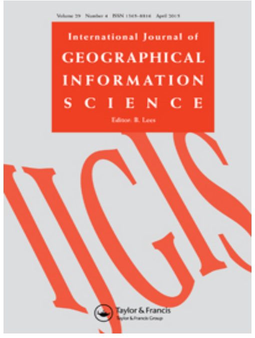
2015

A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management

International Journal of Geographical Information Science,London : Taylor and Francis,v.29, n.4, p.667-689, 2015
http://www.producao.usp.br/handle/BDPI/50924



International Journal of Geographical Information Science

ISSN: 1365-8816 (Print) 1362-3087 (Online) Journal homepage: http://www.tandfonline.com/loi/tgis20

A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management

João Porto de Albuquerque, Benjamin Herfort, Alexander Brenning & Alexander Zipf

To cite this article: João Porto de Albuquerque, Benjamin Herfort, Alexander Brenning & Alexander Zipf (2015) A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management, International Journal of Geographical Information Science, 29:4, 667-689, DOI: 10.1080/13658816.2014.996567

To link to this article: http://dx.doi.org/10.1080/13658816.2014.996567

International Journal of Geographical Information Science, 2015
Vol. 29, No. 4, 667–689, http://dx.doi.org/10.1080/13658816.2014.996567

A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management

João Porto de Albuquerque[a,b]*, Benjamin Herfort[b], Alexander Brenning[b,c,d] and Alexander Zipf[b]

[a]*Department of Computer Systems/ICMC, University of São Paulo, São Carlos, SP, Brazil;* [b]*GI Science Group, Department of Geography, Heidelberg University, Heidelberg, Baden-Württemberg, Germany;* [c]*Department of Geography and Environmental Management, University of Waterloo, Waterloo, ON, Canada;* [d]*Department of Geography, University of Jena, Jena, Thuringia, Germany*

(*Received 29 November 2014; final version received 3 December 2014*)

In recent years, social media emerged as a potential resource to improve the management of crisis situations such as disasters triggered by natural hazards. Although there is a growing research body concerned with the analysis of the usage of social media during disasters, most previous work has concentrated on using social media as a stand-alone information source, whereas its combination with other information sources holds a still underexplored potential. This article presents an approach to enhance the identification of relevant messages from social media that relies upon the relations between georeferenced social media messages as Volunteered Geographic Information and geographic features of flood phenomena as derived from authoritative data (sensor data, hydrological data and digital elevation models). We apply this approach to examine the micro-blogging text messages of the Twitter platform (tweets) produced during the River Elbe Flood of June 2013 in Germany. This is performed by means of a statistical analysis aimed at identifying general spatial patterns in the occurrence of flood-related tweets that may be associated with proximity to and severity of flood events. The results show that messages near (up to 10 km) to severely flooded areas have a much higher probability of being related to floods. In this manner, we conclude that the geographic approach proposed here provides a reliable quantitative indicator of the usefulness of messages from social media by leveraging the existing knowledge about natural hazards such as floods, thus being valuable for disaster management in both crisis response and preventive monitoring.

Keywords: Volunteered Geographic Information; social media; crisis; disaster; emergency management; Twitter; flood; Germany

1. Introduction

In different catastrophic events of the past few years – from Southern California wildfires in 2007 to the 2010 Haiti earthquake and typhoon Haiyan in the Philippines in 2013 – social media have enabled the affected population to timely publicize an overwhelming amount of disaster-related information (Goodchild and Glennon 2010, Vieweg *et al.* 2010, Zook *et al.* 2010, Yates and Paquette 2011, Kaewkitipong *et al.* 2012, Chatfield and Brajawidagda 2013).

Since disasters are generally characterized by high levels of information need and low levels of information availability (Shklovski *et al.* 2010), it seems intuitive to consider

*Corresponding author. Email: jporto@icmc.usp.br

social media as an additional information source for coping with crises. Of particular interest here are social media messages that carry a geographic reference, which can be considered Volunteered Geographic Information (VGI) (Goodchild 2007, Sui and Goodchild 2011), since they can be used for composing a picture of what is happening in a specific place. The growing adoption of electronic devices equipped with Global Positioning System (GPS) receivers (e.g. smartphones and tablets) in the past few years has made an increasing the amount of geoinformation available in social media platforms and thereby transformed them into location-based social networks (Roick and Heuser 2013). However, due to the sheer volume, high velocity and varied structure of social media content, one significant challenge that arises in this context is how to deal with this 'big data' to separate the wheat from the chaff, i.e. how to pick up the relevant pieces of information out of the deluge of, mostly irrelevant, social media messages.

In the past few years, the problem of analysing information produced via social media in the context of crises has been addressed by a growing body of literature (see Landwehr and Carley 2014 for a survey). Most of the research performed in this field approaches the problem of seeking to detect patterns and extract information by looking exclusively at data from social media, i.e. using social media as a stand-alone information source. However, in many crises situations triggered by natural hazards, data from other information sources (e.g. *in situ* sensors, space-borne data from satellites and existing authoritative geographic data) are available which could profitably be leveraged upon in order to make the analysis of social media more effective.

Building upon this motivation and based on our previous work (Herfort *et al.* 2014a, 2014b), a geographic approach is proposed in this article to leverage the existing geographic knowledge related to natural hazards (such as floods) for the analysis of georeferenced social media messages (i.e. VGI). This article complements and substantially extends our previous studies (Herfort *et al.* 2014a, 2014b) by adding: (a) a more comprehensive and general account of the proposed geographic approach for combining social media and authoritative data with the goal of identifying the most useful messages for disaster management; (b) an improved data basis of the case analysed, which includes a more rigorous classification of messages of the Twitter platform during the 2013 floods of the river Elbe in Germany, as well as a more comprehensive data set of *in situ* water level sensor measurements; (c) robust statistical methods based on a generalized additive model (GAM) to provide compelling quantitative evidence of the association between the relevance of social media messages with proximity to and severity of flood events; (d) a discussion of the results in comparison to the extant work on the subject.

The remainder of the article is organized as follows. Section 2 provides the background for the current work by reviewing the extant research on the analysis of social media for disaster management. Section 3 explains our approach, whilst Section 4 describes the case study to which the approach is applied together with the data sources used. Section 5 describes the methodology employed. Section 6 then presents the results of this study, whereas Section 7 discusses the results and makes suggestions for future work. Section 8 casts some conclusions.

2. Background: social media analysis for disaster management

In the past few years, an increasing number of studies have examined the use of social media data for gaining knowledge about areas of human activity that are as diverse as detecting disease surveillance for detecting epidemic outbreaks (Gomide *et al.* 2011, Bernardo *et al.* 2013) and predicting the stock market (Bollen *et al.* 2011).

In the particular field of disaster management, a large part of the existing research focused on the analysis of short messages of the Twitter platform, the so-called tweets. Sakaki *et al.* (2010) and Crooks *et al.* (2013) investigated the use of Twitter for detecting and estimating the trajectory of earthquakes in real time. De Longueville *et al.* (2010) proposed the use of VGI as a sensor for detecting forest fire hot spots, based on previous work that analysed the application of Twitter as a source of spatiotemporal information for wildfire events in France. In contrast, Fuchs *et al.* (2013) showed that event detection based on peaks of Twitter activity did not work for the 2013 floods in Germany and presented an analysis of spatiotemporal clusters. Bakillah *et al.* (2014) applied graph clustering to support the detection of geolocated communities in Twitter after the typhoon Haiyan in the Philippines. Furthermore, a number of studies are concerned about developing tools for visualizing social media data in order to enable make-sensing and location-based knowledge discovery (MacEachren *et al.* 2011, Terpstra and de Vries 2012, Croitoru *et al.* 2013, Spinsanti and Ostermann 2013).

Another group of studies seek to identify useful information from social media that could be valuable for improving situation awareness (Yin *et al.* 2012), i.e. for improving 'the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future' (Endsley 1995). Vieweg *et al.* (2010) and Starbird *et al.* (2010) analysed Twitter messages during the flooding of the Red River Valley in the United States and Canada in 2009, seeking to discern activity patterns and extract useful information. Acar and Muraki (2011) applied open-ended questionnaires to selected Twitter users and also analysed the tweets sent in response to the Tohoku earthquake and the consequent tsunami in Japan, 2011. Starbird and Muzny (2012) resorted to machine learning to identify messages from Twitter users who were likely to be 'on the ground' during a crisis event. Imran *et al.* (2013) employed machine learning for successfully extracting structured information from unstructured, text-based Twitter messages and compared their results with manual classification based on crowdsourcing.

These previous analyses on social media usage in disasters identified a distinct role of users local to the event (or 'on the ground'), who are more probable to generate useful information for improving situational awareness (Starbird *et al.* 2010, Vieweg *et al.* 2010, Acar and Muraki 2011, Bruns *et al.* 2012, Dugdale *et al.* 2012, Starbird and Muzny 2012, Imran *et al.* 2013). For instance, Acar and Muraki (2011) found that people in directly affected areas tend to tweet about their unsafe situation and survival-related topics, while people in remote areas post messages about secondary effects (e.g. transportation) and for informing others that they are safe. As pointed out by Starbird and Muzny (2012, p. 2), 'people who are on the ground are uniquely positioned to share information that may not yet be available elsewhere in the information space'. These works usually perform a binary classification of the messages into local/non-local, by resorting to a hand-analysis of the addresses provided in the user profiles (Starbird *et al.* 2010, Vieweg *et al.* 2010, Acar and Muraki 2011) or using machine learning algorithms based on the content of messages to classify messages as 'on the ground' (Starbird and Muzny 2012) or as coming from an 'eyewitness' (Imran *et al.* 2013) that may provide 'first-hand' observations (Landwehr and Carley 2014). However, these studies do not provide compelling statistical evidence on the correlation between the semantics/usefulness of social media messages and their distance to areas affected by disasters.

As for quantitative spatiotemporal analyses, most of the existing work in the area has sought to make sense of social media data as a stand-alone source by analysing aggregated patterns, e.g. by defining thresholds for the size of spatiotemporal clusters of messages that would serve as signals for crisis events of earthquakes (Sakaki *et al.* 2010, Crooks *et al.* 2013), wildfires (De Longueville *et al.* 2010, Slavkovikj *et al.* 2014) or disease surveillance (Gomide *et al.* 2011, Bernardo *et al.* 2013). However, with such an approach the actual content of social media messages is largely ignored, and with this, much of their potential to improve the current knowledge about the unfolding situation is lost. Furthermore, although event detection is useful for sudden-onset crises for which there do not exist any other related data, in many concrete cases, there are additional information sources available. As pointed out by Lazer *et al.* (2014), one should not see 'big data' as a substitute for all existing data, but rather take the challenge of doing innovative analytics by using data from all traditional and new sources.

This is in line with a nascent research stream that uses VGI in combination with other geodata sources in the field of disaster management (Spinsanti and Ostermann 2013, Triglav-Čekada and Radovan 2013, Schnebele *et al.* 2014, Tomaszewski *et al.* 2014). Within this group, Spinsanti and Ostermann (2013) and Tomaszewski *et al.* (2014) are the only studies that we found to use external data about the geographic context to analyse social media data. Tomaszewski *et al.* (2014) present a work-in-progress aimed at retrieving authoritative data related to the contents of a message from Twitter for providing visual context, without further integrating the two data sets. Spinsanti and Ostermann (2013) used external data sets to enrich social media, achieving good results in detecting spatiotemporal clusters of social media messages about forest fires. However, they do not use data streams from official sensors, but resort to more static information such as population density and ratio of forest cover. Furthermore, none of these studies was able to perform statistical analyses of the geographical relations between social media and authoritative data.

3. Research approach

This article addresses the problem of identifying useful information from VGI, in particular georeferenced social media, for improving situation awareness during emergencies. In contrast to most approaches reviewed in the previous section, which try to leverage VGI as a stand-alone information source, our approach explores external data sources to establish geographical relations between flood phenomena and social media messages. The basic idea of our approach follows from the observation that in practical settings there is usually some information available about the natural phenomena that trigger a disaster. Thus, we propose that the existing information basis could be exploited when seeking to identify relevant additional information contained in social media messages.

Floods, in particular, are phenomena which are closely spatially correlated to geographical features of water streams. Existing geographical information about affected river basins and watersheds can thus be profitably used in this context. Furthermore, in many practical cases, additional information sources are available in (near) real time, such as *in situ* sensors of river gauging stations and/or airborne observations from satellites. This information can be used to determine the spatiotemporal characteristics of the flood phenomena being analysed. Therefore, in the case of floods, it makes less sense to use georeferenced social media to do event detection, as has been previously done for earthquakes (Sakaki *et al.* 2010, Crooks *et al.* 2013).

Furthermore, spatiotemporal characteristics of the floods affect the spatiotemporal characteristics of VGI and social media messages. As previously mentioned, existing studies have shown that social media messages coming from people local to the events should contain more useful information (Acar and Muraki 2011, Bruns *et al.* 2012, Dugdale *et al.* 2012, Starbird and Muzny 2012, Imran *et al.* 2013, Landwehr and Carley 2014). Based on this, the hypothesis posed here is that social media messages which are closer to the flooded areas are more likely relevant and/or more strongly related to the unfolding event, thus being more useful for improving situation awareness. Our approach thus explores the relations between spatial information from social media messages and geographic information about flood phenomena from both hydrological data and official sensor data. The goal is to test our hypothesis that the proximity to and severity of observed flood phenomena can be a significant resource to identify useful messages, with the goal of improving situation awareness, thus supporting disaster management.

Figure 1 schematically depicts our approach, which is divided into three main components:

(1) Gathering information on flood phenomena, i.e. identifying flood-affected regions;
(2) Gathering information from social media, i.e. georeferenced Twitter messages;
(3) Analysing the geographical relations between the information on flood phenomena (1) and social media messages (2) to assess the usefulness of social media messages.

In this manner, our approach seeks to leverage the existing knowledge and data about the spatiotemporal characteristics of flood phenomena in order to improve the identification

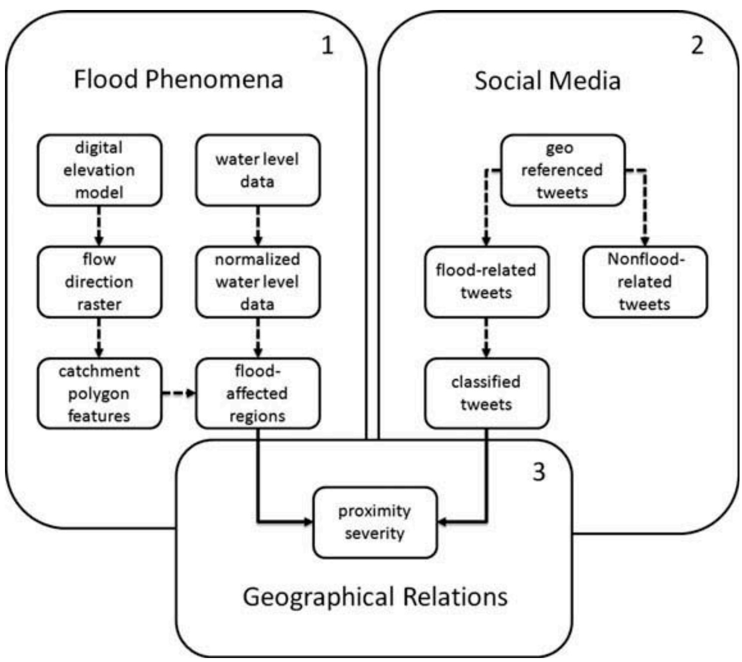


Figure 1. Research approach.

of useful information from georeferenced social media. It is thus consistent with the suggestion of Gao *et al.* (2011) that scientific data could be used to augment user-generated data so as to provide more detailed insights into information requirements and needs during a disaster.

In this article, this approach is applied to analyse the use of Twitter during the River Elbe flood in 2013, as described in the next sections.

4. Description of the case study and data sets

This section provides a description of our case study followed by an explanation of the data sets we employed.

4.1. River Elbe flood

In the period from 30 May 2013 to 3 June 2013, extreme heavy rain affected large parts of eastern and central Europe. According to the State Agency for Environment, Agriculture and Geology of Saxony (Sächsisches Landesamt für Umwelt Landwirtschaft und Geologie 2013), the distribution of precipitation in the basin of the rivers Elbe and its tributaries Moldau and Saale reached values two to three times as high as the average month of June, which is equivalent to a centennial return period. The soil was already highly saturated at this time due to precipitations in May 2013. Therefore, the heavy rain rapidly resulted in surface run-off causing the severe flood situation.

Some gauging stations measured values that were never recorded before. For instance, at 'Magdeburg-Strombrücke', the water level reached 7.46 m, which is more than 70 cm higher than the former maximum. Another characteristic of the flood was the huge stretch of the flood wave. The alert phase 4 (the highest in Germany) that was announced by the government lasted for 6 days along the rivers Elbe, Mulde, Elster and Neiße in Saxony and Saxony-Anhalt (Sächsisches Landesamt für Umwelt Landwirtschaft und Geologie 2013).

4.2. Data sets

4.2.1. Twitter data

The Twitter data set contains 60,524 georeferenced short text messages ('tweets') within the territory of Germany. Each message consists of up to 140 Unicode characters. Besides the text message, every tweet contains several metadata fields, such as a timestamp (UTC time) when the tweet was created, *hashtags* (i.e. keywords preceded by #), URLs, an integer unique ID of the tweet and information about the user who posted the tweet. The geographic location of a tweet is described in the metadata field 'coordinates', which is also known as *geotag*. The inner coordinate array is formatted as geoJSON.[1]

Users can georeference messages in Twitter in different ways: either manually (e.g. by entering the name of a city in the field 'location') or automatically when a client application has access to the coordinates of a GPS receiver. Unfortunately, only a small fraction of tweets are currently georeferenced by users. A recent study found that the prevalence of geolocated tweets was only about 3%; however, city and state could be determined for 17% of user profiles using a simple text-matching approach, with a high agreement (88%) between GPS data and text-matching in the United States (Burton *et al.* 2012). Another study estimates that 11–13% of the tweets in Europe and 1% in Germany are geolocated (Fuchs *et al.* 2013). While this may limit analyses based on the geolocation such as the current study, the absolute number of geotagged tweets is actually high, since the size of the overall data set tends to be large. Furthermore, the availability of georeferenced social media messages can be expected to increase in the next years with the widespread adoption of GPS-enabled devices.

Twitter offers a number of application programming interfaces (APIs), which can be used for automatically retrieving data. For this study, we used the Twitter streaming API, which provides access to a 1% sample of the real-time stream of total tweets sampled by taking every 100th tweet (Burton *et al.* 2012). The data were collected by querying the streaming API during the period from 8 June 2013 1:30 pm to 10 June 2013 midnight for georeferenced tweets within a bounding box covering Germany. Afterwards, we further filtered tweets by their location and excluded those outside the territory of Germany.

4.2.2. Authoritative data

As authoritative data about the flood phenomena, we gathered official water level data from 185 monitoring stations along the German federal waterways provided by the German Federal Waterways and Shipping Administration and the German Federal Institute for Hydrology. The water level measurements were provided in a 15-minute resolution for the whole period analysed. Through the German online gauge system 'Pegel Online',[2] we acquired an additional data set that includes information about the location of each measurement station, the average flood water level over a time period from 1 November 2000 to 31 October 2010 and the highest water level ever recorded.

Additionally, we used HydroSHEDS drainage direction information derived from elevation data of the Shuttle Radar Topography Mission (SRTM) at 3 arc-second resolution (Lehner *et al.* 2008). The data are already verified and are considered to be of adequate quality for our analysis in spite of its limited resolution.

5. Methodology

This section describes the detailed methodology used in this article, by further elaborating the procedures used to apply the approach described in Section 3 and schematically depicted in Figure 1. The next section explains the steps conducted in preparing the data sets employed (Section 5.1), followed by the description of the analytical procedures used in Section 5.2.

5.1. Data preparation

5.1.1. Characterizing the flood phenomenon

The first part of our data preparation (left-hand box in Figure 1) consisted of defining the flood-affected regions based on the digital elevation model (for catchment areas) and on official data (river water levels). It is further described as follows.

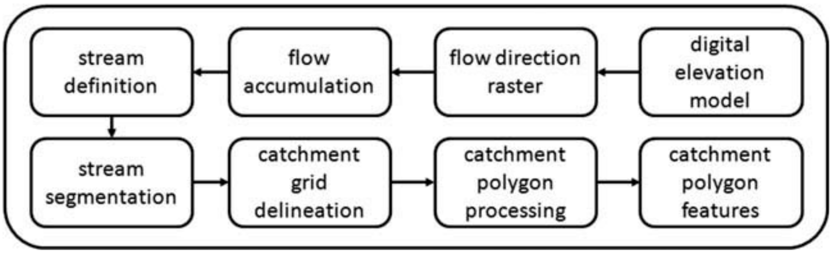


Figure 2. Catchment processing workflow.

5.1.2. *Identifying catchment areas*

The delineation of small catchment areas is based on the HydroSHEDS drainage direction raster and was implemented using the ArcHydro toolset for ArcGIS. The workflow to calculate catchment areas with ArcGIS is depicted in Figure 2 and described in detail by Zhang *et al.* (2010) and Merwade (2012). Starting with flow direction information, we computed the flow accumulation. This information was then used to define a stream network. In this case study, grid cells are considered as drainage channels if 2000 or more upstream cells drain into it. The drainage channels were exported as vector data. Finally, catchment areas were delineated using all river junctions, calculated from the drainage channel vector file. This procedure ensures that all cells within the same catchment drain into the same stream. As a result, we obtained 779 unique catchment polygons.

5.1.3. *Calculating the relative water level (flood severity) of catchments*

In this step, we analysed the water level data collected from 185 water level measurement stations along the German Federal waterways. To assess the local water level at a given gauge station, we computed the difference between the daily maximum water level and the average flood water level for the time period from 1 November 2000 to 31 October 2010. From now on, we refer to this difference as the 'relative water level' and use this as the variable for the measuring the severity of a flood. Thus, negative values indicate that the local water level at the gauge station was below an average flood water level. Therefore, this station can be considered as not flood affected. Conversely, positive values indicate that the gauging station was flood affected. The use of a daily maximum is justified in this case since this was a slow-onset flood and the Twitter data set is sparse. However, for more dynamic scenarios such as flash floods, a higher temporal resolution could be used, e.g. by calculating maximum water levels hourly, or even in a finer timescale.

We thus combined geometric information on catchments and water levels as attribute values based on the location of the monitoring stations. The relative water level values were matched to the corresponding catchments. If more than one water level measurement station was found to be within one given catchment, we assigned their arithmetic mean to the catchment and classified it as flood affected based on this value.

5.1.4. *Processing georeferenced tweets*

The processing of tweets (right-hand box in Figure 1) enclosed three steps (keyword-based filtering, content analysis and thematic coding) which are explained as follows.

5.1.5. *Keyword-based filtering*

For identifying messages containing relevant information, we first filtered the Twitter messages that referred to the flooding event. This was accomplished by keyword filtering, which is common practice in the analysis of Twitter messages (Vieweg *et al.* 2010, Graham *et al.* 2012, Kongthon *et al.* 2012). Tweets containing the German-language keywords 'Hochwasser', 'Flut', 'Überschwemmung' (meaning 'flood') or the English word 'flood', regardless of capitalization, were retained. Keyword selection was based on the definition of the German dictionary 'Duden' for the word 'Hochwasser'. Furthermore, we included the additional words 'Deich' (dike) and 'Sandsack' (sandbag), which were found to be common in media reports. Hyperlinks contained in the tweets were not examined at this stage.

5.1.6. *Content analysis: assessment of text and hyperlinks*

Tweets that did not contain the keywords defined above were marked as 'off topic' without any further content examination. Messages containing the keywords were then scrutinized individually by three independent persons and classified into the following categories: (0) off topic (i.e. the message was not related to floods even though it contained one of the keywords), (1) on topic but not relevant and (2) on topic and relevant. An on-topic tweet was considered 'relevant' if it contained information that may contribute to situation awareness. For example, tweets containing situational updates and other information that could be useful for other persons and/or emergency agencies were classified as 'relevant.' After the independent classification by the three researchers, cases of disagreement were discussed individually to reach a consensus in each case (Table 1).

Tweet relevance was not only assessed based on its text content itself, but also following the hyperlinks (e.g. to pictures) contained in the text. For example, the text of

Table 1. Classification of tweets based on their relation to the floods.

Classification	Description
(0) 'off topic'	The tweet does not refer to the flooding event. Example: 'I'm at Hochwasserbehälter der Stadtwerke Gießen [pic]: http://t.co/uegl13zx22' (Tweet 44468)
(1) 'on topic, not relevant'	The tweet refers to the flooding event, but does not contain relevant information. Example: 'Ich wünsche den #Hochwasser betroffenen weiterhin alles Gute, und trotz alledem allen einen schönen #Sonntag' (Tweet 18913) ('all the best for anyone affected by the flood, despite all that have a nice Sunday.')
(2) 'on topic, relevant'	The tweet refers to the flooding event and contains relevant information. Examples: 'am Deich in #Lostau werden noch Leute mit Gummistiefeln benötigt #Hochwasser #AltLostau http://t.co/n0FEuapA3r' (Tweet 2707) ('We still need people with rubber boots at the Dike in Lostau.') '#hohnstorf #elbe #flut #hochwasser #2013 @ Hohnstorf http://t.co/PrPWLBg29z' (Tweet 26638)

Figure 3. Example of an on-topic tweet.

the tweet in Figure 3 does not contain any relevant information, but the referenced picture does, since it depicts the current situation corresponding to the timestamp and the geographic coordinate of the tweet. It was therefore classified as 'relevant'.

5.1.7. *Thematic coding of on-topic tweets (a bottom-up approach)*

On-topic tweets were also coded considering their contents. The content-based classification of messages requires a well-defined set of categories, which heavily depends on the crisis context analysed, i.e. it varies for each crisis phenomenon and event. We adopted the categories proposed by Imran *et al.* (2013) ('caution and advice', 'information source', 'donation', 'causalities and damages', 'unknown') and Vieweg *et al.* (2010) (warning, preparatory activity, fire line/hazard location, flood level, weather, wind, visibility, road conditions, advice, evacuation information, volunteer information, animal management and damage/injury reports). However, neither of the previous sets of categories was well suited for our case study, the River Elbe flood. We therefore used these previous classifications as a guideline and adapted them to derive a modified classification for this study.

We chose a bottom-up approach to classify tweets considering their thematic context. Three independent persons qualitatively coded all on-topic tweets by assigning any number of codes they felt necessary to express the thematic context of the messages. Following this, the labels were compared and merged. Both text and pictures of the Twitter messages were used for thematic coding.

As a result, we grouped on-topic tweets into seven thematic groups: (1) 'volunteer actions', (2) 'media reports', (3) 'traffic conditions', (4), 'first-hand observations', (5) 'official actions', (6) 'infrastructure damage' and (0) 'other'. Table 2 presents a detailed description of the thematic groups and their characteristics.

Table 2. Thematic groups used for classifying tweets.

Thematic groups	Description
(1) 'volunteer actions'	Tweets referring to flood combating actions by volunteers and non-professionals. Examples: 'In #Lostau am Netto sind jetzt ca. 200 Leute am Sandäcke füllen – vielen Dank #hochwasser #altLostau http://t.co/ktLxQngsYQ' (Tweet 2625) ('About 200 people filling sandbags near the Netto (supermarket) in Lostau. Thank you!') 'gegen das Hochwasser kämpfen' ('combating the flood')
(2) 'media reports'	Tweets referring to media reports. Examples: '#Hochwasser #Flutopfer heute Thema bei #güntherjauch mit #albertschwinghammer aus #fischerdorf #deggendorf @DasErste' (Tweet 35072) ('Flood and floodvictims are todays topics on Günther Jauch's TV show.') 'jetzt der @MDR_SAN live vor der tür mit kristin schwietzer. #magdeburg #hochwasser #zollstraße http://t.co/ljAgJkuLS1' („ MDR SAN radio station live reports presented by kristin schwietzer")
(3) 'traffic conditions'	Tweets referring to traffic (road and rail) disruptions. Examples: 'Neues aus dem Zug vom Zug: #ice644 soll um 11.30 Uhr Hannover erreichen, also drei Std. später als geplant. #hochwasser' (Tweet 43792) ('News from the train. Ice 644 will arrive in Hannover with a delay of three hours at 11.30 am.') 'ICE-Hopping wg. #hochwasser. (@ Berlin Hauptbahnhof w/ 13 others) http://t.co/UYV6wyOaGe' ('Changing ICE train because of flood')
(4) 'first-hand observations'	Tweets referring directly or indirectly to water level measurements or the expansion of flooded areas. Examples: '724 Meter an Pegel #strombrücke #Magdeburg #Hochwasser 100145Bjun13' (Tweet 38630) (water level at 'Magdeburg-Strombrücke' reaches 724 m) '#hohnstorf #elbe #flut #hochwasser #2013 @ Hohnstorf http://t.co/PrPWLBg29z' (Tweet 26638) 'direkt dazu: heftig, diese ausmaÃŸe "live" zu sehen. das ist wirklich negativ beeindruckend. #hochwasser' ('tough to see the extent of the flood, negatively impressing')
(5) 'official actions'	Tweets referring to official actions by professionals like police, civil protection or red cross. Examples: http://t.co/bSscH1Z0DI #Einsatz #Hochwasser #Feuerwehr #Elbe (Tweet 21921) ('flood combating, fire brigade, river Elbe') 'Nach nem #Mittelwächter ein neuer Versuch im kleinsten Ruhetag der Welt. #Hochwasser #Rettungswache http://t.co/0YQcsJ9S3t' ('next try during rest day.')
(6) 'infrastructure damage'	Tweets referring to the status of critical infrastructures. Example: 'strom abgeschaltet ohne vorwarnung. wo blieb die information @Ottostadt? #magdeburg #hochwasser #zollstraße' (Tweet 3698) ('no electicity at Magdeburg Zollstraße.')
(0) 'other'	Tweets not referring to any of the previous categories.

5.1.8. Establishing the geographical relations between tweets and the flood phenomena

The final part of our data preparation consisted of calculating the geographical relations based on both authoritative data and tweets (box in the centre of Figure 1). The proximity relationship for each tweet was calculated as the distance in meters between the location of the tweet and the nearest flood-affected catchment. Tweets that are located within the area of flood-affected catchments had the distance variable assigned with zero meters (‘0 m’). The severity relationship, in turn, is defined as the relative water level of the catchment in which the tweet was located.

5.2. Statistical data analysis

The purpose of the statistical analysis of Twitter data was (1) to identify general spatial patterns in the occurrence of on-topic tweets that may be associated with distance to and relative water level of flood events and (2) to further explore the possible differences in spatial patterns among the subtypes of on-topic tweets. Challenging aspects in this analysis relate to possible nonlinearities, the expected (statistical) interaction between relative water level and distance to flood and spatial autocorrelation among observations. Interaction, in this context, refers to the possibility that, for example, on-topic tweets cluster more strongly around catchments with extremely high water levels compared to catchments with lower water levels.

We address these challenges by using GAMs in conjunction with a spatial bootstrap procedure to estimate spatial differences in on-topic tweet frequency. Only tweets located within a 100 km distance of flood-affected catchments were used (320 on-topic and 10% of the 27,410 available off-topic tweets).

GAMs are nonlinear, or partly nonlinear, extensions of GLMs, such as logistic regression, which replace the linear predictor terms with nonlinear (spline-type) smoothers of adjustable flexibility (Wood 2006). Examples of their application in geospatial modeling include landslide susceptibility modeling and spatial epidemiology (among others Vieira *et al.* 2008, Goetz *et al.* 2011).

For the analysis of general pattern in the distribution of on-topic tweets, we use GAMs with a logistic link function and two numeric predictors, relative water level (as defined above, in m) and the logarithm (base 10) of the Euclidean distance (in km) to the nearest flood-affected catchment. To avoid that the results are excessively influenced by extreme values, we trimmed the relative water level at ± 1.0 m. To mitigate the coarse nature of the ‘0’ distance corresponding to a location within a flood-affected catchment, all distances <10 km were assigned a value of 10 km prior to taking the logarithm.

We used the GAM implementation of Wood (2006) in the R package ‘mgcv’, which automatically adjusts the effective degrees of freedom of the spline smoothers using a generalized cross-validation procedure. The ‘bam’ implementation for large data sets was chosen. Alternative GAMs were fitted that represent the two predictors as additive terms (two univariate thin plate splines) or as an interactive term (one bivariate thin-plate spline smoother). Upper limits of 3 and 5 effective degrees of freedom were used in the additive and interactive models, respectively, in order to avoid excessive oscillations in the resulting smoothers.

In addition to the visual summaries provided by the GAM, we used the GAMs to calculate the odds ratios and relative risks associated with distance and water level. The odds, $p/(1-p)$, are a common way of re-expressing a probability p in the context of logistic models, and the ratio of odds corresponding to different levels of a predictor variable is a measure of its effect size. Similarly, the relative risk is the ratio of probabilities predicted by the GAM. In this study, odds ratios and relative risk were calculated for ≤10 km versus 30 km distance from flood-affected areas, and for a relative water level of +0.75 m versus −0.75 m while keeping the other predictor constant. In the case of the GAM with an interaction of distance and water level, we calculated the odds ratios and relative risk of one predictor at different levels of the other predictor.

Since the GAM does not provide parametric estimates of the sampling variability of odds ratio and relative risk, we applied a spatial block bootstrap to obtain percentile confidence intervals at the 95% level. The bootstrap is a resampling-based estimation procedure that simulates the natural sampling variability by drawing observations from the available data (Davison *et al.* 2003). Since observations close to each other may be autocorrelated, we resampled the observations at a spatially aggregated level (blocks) rather than individual tweets, similar to the procedure used by Brenning *et al.* (2014). We used 100 blocks defined by 100-means clustering of the spatial coordinates of tweets, drew 100 out of these 100 blocks randomly with replacement, and used this set as a training set for refitting the GAM. The entire sample was then used to obtain an estimate of the odds ratio and relative risk, and the procedure was repeated 2500 times in order to obtain the resampling distribution of these parameters and derive their 95% percentile confidence intervals.

Spatial patterns of subtypes of on-topic tweets were furthermore explored using GAMs to model the probability that an on-topic tweet belongs to a specific subtype. This analysis was based on the sample of on-topic tweets within the 100 km buffer ($N = 320$). On the one hand, one model was fitted to identify patterns of tweets identified as relevant ($N = 169$) versus not relevant in relation to distance to flood and relative water level. This addresses the question whether more relevant tweets are more strongly concentrated in proximity to flood-affected areas or in catchments with higher relative water levels. On the other hand, separate models were built to relate the occurrence of a specific thematic category to distance and water level. The expectation is that thematic classes that are more strongly related to local conditions (e.g. first-hand observations) are also more strongly concentrated near flood-affected areas and where relative water levels are higher. Three aggregated thematic classes were considered due to sample size limitations, and the 'other' category was omitted: (1) 'volunteer actions' ($N = 67$); (2) 'media reports' and 'traffic conditions' ($N = 55$); (3) 'first-hand observations', 'official actions' and 'infrastructure damage' ($N = 92$). Due to the smaller sample size, only GAMs without interaction term were considered, and only basic graphical and numeric summaries are provided for exploratory analysis of these patterns.

6. Results

The results of our study are presented in the following sections. The next section provides an exploratory description of the data collated, serving as a basis for the detailed analysis based on our research questions.

6.1. Data description

Figure 4 shows flood-affected catchments and the relative water level of the flooding calculated from digital elevation data and water level data for the time period from 8 to 10 June 2013. Clearly visible is the shift of the flood peak from the upper reaches (southeast) on 8 June to the lower reaches (north) on 10 June. On 8 June 2013, the catchments along the river Elbe in the federal state of Saxony were most affected, whilst the lower reaches of the river Elbe were not affected until 10 June 2013.

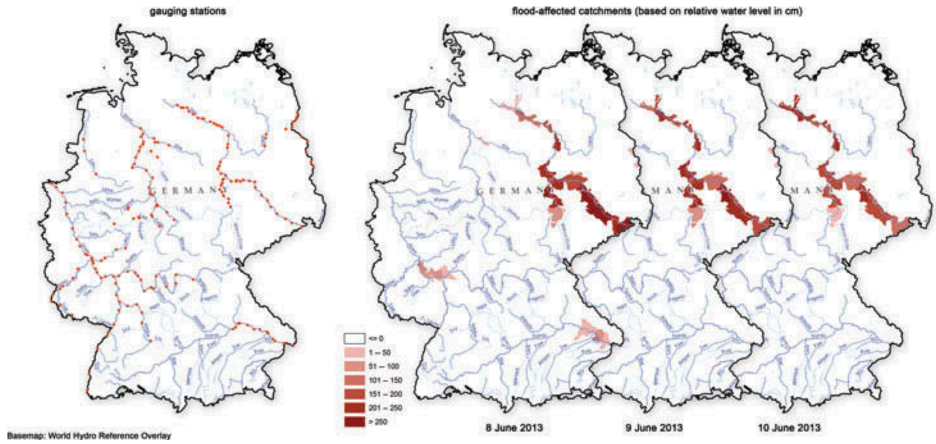


Figure 4. Spatiotemporal distribution of flood-affected catchments based on official water level information.

Overall, we examined 60,524 tweets within the territory of Germany from the 8–10 June 2013 period. Of these, only 370 tweets could be labelled as 'on topic' based on keyword filtering and manual classification of tweets, while more than 99% were classified as 'off topic'. On-topic tweets distribute nearly equal into relevant and not relevant tweets (Table 3).

In terms of their content, about two-fifth of all on-topic tweets contained information referring to volunteer actions (19.2%) or first-hand observations (18.6%), whereas on-topic tweets referring to traffic conditions, official actions or infrastructure damage reach a much lower share (Table 4). About one-third (32.4%) of the on-topic tweets were classified as 'other'.

Table 3. Relevance of Twitter messages.

Period	8–10 June 2013		8 June 2013		9 June 2013		10 June 2013	
	#	%	#	%	#	%	#	%
All tweets	60,524	100.0	14,286	100.0	23,093	100.0	23,145	100.0
Off topic	60,154	99.4	14,221	99.5	22,908	99.2	23,025	99.5
On topic, not relevant	187	0.3	23	0.2	94	0.4	70	0.3
On topic, relevant	183	0.3	42	0.3	91	0.4	50	0.2

Table 4. Classification of Twitter messages based on content analysis.

Period	8–10 June 2013		8 June 2013		9 June 2013		10 June 2013	
	#	%	#	%	#	%	#	%
All tweets	370	100.0	65	100.0	185	100.0	120	100.0
Volunteer actions	71	19.2	14	21.5	45	24.3	12	10.0
Media reports	54	14.6	9	13.8	29	15.7	16	13.3
Traffic conditions	26	7.0	2	3.1	7	3.8	17	14.2
First-hand observations	69	18.6	18	27.7	30	16.2	21	17.5
Official actions	21	5.7	3	4.6	7	3.8	11	9.2
Infrastructure damage	9	2.4	3	4.6	5	2.7	1	0.8
Other	120	32.4	16	24.6	62	33.5	42	35.0

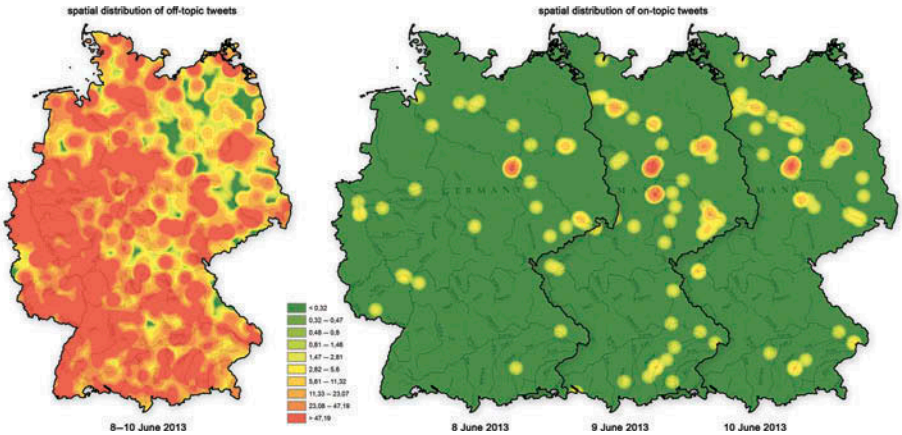


Figure 5. Spatial distribution of flood-related and non-related tweets.

Figure 5 shows the density of tweets for each keyword classification. On-topic tweets show peaks in the regions of Magdeburg, Berlin and Halle. Overall, on-topic tweets appear only in a few parts of Germany. Off-topic tweets concentrate in densely populated regions, e.g. urban areas like Berlin, Hamburg, Munich and the Ruhr area. The tweets cover almost all of Germany, except for some regions in the federal states of Brandenburg and Mecklenburg-Hither Pomerania.

A comparison of the spatial distributions of on-topic tweets and flood-affected catchments (see Figures 4 and 5) shows that a considerable portion corresponds to flood-affected catchments. To further examine this relationship, we statistically analysed the distance of all tweets to flood-affected catchments.

6.2. *Spatial analysis*

The spatial analysis of tweets using the GAM showed a strong association of on-topic tweets with distance to flood-affected catchments and relative water level (Table 5; Figure 6). On-topic tweets were 11.0 times (95% confidence interval: 2.5–35.6) as likely to occur near (≤10 km away from) flood-affected catchments with a high relative water level (+0.75 m) than at 30 km from such catchments. At medium-to-low relative water levels (0 and −0.75 m), in contrast, there was no significant association with distance.

Even more pronounced – but also subject to greater uncertainty – was the association of on-topic tweets with relative water level when considering areas in close proximity to flood-affected catchments based on the GAM with interaction (Table 5; Figure 7). At distances ≤10 km, tweets near strongly affected catchments with a relative water level of +0.75 m were 54 times as likely to be on topic as tweets in proximity to unaffected catchments with a relative water level of −0.75 m. While an association with relative water level was still marginally significant at 30 km distance to flood-affected areas, there was, not surprisingly, no association at greater distances (see Figure 8).

Compared with general flood-related tweets, there is perhaps a tendency for ‘relevant’ on-topic tweets to be closer to flood-affected catchments (odds ratio 2.2 at ≤10 km

Table 5. Odds ratios of the occurrence of on-topic tweets for distance and relative water level increments in the GAM without and with interaction.

Model	Distance ≤10 km versus 30 km	Relative water level +0.75 m versus −0.75 m
GAM without interaction	13.1 (3.5–46.2)	5.5 (1.6–24.5)
GAM with interaction	0.9 (0.1–4.1) at relative water level −0.75 m	54.4 (5.4–1453) at distance ≤10 km
	3.0 (0.6–12.5) at relative water level 0 m	4.3 (1.0–45.4) at distance 30 km
	11.0 (2.5–35.6) at relative water level +0.75 m	0.9 (0.2–8.4) at distance 80 km

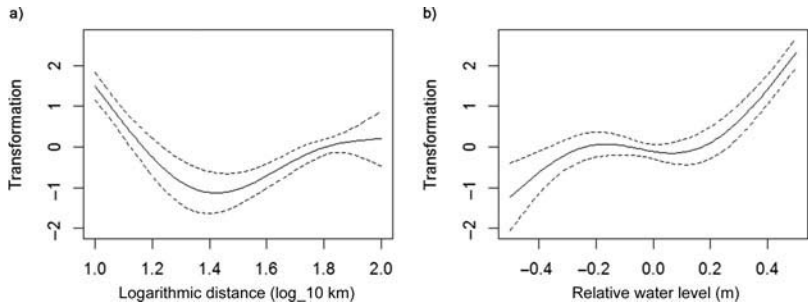


Figure 6. Transformation plots of the GAM without interactions showing the modeled relationship between the frequencies of on-topic tweets and (a) distance to flood and (b) relative water level. Values on the *y* axis are relative measures; see Table 5 for odds ratios as estimates of effect size.

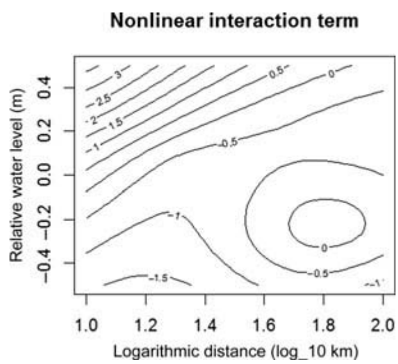


Figure 7. Transformation plot of the GAM with interaction between distance to flood and relative water level. Contour values are relative measures; see Table 5 for odds ratio estimates.

compared to 30 km distance), and in particular close to catchments with higher relative water level (odds ratio 2.9 for relative water level of +0.75 m versus −0.75 m).

Associations of thematic categories of on-topic tweets with flood distance and relative water level were comparatively weak and highly uncertain (Table 6). The thematic group

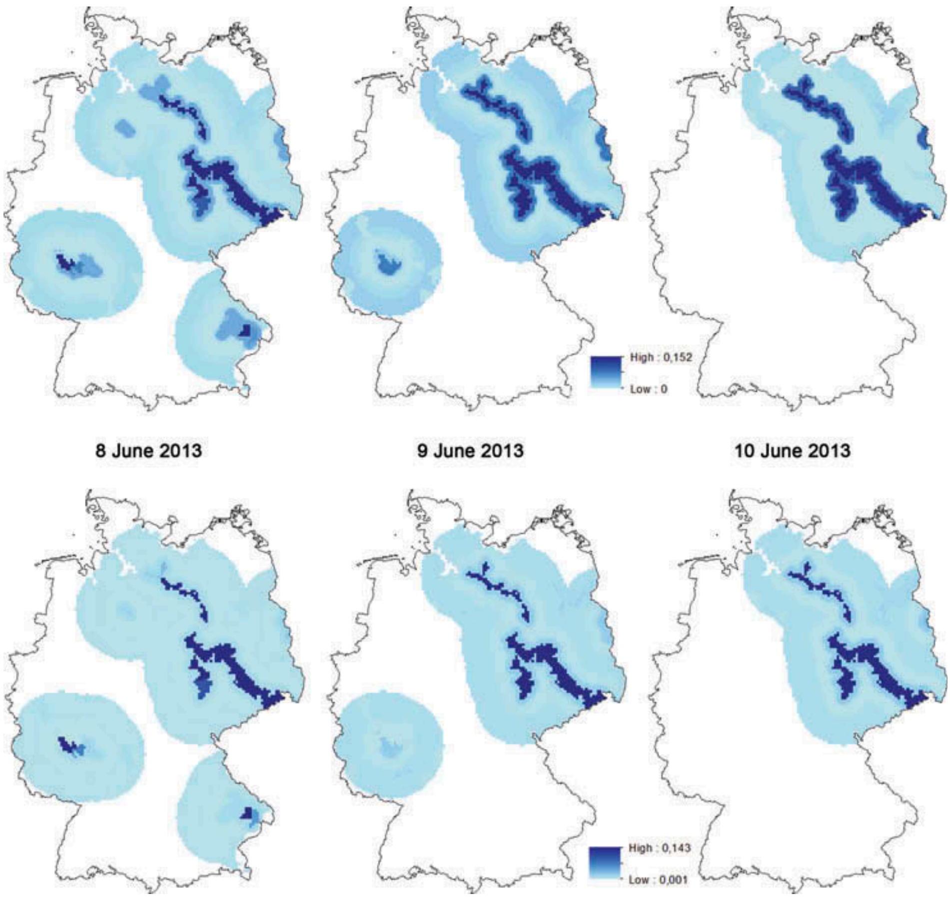


Figure 8. Spatial distribution of the frequency of on-topic tweets on 8, 9 and 10 June based on the GAM without interaction (top row) and with an interaction between distance to flood and relative water level (bottom row).

Table 6. Odds ratios of the occurrence of subtypes of on-topic tweets for distance and relative water level increments according to GAMs without interaction term.

Subtype	Distance ≤10 km versus 30 km	Relative water level +0.75 m versus −0.75 m
Volunteer actions (VA)	0.4	4.0
Media and traffic situation (MT)	0.6	0.6
First-hand observations, official actions, infrastructure damage (FOI)	1.6	2.0

Note: This analysis is based on on-topic tweets only (N = 320).

of tweets related to first-hand observations, official actions and infrastructure damage appears to be somewhat more frequent at shorter distances and higher relative water levels compared to general flood-related tweets (odds ratios 1.6 and 2.0, respectively), while tweets concerning media reports and traffic situation tended to be more weakly associated with distance and relative water levels (odds ratios 0.6). Tweets related to volunteer actions appear to be less associated with distance and more strongly with relative water level compared to general flood-related tweets (odds ratios 0.4 and 4.0, respectively).

7. Discussion

This article presents a geographical approach for identifying relevant georeferenced social messages based on authoritative data on flood phenomena. The goal was to investigate if this approach is able to identify the most useful messages for the purpose of extracting information that can be valuable for improving situation awareness in flood events.

The statistical analysis of the tweets sent during the floods in Germany 2013 has confirmed the relevance of our approach. Tweets related to the flood (i.e. on topic) were 11 times more likely to occur near (≤10 km away from) flood-affected areas, i.e. in catchments with a high relative water level (+0.75 m), than 30 km away from such areas. Furthermore, tweets near severely affected catchments with a relative water level of +0.75 m are 54 times more likely to be on topic than tweets in proximity to unaffected catchments. In this manner, the hypothesis can be accepted that the geographical relation proximity and the relative water level are both strong predictors of the usefulness of tweets in the analysed case. Thus, by using the calculated values for the geographical relation proximity to and severity of floods for prioritizing social media messages, one can expect a significantly higher probability of identifying information that is useful for improving situational awareness in disaster management.

These findings are consistent with previous analyses on social media usage in disasters, which identified a distinct role of users local to the event (or 'on the ground'), who are more probable to generate useful information for improving situational awareness (Starbird *et al.* 2010, Vieweg *et al.* 2010, Acar and Muraki 2011, Starbird and Muzny 2012, Imran *et al.* 2013). However, these approaches analyse the contents of the messages, based on which they seek to classify messages/users as 'local' or 'on the ground'. The increasing amount of georeferenced social media messages that is becoming available in the last years enables us to work the other way round by taking a geographical approach: based on the relative location of social media messages, we can determine the most useful ones. In this way, we were able to do a more precise, quantitative assessment of the messages based on their calculated geographical relations with flooded areas (proximity and relative water level). These relations offer a much more fine-grained distinction than the binary classifications (local/non-local) previously used.

Another advantage of the geographical approach is that it enables a rigorous statistical data analysis by the use of a GAM that is able to cope with possible nonlinearities and the expected interaction between relative water level of and distance to flood, as well as with spatial autocorrelation in social media data. As a result, this article adds to previous research on spatial analysis of social media in disasters (Croitoru *et al.* 2013, Crooks *et al.* 2013, Fuchs *et al.* 2013) by presenting more rigorous evidence for a strong spatial association between locational proximity to floods and the usefulness of the messages for crisis management, and it transfers modeling approaches from the broader field of hazard modeling (Brenning *et al.* 2014) to the analysis of social media data.

However, these results should be considered within the scope and limitations of the present study. As for its external validity, this study must be replicated for different scenarios and hazard types to allow a wider generalization. Even though this work examined a large and dense data set, the messages related to floods consist of a small fraction (0.6%) of the total number of messages. This can be partially explained by the low ratio of tweets to Internet users in Germany (Stephens and Graham 2012), and possibly also to the unknown proportion of the overall tweet population that was available for this study. However, the small percentage of tweets that are related to the floods in Germany in 2013 was also observed in the study of Fuchs *et al.* (2013). This may have influenced also the weaker associations we found between the thematic categories of tweets and the geographical relations, since the number of messages in each category was relatively small. Furthermore, the bottom-up approach we used in the categorization has the advantage of yielding meaningful categories for the case at hand, but imposes limitations on the generalizability of our results to other cases and scenarios. Thematic categorization is indeed generally problematic in social media analysis, as it can be noticed from the lack of standards for categories in the existing work, in particular in the context of disaster management (Vieweg *et al.* 2010, Imran *et al.* 2013).

Additionally, during the manual scrutiny of the set of tweets obtained after the keyword-based filtering (see Section 5.1), we found out that in some cases the relevance of a message for improving situational awareness depends more on the picture itself than on its accompanying text, as is the case of Figure 3. A georeferenced picture of a flooded area can be a very useful piece of information during crisis response, since it is able to depict the current situation in a very granular way, and thus contribute to decision-making. For instance, a picture could contain information about whether a particular street, or even a specific part of the street, is usable or not for evacuation purposes.

In the case of the tweet in Figure 3, the user additionally provided the hashtags '#hochwasser' and 'flut' (flood), and that is why it was included after our initial filtering. Nevertheless, it may be the case that some messages of our data set contain similar content but did not include any of the selected keywords and were thus classified as off topic. In this manner, owing to the manual screening of all 'on-topic tweets' we can be sure not to have any misclassified on-topic messages (i.e. 'false positives'), but we cannot rule out the existence of misclassified off-topic tweets (i.e. 'false negatives'). This is a common limitation of studies that work with text-based analysis of social media (e.g. De Longueville *et al.* 2009, MacEachren *et al.* 2011, Terpstra and de Vries 2012, Fuchs *et al.* 2013, Spinsanti and Ostermann 2013), which could only be completely overcome either with a very costly manual verification of the whole data set (alternatively, of significant random samples), or by developing a filter based on precise image-processing algorithms. Unfortunately, none of these alternatives were feasible in the present study due to time and resource constraints, but this is an interesting direction for future work.

Although this limitation may introduce a bias into the statistical results, it is unlikely that this would completely reserve the strong and significant statistical relationships that we observed between locational proximity/relative water level and usefulness of tweets. Furthermore, the difficulty in classifying pictures actually speaks in favour of the geographical approach as a whole, since the location-based identification of relevant messages we propose could be performed independently of the content of the social media messages, as opposed to other approaches based on natural language processing and machine learning (Starbird and Muzny 2012, Imran *et al.* 2013). Hence, future work can explore the application of the geographical approach to other social media platforms that are mainly based on photo and video sharing (e.g. Flickr, Instagram). Furthermore, the location-based approach proposed here could be easily combined both with automated classification algorithms (e.g. being considered as weights for the classification of relevance) and with manual/crowdsourced examination (e.g. being used for ranking messages before human verification/processing), thus improving the accuracy and efficiency of existing approaches. Therefore, this consists of an important avenue for future research endeavours.

In this manner, despite the limitations of this study, our findings imply that the geographical approach can serve as a basis for improving existing online monitoring systems. This could be accomplished by relying upon the quantitative indicators that we define for measuring the geographical relations proximity to and severity of floods, in order to automatically rate and prioritize the incoming social media messages 'on-the fly'. This approach may thereby offer a contribution for extending existing commercial tools (e.g. Geofeedia,[3] Twitcident[4]) and research studies (MacEachren *et al.* 2011, Terpstra and deVries 2012, Croitoru *et al.* 2013, Spinsanti and Ostermann 2013) that aim for location-based knowledge discovery from social media. Most of these approaches (MacEachren *et al.* 2011, Terpstra and de Vries 2012, Croitoru *et al.* 2013) provide visualizations exclusively based on inherent relations of social media data (e.g. semantic clustering or user network analyses) and could thus be improved by additionally resorting to external data sources for considering the geographical relations to disaster phenomena proposed here. Thus, our approach can offer a significant aid to the task of identifying useful messages by both emergency management professionals and the affected population of 'everyday analysts' (Palen *et al.* 2010), who currently mostly manually 'follow' the flow of social media activity and strive to find useful information, as reported for instance by Latonero and Shklovski (2011).

8. Conclusion

This article seeks to make an additional contribution to the nascent research that combines social media data with geoinformation coming from other sources, particularly for the context of disaster management (Spinsanti and Ostermann 2013, Triglav-Čekada and Radovan 2013, Schnebele *et al.* 2014). Results show that the geographical approach proposed here for quantitatively assessing social media messages based on authoritative data can be a viable and useful way to improve the identification of messages that contain useful information for managing disasters.

In this manner, the analysis of social media messages based on their geographical relations to the disaster phenomena is a relevant approach for coping with the characteristic noisiness/variability, volume and velocity of data stemming from social media. Existing geographical knowledge and authoritative data consist of valuable resources for spatially parsing 'big' social media data, by making it possible to efficiently order, and thereby ultimately reducing, the information space that must be searched for useful pieces of information. Future work should thus further develop this approach by considering other information sources (e.g. satellite or aerial images, land-use data from authoritative sources or OpenStreetMap) and by deriving new geographical relations that better help us to explore the potential opened by social media by leveraging geographical knowledge.

Acknowledgements

The authors would like to thank the German Federal Waterways and Shipping Administration and the German Federal Institute for Hydrology for providing the water level data. João Porto de Albuquerque is grateful for FAPESP (grant no. 2012/18675-1), CAPES (grant no. 12065-13-7) and Heidelberg University (Excellence Initiative II/Action 7) for providing funding for his research stay and visiting professorship at Heidelberg University. Alexander Brenning is grateful to the Alexander von Humboldt Foundation for a research fellowship at Heidelberg University, which supported his contribution to this research. The authors are grateful to the anonymous reviewers for their helpful suggestions.

Notes

1. https://dev.twitter.com/docs/platform-objects/tweets, accessed on 15 August 2014.
2. http://www.pegelonline.wsv.de, accessed on 15 October 2013.
3. http://www.geofedia.com, accessed on 15 July 2014.
4. http://twitcident.com/, accessed on 15 July 2014.

References

Acar, A. and Muraki, Y., 2011. Twitter for crisis communication: lessons learned from Japan's tsunami disaster. *International Journal of Web Based Communities*, 7 (3), 392–402. doi:10.1504/IJWBC.2011.041206

Bakillah, M., Li, R.-Y., and Liang, S.H.L., 2014. Geo-located community detection in Twitter with enhanced fast-greedy optimization of modularity: the case study of typhoon Haiyan. *International Journal of Geographical Information Science*, 1–22. doi:10.1080/13658816.2014.964247

Bernardo, T.M., *et al*., 2013. Scoping review on search queries and social media for disease surveillance: a chronology of innovation. *Journal of Medical Internet Research*, 15 (7), e147. doi:10.2196/jmir.2740

Bollen, J., Mao, H., and Zeng, X., 2011. Twitter mood predicts the stock market. *Journal of Computational Science*, 2 (1), 1–8. doi:10.1016/j.jocs.2010.12.007

Brenning, A., *et al*., 2014. Landslide susceptibility near highways is increased by one order of magnitude in the Andes of southern Ecuador, Loja province. *Natural Hazards and Earth System Sciences Discussions*, 2 (3), 1945–1975. doi:10.5194/nhessd-2-1945-2014

Bruns, A., *et al*., 2012. *# qldfloods and@ QPSMedia: Crisis communication on Twitter in the 2011 south east Queensland floods*. Brisbane: ARC Centre of Excellence for Creative Industries and Innovation.

Burton, S.H., *et al*., 2012. "Right time, right place" health communication on Twitter: value and accuracy of location information. *Journal of Medical Internet Research*, 14 (6), e156. doi:10.2196/jmir.2121

Chatfield, A.T. and Brajawidagda, U., 2013. Twitter early Tsunami warning system: a case study in Indonesia's natural disaster management. *In*: *System sciences (HICSS), 2013 46th Hawaii international conference on System Sciences*, 7–10 January, Wailea, HI. Washington, DC: IEEE, 2050–2060.

Croitoru, A., *et al*., 2013. Geosocial gauge: a system prototype for knowledge discovery from social media. *International Journal of Geographical Information Science*, 27 (12), 2483–2508. doi:10.1080/13658816.2013.825724

Crooks, A., *et al*., 2013. #Earthquake: Twitter as a distributed sensor system. *Transactions in GIS*, 17 (1), 124–147. doi:10.1111/j.1467-9671.2012.01359.x

Davison, A.C., Hinkley, D.V., and Young, G.A., 2003. Recent developments in bootstrap methodology. *Statistical Science*, 18 (2), 141–157. doi:10.1214/ss/1063994969

De Longueville, B., *et al*., 2010. Digital Earth's nervous system for crisis events: real-time sensor web enablement of volunteered geographic information. *International Journal of Digital Earth*, 3 (3), 242–259. doi:10.1080/17538947.2010.484869

De Longueville, B., Smith, R.S., and Luraschi, G., 2009. OMG, from here, I can see the flames! *In: Proceedings of the* 2009 *international workshop on location based social networks – LBSN '09*. New York, NY: ACM Press, 73.

Dugdale, J., Van de Walle, B., and Koeppinghoff, C., 2012. Social media and SMS in the Haiti earthquake. *In: 21st international conference companion on World wide web*. New York, NY: ACM.

Endsley, M.R., 1995. Toward a theory of situation awareness in dynamic systems. *Human Factors: the Journal of the Human Factors and Ergonomics Society*, 37 (1), 32–64. doi:10.1518/001872095779049543

Fuchs, G., Andrienko, N., and Andrienko, G., 2013. Tracing the German centennial flood in the stream of tweets: first lessons learned. *In*: *Proceedings of the second ACM SIGSPATIAL* *international workshop on crowdsourced and volunteered geographic information*, November, Orlando, FL. New York: ACM Press, 31–38.

Gao, H., Barbier, G., and Goolsby, R., 2011. Harnessing the crowdsourcing power of social media for disaster relief. *IEEE Intelligent Systems*, 26 (3), 10–14. doi:10.1109/MIS.2011.52

Goetz, J.N., Guthrie, R.H., and Brenning, A., 2011. Integrating physical and empirical landslide susceptibility models using generalized additive models. *Geomorphology*, 129 (3–4), 376–386. doi:10.1016/j.geomorph.2011.03.001

Gomide, J., *et al.*, 2011. Dengue surveillance based on a computational model of spatio-temporal locality of Twitter. *In: Proceedings of the 3rd international web science conference on – WebSci '11*. New York, NY: ACM Press, 1–8.

Goodchild, M.F., 2007. Citizens as sensors: the world of volunteered geography. *GeoJournal*, 69 (4), 211–221. doi:10.1007/s10708-007-9111-y

Goodchild, M.F. and Glennon, J.A., 2010. Crowdsourcing geographic information for disaster response: a research frontier. *International Journal of Digital Earth*, 3 (3), 231–241. doi:10.1080/17538941003759255

Graham, M., Poorthuis, A., and Zook, M., 2012. *Digital trails of the UK floods – how well do tweets match observations?* [online]. The Guardian Datablog. Available from: http://www.guardian.co.uk/news/datablog/2012/nov/28/data-shadows-twitter-uk-floods-mapped [Accessed 20 June 2013].

Herfort, B., *et al.*, 2014a. Exploring the geographical relations between social media and flood phenomena to improve situation awareness a study about the River Elbe Flood in June 2013. *In*: J. Huerta, S. Schade, and C. Granell, eds. *Connecting a digital Europe through location and place*. Heidelberg: Springer International Publishing, 55–71.

Herfort, B., *et al.*, 2014b. Does the spatiotemporal distribution of tweets match the spatiotemporal distribution of flood phenomena ? A study about the River Elbe Flood in June 2013. *In*: S.R. Hiltz, *et al.*, eds. *Proceedings of the 11th international ISCRAM conference*. University Park, PA: ISCRAM, 747–751.

Imran, M., *et al.*, 2013. Extracting information nuggets from disaster-related messages in social media. *In*: *Proc. of ISCRAM*, Baden-Baden.

Kaewkitipong, L., Chen, C., and Ractham, P., 2012. Lessons learned from the use of social media in combating a crisis: a case study of 2011 Thailand flooding disaster. *In: ICIS* 2012 *proceedings*. Atlanta, GA: AIS.

Kongthon, A., *et al.*, 2012. The role of Twitter during a natural disaster: case study of 2011 Thai Flood. *In*: *Technology Management for Emerging Technologies (PICMET)*, *2012 proceedings of PICMET'12*, 29 July–2 August, Vancouver, BC. Washington, DC: IEEE, 2227–2232.

Landwehr, P.M. and Carley, K.M., 2014. Social media in disaster relief. *In*: W. Chu, ed. *Data mining and knowledge discovery for Big Data*. Vol. 1. Heidelberg: Springer, 225–257.

Latonero, M. and Shklovski, I., 2011. Emergency management, Twitter, and social media evangelism. *International Journal of Information Systems for Crisis Response and Management*, 3 (4), 1–16. doi:10.4018/jiscrm.2011100101

Lazer, D., *et al.*, 2014. Big data. The parable of Google Flu: traps in big data analysis. *Science (New York, N.Y.)*, 343 (6176), 1203–1205. doi:10.1126/science.1248506

Lehner, B., Verdin, K., and Jarvis, A., 2008. New global hydrography derived from spaceborne elevation data. *EOS, Transactions American Geophysical Union*, 89, 10. doi:10.1029/2008EO100001

MacEachren, A.M., *et al.*, 2011. Geo Twitter analytics: applications in crisis management. *In*: *Proceedings, 25th international cartographic conference*. Paris: ICA, 1–8.

Merwade, V., 2012. *Watershed and stream network delineation using arcHydro tools* [online]. 1–22. Available from: http://web.ics.purdue.edu/~vmerwade/education/terrain_processing.pdf [Accessed 15 July 2014].

Palen, L., Vieweg, S., and Anderson, K.M., 2010. Supporting "Everyday Analysts" in safety- and time-critical situations. *The Information Society*, 27 (1), 52–62. doi:10.1080/01972243.2011.534370

Roick, O. and Heuser, S., 2013. Location based social networks – definition, current state of the art and research Agenda. *Transactions in GIS*, 17 (5), 763–784.

Sächsisches Landesamt für Umwelt Landwirtschaft und Geologie, 2013. *Gewässerkundlicher Monatsbericht mit vorläufiger Auswertung des Hochwassers Juni 2013* [online]. Available from: http://www.umwelt.sachsen.de/umwelt/wasser/download/Kurzbericht_Juni_2013_130820.pdf [Accessed 15 July 2014].

Sakaki, T., Okazaki, M., and Matsuo, Y., 2010. Earthquake shakes Twitter users: real-time event detection by social sensors. *In*: *Proceedings of the 19th international conference on World wide web*, 26–30 April, Raleigh, NC. New York: ACM Press, 851–860.

Schnebele, E., Cervone, G., and Waters, N., 2014. Road assessment after flood events using non-authoritative data. *Natural Hazards and Earth System Science*, 14 (4), 1007–1015. doi:10.5194/nhess-14-1007-2014

Shklovski, I., *et al*., 2010. Technology adoption and use in the aftermath of hurricane Katrina in New Orleans. *American Behavioral Scientist*, 53 (8), 1228–1246. doi:10.1177/0002764209356252

Slavkovikj, V., *et al*., 2014. Review of wildfire detection using social media. *Fire Safety Journal*, 68, 109–118. doi:10.1016/j.firesaf.2014.05.021

Spinsanti, L. and Ostermann, F., 2013. Automated geographic context analysis for volunteered information. *Applied Geography*, 43, 36–44. doi:10.1016/j.apgeog.2013.05.005

Starbird, K. and Muzny, G., 2012. Learning from the crowd : collaborative filtering techniques for identifying on-the-ground Twitterers during mass disruptions. *In*: L. Rothkrantz, J. Ristvej, and Z. Franco, eds. *Proceedings of the 9th international ISCRAM conference,* Vancouver, April. Brussels: ISCRAM, 1–10.

Starbird, K., *et al*., 2010. Chatter on the red: what hazards threat reveals about the social life of microblogged information. *In*: *Proceedings of the 2010 ACM conference on computer supported cooperative work*, 6–10 February, Savannah, GA. New York: ACM Press, 241–250.

Stephens, M. and Graham, M., 2012. *A Geography of Twitter* [online]. Available from: http://www.oii.ox.ac.uk/vis/?id=4fe09570 [Accessed 15 July 2014].

Sui, D. and Goodchild, M., 2011. The convergence of GIS and social media: challenges for GIScience. *International Journal of Geographical Information Science*, 25 (11), 1737–1748. doi:10.1080/13658816.2011.604636

Terpstra, T. and de Vries, A.D., 2012. Towards a realtime Twitter analysis during crises for operational crisis management. *In*: *Proceedings of ISCRAM 2012*, April, Vancouver, BC. Brussels: ISCRAM, 1–9.

Tomaszewski, B., *et al*., 2014. Visually contextualizing social media within spatial, temporal and thematic constraints for disaster situation awareness. *In*: *GeoVisual analytics: interactivity, dynamics, and scale, workshop @ GIScience*, 23 September. Vienna: ICA, 1–4.

Triglav-Čekada, M. and Radovan, D., 2013. Using volunteered geographical information to map the November 2012 floods in Slovenia. *Natural Hazards and Earth System Science*, 13 (11), 2753–2762. doi:10.5194/nhess-13-2753-2013

Vieira, V.M., *et al*., 2008. Spatial-temporal analysis of breast cancer in upper Cape Cod, Massachusetts. *International Journal of Health Geographics*, 7, 46. doi:10.1186/1476-072X-7-46

Vieweg, S., *et al*., 2010. Microblogging during two natural hazards events: what twitter may contribute to situational awareness. *In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*.

Wood, S., 2006. *Generalized additive models: an introduction with R*. Boca Raton, FL: CRC Press.

Yates, D. and Paquette, S., 2011. Emergency knowledge management and social media technologies: a case study of the 2010 Haitian earthquake. *International Journal of Information Management*, 31 (1), 6–13. doi:10.1016/j.ijinfomgt.2010.10.001

Yin, J., *et al*., 2012. Using social media to enhance emergency situation awareness. *IEEE Intelligent Systems*, 27 (6), 52–59. doi:10.1109/MIS.2012.6

Zhang, J., *et al*., 2010. Hydrologic information extraction based on Arc Hydro tool and DEM. *In*: *2010 international conference on Challenges in Environmental Science and Computer Engineering (CESCE)*, 6–7 March, Wuhan. Washington, DC: IEEE, 503–506.

Zook, M., *et al*., 2010. Volunteered geographic information and crowdsourcing disaster relief: a case study of the Haitian earthquake. *World Medical & Health Policy*, 2 (2), 6–32. doi:10.2202/1948-4682.1069