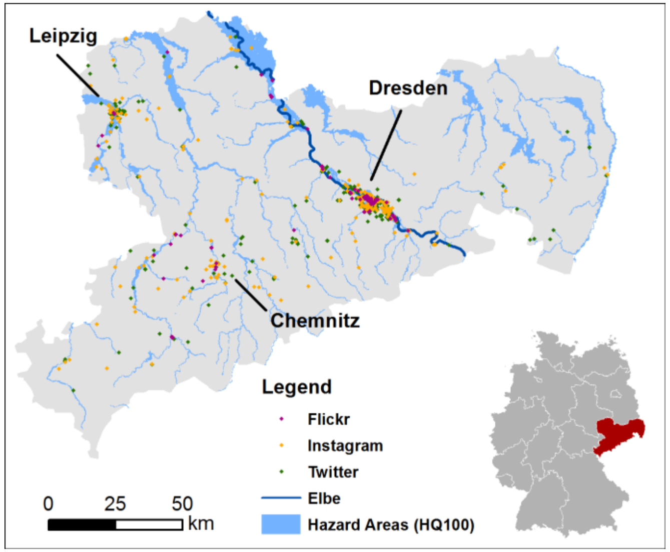

Figure 3. Overview of Saxony with major cities and hazard areas as well as the spatial distribution of all on-topic messages.

The spatial distribution shows a clear focus of on-topic messages around the urban area of Dresden (Figure 3 and 4). This is true for all platforms. Instagram and Twitter also show a concentration around Leipzig and Chemnitz. All three cities are situated within hazard areas and on rivers that were affected by the floods in 2013 (LfULG, 2014). Considering this, a merge of all sources increases the density of the mentioned areas but also increases the spatially coverage for areas besides the bigger cities.

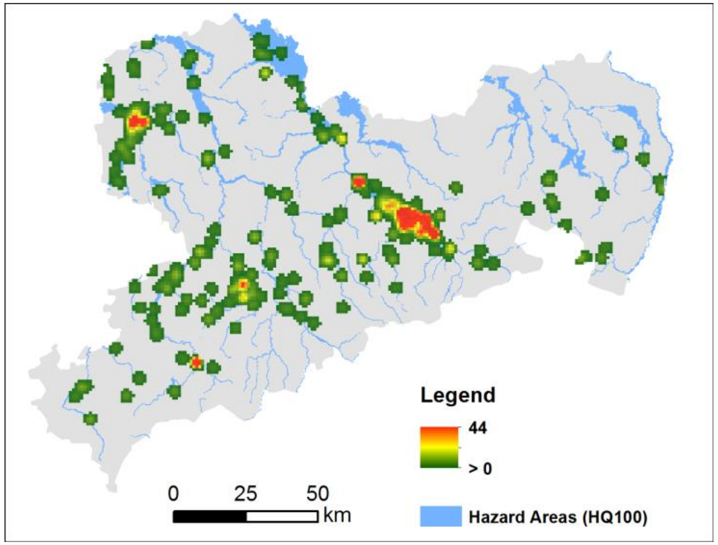

Figure 4. Result of kernel density function with all on-topic messages (grid size = 1 km; search radius = 2.5 km; operated by ArcGIS[4])

According to the spatial relation between messages and hazard areas, on-topic messages of every social media source tend to be closer to the hazard areas (Table 2). The standard deviation as well as the differences between average and median distances indicate a large variation, influenced by outliers. Figure 5 shows boxplots of distribution of all groups and confirms the existence of outliers. Besides on-topic vs. off-topic, the image-based social media sources Flickr & Instagram are clearly closer to the hazard areas than Twitter. The results of a U-test shows for all compared groups (on-topic vs. off-topic for Flickr and Twitter) statistically significance ($p < 0.000$). The highest share of messages within the hazard areas (i.e. calculated distance is zero) is found in Flickr (45%) followed by Instagram (40%) and Twitter (25%).

[4]http:/help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#/na/009z00000011000000/

social media platform		distance to hazard areas [m]		
		median	25th percentile	75th percentile
Flickr[1]	on-topic (n=281)	19	0	115
	off-topic (n=1,584)	209	0	774
Instagram	on-topic (n=486)	63	0	258
Twitter[2]	on-topic (n=485)	197	1	1,097
	off-topic (n=23,877)	738	251	1,797

[1] U-test results (U=126,320.5; $p \approx 1.49*10^{-33}$)

[2] U-test results (U=3937936.5; $p \approx 1.96*10^{-141}$)

Table 2. Results of the spatial relationship between social media messages and the hazard areas.

A further separated inspection of all on-topic tweets with and without image shows that on-topic tweets with image are closer to the disaster event (Table 3). Furthermore, they have a similar distance like Instagram. Both groups also show a similar distribution with numerous outliers compared to on-topic Flickr (F_o in Figure 5). The distribution shows that most of Tweets with image (T_{oi} in Figure 5) are quite close to the disaster event. Overall, messages with image content are closer to the disaster event, represented by hazard areas (Figure 6 and Table 3).

social media platform		distance to hazard areas [m]		
		median	25th percentile	75th percentile
All[1]	with image (n=964)	40	0	159
	without image (n=288)	431	86	1,672
Twitter[2]	with image (n=197)	77	0	233
	without image (n=288)	431	86	1,672

[1] U-test results (U=71095.5; $p \approx 3.69*10^{-38}$)

[2] U-test results (U=16036.5; $p \approx 1.21*10^{-16}$)

Table 3. Comparison between social media messages with and without image content.

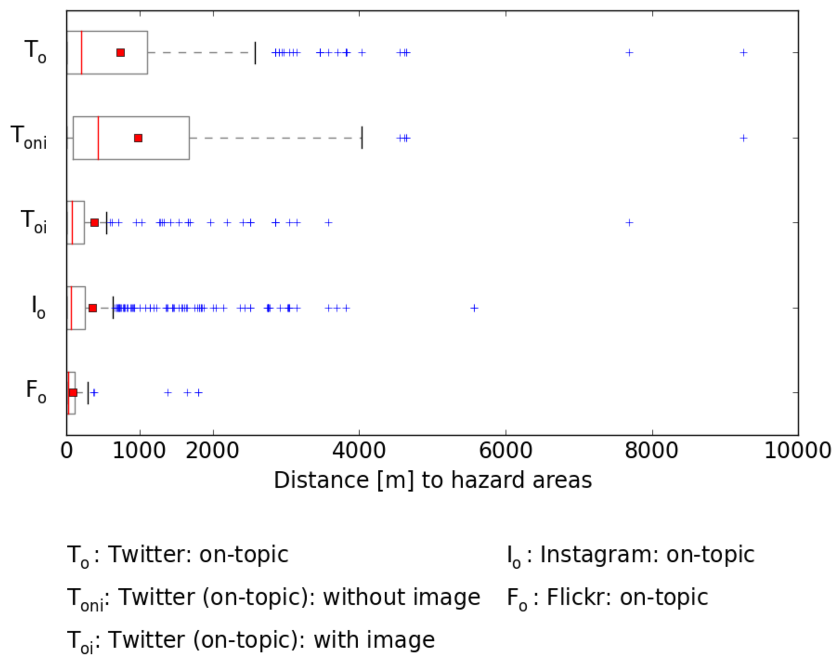

Figure 5. Distribution for all considered groups based on their distance to hazard areas. The boxes describe the range between the low and high quartile (IQR) of the distance values. Red lines show the median, red squares show the average. Blue crosses are values outside the 1.5 times of the IQR and indicate outliers.

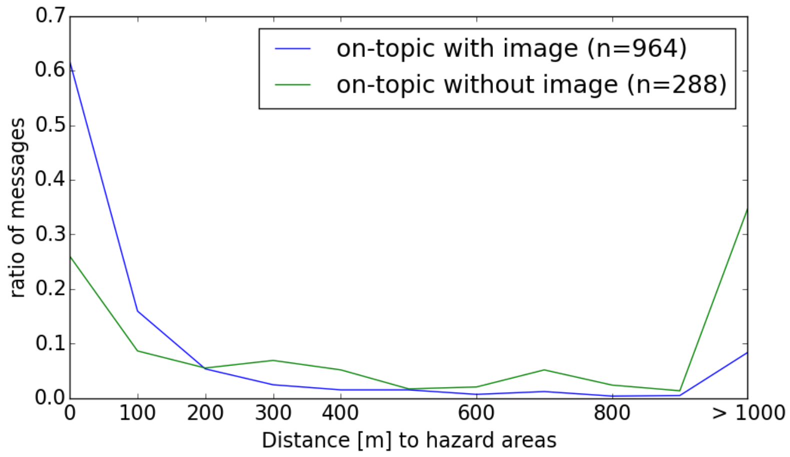

Figure 6. Distribution of on-topic messages with and without image based on their distance to hazard areas.

CONCLUSION AND DISCUSSION

In this study we analyzed social media messages for disaster management. In doing so, we presented new considerations and examined various social media sources, especially image-based platforms that were not given so much attention in the recent research in the context of disaster management. For our case study, merging of social media platforms leads to a higher density of disaster-related messages and higher spatial coverage, what is an advantage for widespread disasters like floods. But this does not necessarily result into a higher information value and requires further examination. For instance, users could post the same message content on multiple platforms. This can happen, for example, when users connect their accounts of different social media platforms - e.g. posting a message on Instagram and share it automatically on Twitter as well.

The distance calculation shows that on-topic messages with image are significantly closer to the disaster event than such messages without image content. In combination with the findings of previous work that relevant messages tend to be closer to the disaster event (Vieweg et al., 2010; Albuquerque et al., 2015), this implies that the existence of an image could be used as a proxy for relevance of social media messages as regards to on-the-ground information which is considered to be very relevant to improve situation awareness. This information can be used to enhance existing approaches and achieve a better classification of social media messages. Since disaster-related messages vary in their informative value and on-the-ground information are considered to have a high potential to be very relevant (Imran et al., 2013), this approach can help to prioritize in a first step disaster-related messages for a further validation process, e.g. by crowdsourcing or approaches based on machine learning. Since checking whether a message contains image content can be fully automated, it is applicable with less effort thus in near real-time. Furthermore, the use of images as indicators may also be used in cases where there is no extensive knowledge of the geographic extent or missing geographical data about the disaster event.

Our results clearly indicate that messages with image are closer to the disaster event, but their contents were not verified to ensure that they also contain relevant information. However, a first manual verification for some selected images of each social media platform indicates that images on-the-ground were found to be highly relevant, except from a small fraction of non-relevant messages. A more thorough examination of the message contents is thus an important task for future work.

A crucial point of concern in using the spatial information of messages is their accuracy. There are indications that some messages are manually georeferenced and not correctly located – e.g. it is not unusual that someone uploads a whole set of photos with the same location on Flickr. Another problem arises with retweets, which are just a re-posting of some other tweet, since the location of a retweet may not match the actual location of the original tweet. However, in our case this affects only 9 on-topic messages, and none of the original tweets were georeferenced and thus not in our dataset. For this reason, this does not affect our results, but would have to be considered if the portion of retweets is higher.

Furthermore, only a small portion of all social media messages are currently georeferenced. For instance, a recent study estimates that 1% of tweets in

Germany are georeferenced (Fuchs, Andrienko and Andrienko, 2013), and this of course consists of a limitation of this study.

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