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Harvesting social media for generation of near real-time flood maps

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Abstract

Social media are a new, big and exciting source of data. Rather than from traditional sensors and models, this data is from local people experiencing real-world phenomena, such as flood events. During floods, disaster managers often have trouble getting an accurate overview of the current situation. At the same time, people affected by the floods Tweet how they are affected, if they need help and how deep the flood water is, providing an important source of information. Tweets about actual floods and containing a reference to a location, can be considered as flood observations. However, the observations are not made by validated instruments or reliable observers. Therefore, a single observation has to be considered as being unreliable. Multiple unique observations reporting the same flood severity however increase the probability of the observations being correct.

In this paper we show how these observations can be used for decision support during floods. The approach is based on the "wisdom of the crowd" principle: a group of independent consistent observations is relatively more reliable than an inconsistent group of observations. The approach uses filtering and geo-statistical methods to take into account that observations in tweets are inherently unreliable. We developed a concept that exploits observed information of the physical characteristics of a flood, such as flood depth and the location. If plotted on a Digital Elevation Map, the flooded area around one flood depth observation can be calculated. With multiple observations over the total affected area, for each of which the reliability is assessed, a flood probability map can be constructed. The method was tested in a pilot project in Jakarta, a city suffering from frequent recurring floods, but also called Twitter capital of the world.

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1. Introduction

In the first hours of a flood event it is difficult to obtain accurate information about the extent and severity of the hazard. This information is very important for disaster management (people in need, property in danger, availability of evacuation routes). Currently, information for disaster management is derived from a few sources such as field reports, traffic cameras, satellite images and aerial images. However, getting a near real-time and accurate picture of the situation on the ground remains a problem.

At the same time, people affected by floods increasingly share their observations and needs through digital social media. It has been recognized that hazards leave a footprint on social media. Guan and Chen [1] show that the ratio between hazard related tweets and average number of tweets (The Disaster-Related-Ratio) can be used to identify hazards. Hazard related tweets have been used to gain information about the social impact [2], the relative impacts [1] and temporal behaviour of floods [3]. However, data from Twitter also contain a large number of real-time observations with physical hazard characteristics such as water depth and location, which reveal the ground truth during a flood event. Although the use of these data is still in its infancy, multiple authors have researched its possible application for disaster monitoring. One of the first to discuss the use of social media for disaster monitoring was Muralidharan at al. [4]. They used Twitter and Facebook during the 2010 earthquake in Haiti. Several applications of using social media for flood monitoring have been published since. Sun et al. [5] assessed the suitability of using geotagged Flickr images to support remote sensing based flood maps. They found that 95 % of selected Flickr observations coincided with their remote sensing derived flood map and used, along with other data sources, the intensity of flood related Twitter messages to map flood likelihood in the city of Calgary, Canada. Jongman et al. [6] researched the suitability of Twitter data for early detection of floods in the Philippines and Pakistan. Floods were mentioned one to several days earlier on Twitter then reported to humanitarian aid organizations. However, they found that the pre-processing of social media data needs to be improved for operational use. Fohringer et al. [7] was the first to utilize flood depth information in Twitter messages for rapid flood inundation mapping. By manually estimating water depths from photographs in the Tweets in combination with a Digital Elevation Model (DEM), water level estimates were generated. These water level observations were interpolated throughout the area. Results showed that social media contain additional and potentially even exclusive information that is useful for flood mapping. They found the uncertainty of interpolated inundation depth maps and the uncontrollable availability of the information to be major threats to the utility of these data for flood mapping. The PetaJakarta project [8] tried to limit the uncertainty involved by building a local community to confirm flood observations from Twitter. Although much more reliable, a limitation to this approach is the necessity of a local community which limits the coverage and scalability of the approach.

In this paper we present results of a feasibility study to use Twitter data for disaster response in the city of Jakarta, Indonesia. We developed a concept that exploits observed information about the physical characteristics of floods, such as flood depth and the location. These observations are used in combination with a Digital Elevation Model (DEM) to derive flood extent in near real-time. The data mining and processing is automated and uncertainties in the data are taken into account. The results could be used in the first hours of an event to trigger action and allocate people and money for disaster response.

2. Pilot Case

Floods pose a continuous thread to Jakarta. Every year, an increasing number of floods are observed during the rainy season, from December to March. The areas mostly struck by the repetitious floods are local dwellings along the river beds and lower parts of polder areas. Less frequently, like in 1996, 2002, 2007 and 2013, higher areas are also flooded, resulting in large scale disruption of life in extensive areas of the city. Around 240 km^2 of Jakarta is estimated to be below sea level. With an ever growing population of now more than 10 million inhabitants there is a lot at stake. The floods of February 2013 alone left 20 fatalities and more than 45,000 people displaced. The total loss was estimated to be more than USD 3.3 billion, of which a quarter was spent on economic recovery [9].

The most regularly occurring floods in Jakarta are caused by intense rain showers. Precipitation rates can reach up to 30-100 $mm \cdot h^{-1}$. Daily precipitation volumes vary from 90-265 mm for an every year to 100 year return period [10].

Intense local rainfall often leads to floods due to a lack of infiltration capacity, low drainage gradients and lack of retention storage. Less regular, but still yearly occurring, are riverine floods. There are many rivers crossing Greater Jakarta that originate in the mountainous area south of Jakarta. The combination of high elevation and tropical climate results in intensive precipitation. In the more plain northern part of Jakarta flood waves slow down and water levels rise quickly, easily overtopping canals. Another major thread is storm surges at sea: when spring tide and storm surge coincide, the basic flood walls might not withstand the water levels and large parts of Jakarta can flood. Floods are expected to increase in frequency and impact as a result of land subsidence rates of up to 30 centimeters per year [11].

At the same time, Jakarta's inhabitants are very active on Social Media, particularly on Twitter. In fact, a study by ComScore [12] has found that Indonesians are the most active users of Twitter on the planet: 20.8 % of internet users aged over 15 regularly post on this social network. Jakarta has therefore been called Twitter Capital of the World [13]. Mobile internet has bypassed fixed internet connections; the majority of Indonesians access the internet via mobile devices. Also during floods, many Indonesians post their experiences on social media.

In order to strengthen resilience against flooding a Flood Early Warning System was setup in the Department of Public Works of Jakarta [14]. The system combines meteorological and hydrological monitoring data and models to forecast water levels. A test was run to show flood observations from Twitter in this framework to offer government officials near real-time insight in both the temporal and spatial behaviour of the flood. In addition, a new method was developed to use the large numbers of observations in combination with a DEM in order to create flood extent maps. This method was tested in this study for the flood event of 9-11 February 2015.

3. Methods

A fundamental assumption when dealing with data obtained from social media is that it cannot be considered as reliable as reports from professional observers. In the case of flood observations, the messages can contain information about past floods, or floods in other areas. The word "flood" can also be used as a synonym for a totally different subject. Moreover, references to a location in a message are generally not pointing to a fully specified address but to an imprecise location such as a street name or neighbourhood. Likewise, mentioned flood depths are in most cases just estimates by the user.

As the number of flood observations from Twitter is too large to be checked manually, big data techniques that search for patterns in the data are necessary. An important characteristic of these techniques is that it considers each data point as being unreliable. Only by assessing large amounts of data, reliable patterns in the data start emerging. This concept, also known as "wisdom of the crowd" [15] was implemented and is discussed in this section. The approach applied contains a combination of filters, GIS techniques and probabilistics to estimate the flood extent using the flood observations collected from Twitter.

3.1. Harvesting and filtering

We applied a straightforward approach to harvest tweets about floods in Jakarta. To build up a database with flood observations shared by social media, we used the streaming API from Twitter to harvest all tweets since 2013 that contain the word "banjir", including those with a hashtag prefix (i.e. #banjir). From this dataset, we excluded re-tweets and modified tweets. We defined a tweet to be modified (and not original) when an identical string of five words was found in one of the previous 10.000 tweets. All these tweets, which often include photos linked to them, were stored in our database. We then looked for the tweets that had water depth mentions, by looking for tweets that contained numbers immediately followed by "m" or "cm". From a comparison of observation text and photos we found that the water depth mentioned often referred to the maximum observed water depth. If a range of water depths was mentioned we took the maximum value. The corresponding water depth (from the combination of number and "m" or "cm") in our database was attached to the tweet as an attribute.

3.2. Geolocating the observations

The main geographical entity in Jakarta is the neighbourhood, also called "*kelurahan*". This entity is often used by the inhabitants of Jakarta to refer to areas of interest, and is therefore found often in tweets on floods. In order to geo-locate the observations in this dataset, we looked for mentions of the 267 *kelurahan* in Jakarta. We also added a large number of points of interest to the search routine, using Open Street Maps as a reference. Any tweet that could be located was given the respective *kelurahan* as geolocation attribute. Note that we did not use georeferences of the (mobile) device that was used to send the tweet. The availability of this information is limited. Moreover, the location of a flood does not necessarily correspond to the location of the telephone. There are many known cases of people reporting floods from a different location (than the flood). A comparison between georeferences included in tweets (geotag) and reported locations showed that the geotag may deviate from the reported location [16].

3.3. Flood probability maps

To derive flood maps a dataset with unique flood observations from Twitter was created. Tweets without mention of a water depth were excluded from this dataset. The tweets included in this dataset were considered to be observations of flood events, although unreliable. In order to include this uncertainty into the flood maps, flood probability maps were derived. These maps use all observations, taking into account the reliability of every single observation to show the likelihood of flooding. The method for deriving the flood probability maps consists of three main steps. First, the reliability of each observation within a given time window is assessed. Secondly, a flood map is generated for each individual observation using a flood fill algorithm. Finally the flood maps within the given time window are combined based on the reliability of each observation. These steps are further elaborated in the next paragraph.

The reliability of a single observation was based on the combined likelihood of a flood in a *kelurahan* and the likelihood of the observed maximum water depth in that *kelurahan* within a timeframe. The likelihood of a flood in a *kelurahan* was defined as the number of tweets in that *kelurahan* relative to the largest number of observations at any other *kelurahan* within the same timeframe. The median observed maximum water depth within a timeframe was taken as the most likely maximum water depth and given a value of one. It was assumed that the likelihood decreases linearly to zero at three standard deviations difference from the median. Based on these assumptions the median observed maximum water depth in the *Kelurahan* with the largest number of observations is most reliable and has a likelihood of one. However, all observations are taken into account. These assumptions are only valid when there are sufficient flood observations within a time window.

A flood extent map was then calculated for each observation. The maximum observed water depth was assumed to be observed at local depressions (i.e. lower lying areas in the terrain) in the *kelurahan*. The local depressions were determined based on the local drainage direction derived with PCRaster software [17] based on a 100 by 100 meter resolution Digital Elevation Model optimized for hydraulic modelling. Using a flood-fill algorithm which assumes a horizontal water level, the flood extent of individual observations was determined on the same resolution. The maximum flood depth was limited to the threshold level of each local depression. Dependent on the location of local depression, the extent can cross the boundaries of the *kelurahan* (location) in which the flood was observed. This flood algorithm is only valid in case of pluvial flooding and insufficient drainage from these areas.

In order to obtain a probabilistic flood maps over a given period, the individual flood extent maps were combined. Each individual flood extent map was assigned the likelihood of the observation. For each cell the maximum likelihood value is taken. The result is a probabilistic flood map over the analysed time window with values ranging from 1 (very likely) to 0 (very unlikely). Water depths were inferred from this map for all cells with a probability higher than 0.2 using the same flood-fill algorithm. This threshold was optimized for this study to filter out outliers of observed maximum water depth.

4. Results

4.1. February 2014 flood

Statistical summaries of flood observations from Twitter were displayed in the Flood Early Warning System of Public Works Jakarta during the floods of February 2014. The accumulated number of tweets and the maximum water depth mentioned were displayed per *kelurahan*, see graphs in Fig. 1a. These graphs show the flood observations from Twitter in combination with a local water level gauge in Pluit; a *kelurahan* in the north of Jakarta. The location of Pluit *kelurahan* is presented in Fig. 1b. A comparison of the number of tweets (bottom graph) and water level observations at the nearby gauging station (top graph) show a clear relation between the timing of the flood wave and peaks in number of tweets. The intensity of flood observations with the mention of a water depth per *kelurahan* at February 8th, 2014 is shown in Fig. 1b. Analysis of the collected tweets showed that this proved to be a good filter, although at the cost of valid tweets. The intensity map is a first rough estimate of the flood extent. Both results show that floods in Jakarta leave a clear footprint on Twitter.

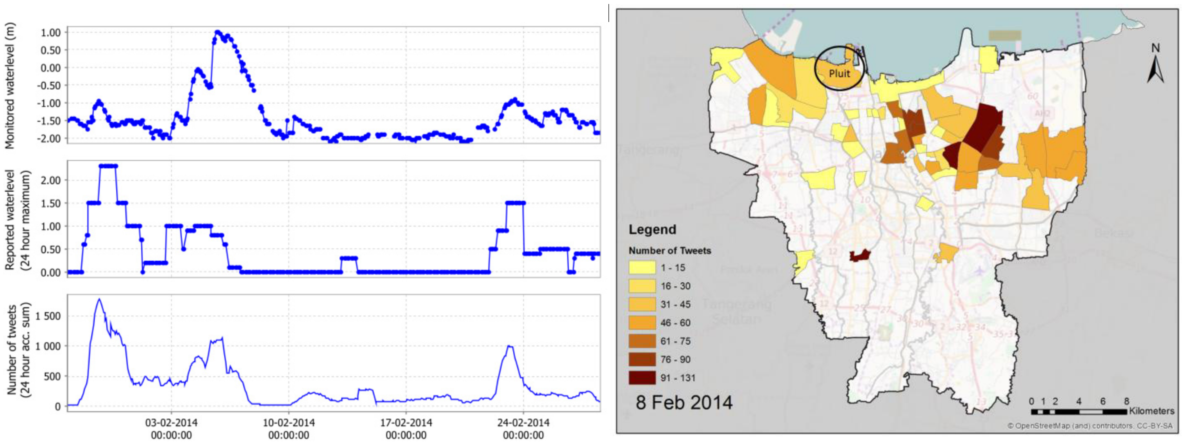

Fig 1. (a) Statistical summaries of flood observation in Pluit from Twitter; (b) number of flood observations per *kelurahan* that contain a water depth

During the 9-11 February 2015, when the city flooded again due to heavy rainfall, almost 728,000 Twitter messages related to flooding in Jakarta were posted on Twitter, peaking at 893 tweets/minute. The Disaster-Related-Ratio, i.e. the number of disaster-related tweets divided by the daily average number of tweets, went up to 13.3 %. A closer inspection of the messages showed that the content proved to be very detailed. We found frequent mentions of the locations where the flood was experienced, e.g. the name of a *kelurahan*. Besides location, a range or maximum water depth was often included in the message. From the messages sent in this period, 2,200 unique tweets contained local water depth observations. Out of these tweets, 40 % could be geo-located based on textual information, resulting in a total of 888 unique geo-located flood depth observations.

The intensity of flood observations per *kelurahan* for February 10th is shown in Fig. 2a. Compared to the intensity map, the flood probability map, see Fig. 2b, gives a more detailed picture about the most likely location and extent of floods. After pre-processing of the DEM to find local depressions, the flood algorithm took only seconds to process all tweets and calculate flood probability and flood depth maps on a 100 by 100 meter resolution.

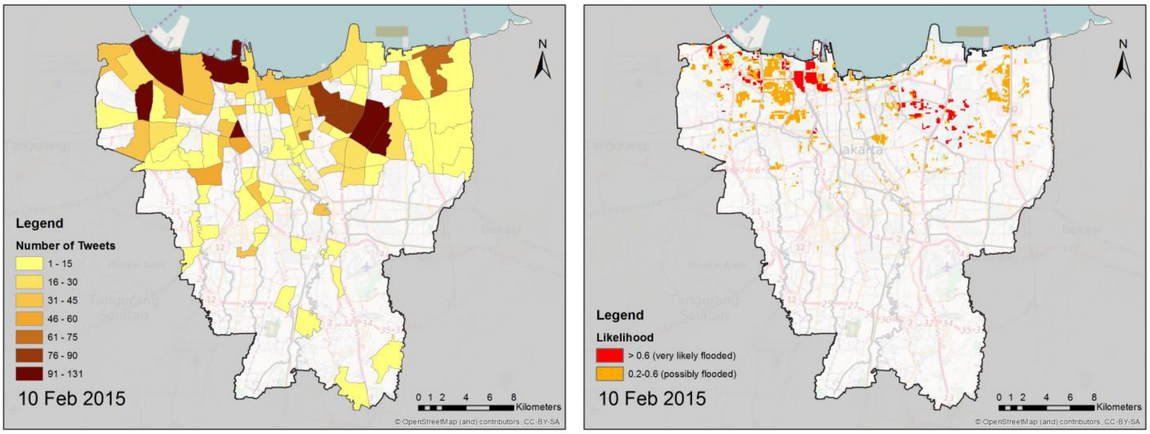

Fig 2. (a) Total number of mined flood observations per kelurahan that contain a water depth; (b) derived flood likelihood map

The resulting flood probability maps were validated by cross-checking the derived flood maps with geo-located photos of floods (validation points). By doing this, true positives and false negatives could be identified. The tweets with photos that we used were independent, as neither the photo nor the accompanying message were used in the flood mapping algorithm. The photos were manually geo-located based on the message and the photo itself with an estimated accuracy of 500 m. In total 103 confirmed flood photos were used for validation, providing a good spatial coverage of the flood area, see Fig. 3a. The results of the validation are shown in Fig 3b. At 69 % of the validation points, flooding had indeed been modelled within a range of 500 m (the accuracy of the validation points) counting as true positives. For two-third of these locations the modelled water depth also matched the water depth manually identified from the photos. At 31 % of the validation points however, no flood had been modelled, counting as false negatives. When we look at the tweet counts at *kelurahan* level only (not using the modelled output, Fig. 2a), we see that 93 % of the validation points are in the *kelurahan* where people tweeted about water depths. In other words, 93 % of our selection of 103 confirmed flood photos with good spatial coverage, were in *kelurahan* where people also tweeted about water depths.

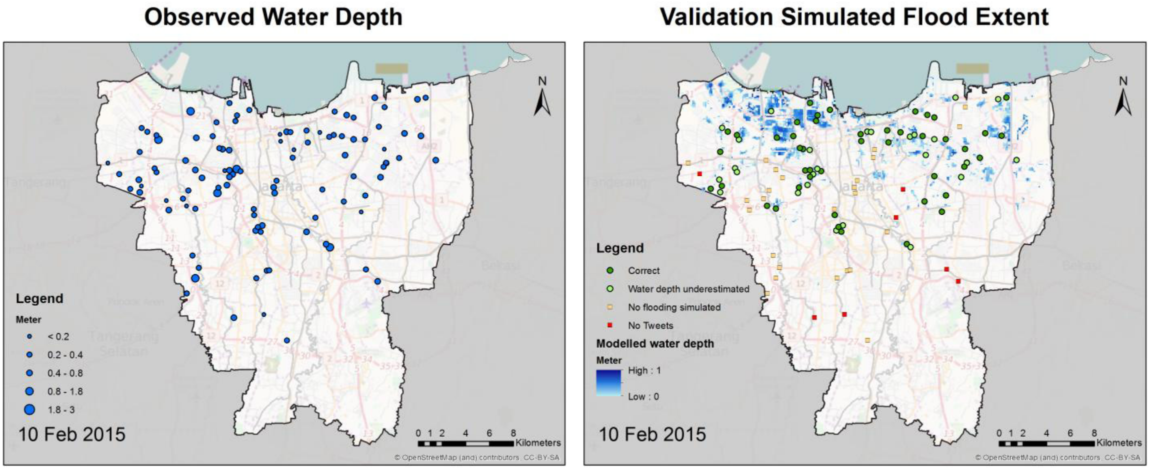

Fig 3. (a) Validation data set of confirmed flood photo; (b) validation of derived flood extent maps

5. Discussion

The pilot area, Jakarta, proved to be a welcome test case for this study as it is frequently struck by floods and the inhabitants tend to intensely use social media to post information about the floods. However, the developed method is not necessarily directly applicable in other flood prone areas as the applicability of the method requires people using social media to post information on the flood event. In other regions less people might be using social media, or posting location information, or sharing the flood depth that they are experiencing. At the same time, there is more information in the cloud than presently automatically harvested. The validation points were not automatically harvested because a reference to a location was not detected or the message did not contain flood depth observation. This illustrates that more useful data can be extracted from social media.

The applied approach requires a minimal amount of independent flood observations in order to derive accurate flood maps. This threshold needs further research at different locations to be determined. Insufficient observations could possibly become a limitation to the near real-time application of this method. Furthermore, as Twitter is a social media platform, many social processes play a role when posting, such as group behaviour based on trending topics. This may affect the independency of Tweets and undermine the "wisdom of the crowd" concept [20]. Whether this is the case and to what degree this affects the obtained results should be addressed in further research. Adding other contemporary social media such as Instagram, Snapchat, Weibo and Facebook counteracts this problem, and by adding more observations the accuracy of the generated flood maps will improve.

The applied flood algorithm performed reasonably well with 69 % of validation points being within 500 m from modelled flood extent. Most of the 'missed' flood locations (the remaining 31 %) are at locations outside local depressions as derived from the DEM. In some cases a local depression was missed because of inaccuracy in the DEM. However, in most cases the flood was not captured as the developed flood fill algorithm does not take into account hydrodynamic aspects of flooding, so it does not capture fluvial floods well. To include fluvial floods a similar flood fill algorithm could be developed based on Height Above Nearest Drainage [18] rather than based on local depressions only. This will be analysed in a continuation of this study.

In this study we used a simple method to define the location of the observed flood. Some locations were not automatically detected due to inaccurate (misinterpreting of the geo-location) or incomplete gazetteer (the place names that are used in the twitter messages, possibly abbreviations, are missing). Tools have come available recently [19] that contain intelligent algorithms to geo-locate messages. Such a tool might help to increase the number of useful observations and improve the accuracy of the flood extent.

Recent years have seen an increased application of telemetric sensor networks and model based forecasting systems. Great benefits are expected when these more traditional data processing methods are combined with data and information mined from the cloud. Data assimilation techniques might increase accuracy of the forecasting systems, while in return observations can be validated.

Next to these more technical approaches, near real-time flood maps from social media would be improved by user interaction. People that post flood observations, or other 'trusted' social media users nearby, can be contacted with the question to provide more detail, such as location and flood depth. Manually estimating water depths from tweets with photos but without a water depth mentioned in the text, see Fohringer et al. [7], can also help to add reliability to the model. Although this does not increase the number of observations, the accuracy of the observations increases thus increasing the reliability of generated flood maps. It needs to be researched how much delay this type of validation would cost in order to test its suitability for near real-time flood monitoring. Further research should also investigate in more detail the correlation and statistics between number of observations and flood characteristics, such as the estimated water depth.

6. Conclusions

The presented results show that social media contain very useful near real-time information for flood disaster management. By combining a Digital Elevation Model with flood depth observations and location references in tweets, we succeeded in creating flood maps for Jakarta in real-time. When validating the output, we found that at 69% of our reference flood locations, flooding had indeed been modelled within a range of 500 metres. We also evaluated floods by just looking at the tweet counts on kelurahan level and found that 93% of the reference locations were actually in kelurahan where people shared water depth tweets. In other words: Tweets that contain water depths provide a very good indication of which kelurahan experience flooding in Jakarta. This shows the high potential of this method for real-time flood mapping based on social media.

Given that data from social media becomes available in near real-time and the applied method takes only seconds to compute, data processing is not a limitation for applying this method for disaster response. The availability of sufficient reliable data is, however, not guaranteed and may turn out to be a limitation, especially in places where social media is less frequently used. On the other hand, more social media are opening up and we see ever more content online. And while in Jakarta we can depend on hundreds of thousands of tweets for a single event, only a fraction of such content can already make a big difference in real-time monitoring.

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