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Citizen observations contributing to flood modelling: opportunities and challenges

Thaine Herman Assumpção[1], Ioana Popescu[1], Andreja Jonoski[1], Dimitri P. Solomatine[1, 2]

[1]Integrated Water Systems and Governance, IHE Delft, Delft, The Netherlands
[2]Water Resources Section, Delft University of Technology, Delft, The Netherlands

Correspondence to: Thaine Herman Assumpção (t.hermanassumpcao@un-ihe.org)

Abstract. Citizen contributions to science have been successfully implemented in many fields – and water resources is one of them. Through citizens, it is possible to collect data and obtain a more integrated decision-making process. Specifically, data scarcity has always been an issue in flood modelling, which has been addressed in the last decades by remote sensing and is already being discussed in a citizen science scenario. In this context, this article aims to review the literature on the topic and analyse the opportunities and challenges that lie ahead. The literature on monitoring, mapping and modelling, was evaluated according to the flood-related variable citizens contributed to. Pros and cons of the collection/analysis methods were summarised. Then, pertinent publications were mapped into the flood modelling cycle, considering how citizen data properties (spatial and temporal coverage, uncertainty and volume) are related to its integration into modelling. It was clear that the number of studies in the area is rising. There are positive experiences reported in collection and analysis methods, for instance with velocity and land cover, and also when modelling is concerned, for example by using social media mining. However, matching the data properties necessary for each part of the modelling cycle with citizen generated data is still challenging. Nevertheless, the concept that citizen contributions can be used for simulation and forecasting is proved and further work lies in continuing developing and improving not only methods for collection and analysis but certainly for integration into models as well. Finally, in view of recent automated sensors and satellite technologies, it is through studies as the ones analysed in this article that the value of citizen contributions is demonstrated.

1 Introduction

The necessity to understand and predict the behaviour of floods has been present in societies around the world. This comes from the fact that floods impact their surroundings - in negative or in positive ways. The most common way used nowadays to better understand and often predict flood behaviour is through modelling and, depending on the system at hand, a variety of models can be used (Teng et al., 2017).

In order to have adequate representation of floods, most models require large amounts of data. This is especially true for pluvial flood modelling, where flow gauging stations may end up being of little use. Remote sensing technologies are a part

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of the solution, as they offer spatially distributed information. However, their availability may be limited, also in terms of space and time and their uncertainties often are not quantifiable (Di Baldassarre et al., 2011; Grimaldi et al., 2016; Jiang et al., 2014; Li et al., 2017). Thus, acquiring the necessary data for simulations and predictions can still be expensive, particularly for rapidly changing systems that require frequent model updates.

In this context, sources of data coming in abundance and at low-costs are needed, together with modified modelling approaches that can use these data and can adapt to changes as fast as they occur. Citizen Observatory (CO) is an emerging concept in which citizens monitor the environment around them. It is often considered under the umbrella of Citizen Science (including citizen participation up to the scientist level) and it is also related to the concept of crowdsourcing (distributing a task among many agents). With technology at hand, it is possible to empower citizens to not only participate in the acquisition of data but also in the process of scientific analysis and even in the consequent decision-making process (Evers et al., 2016). Citizen Observatories have been researched in several EU-funded projects. Finished projects (CITI-SENSE, Citclops, COBWEB, OMNISCIENTIS and WeSenseIt) already resulted in valuable contributions to the field (Alfonso et al., 2015; Aspuru et al., 2016; Friedrichs et al., 2014; Higgins et al., 2016; Uhrner et al., 2013). The currently running CO projects (Ground Truth 2.0, LANDSENSE, SCENT and GROW Observatory) propose to investigate this concept further.

Citizen science concepts have been researched and applied in various fields such as ecology and galaxy inspection (Lintott et al., 2008; Miller-Rushing et al., 2012). Volunteer Geographic Information (VGI), as one of the most active citizen science areas, has developed over the past decade and several researchers reviewed the state of the art of citizen science in the field of geosciences (Heipke, 2010; Klonner et al., 2016). There is also a part of the scientific community dedicated to investigating damage data crowdsourced after flood emergencies (Dashti et al., 2014; Oxendine et al., 2014) and evaluating the cycle of disaster management (Horita et al., 2013). In the context of water resources, Buytaert et al. (2014) reviewed and discussed the contribution of citizen science to hydrology and water resources, addressing the level of engagement, the type of data collected (e.g. precipitation, water level) and case studies where more participatory approaches are being implemented. Le Coz et al. (2016) provided examples and reflections from three projects related to flood hydrology and crowdsourcing.

The present review aims to look at studies that had citizen science connected to floods and analyse in detail how the contributions were made so far in a modelling context. Moreover, we aim to detect the opportunities and challenges related to exploring citizen science for modelling the hydrodynamics of floods.

1.1 Citizen Science

Buytaert et al. (2014) defined citizen science as "the participation of the general public (i.e. non-scientists) in the generation of new knowledge". In the same manner that the involvement of citizens can be diverse, such is the way their participation is found in the scientific literature:

- Citizen Science (Buytaert et al., 2014)
- Citizen Observatory (Degrossi et al., 2014)
- Citizen Sensing (Foody et al., 2013)
- Trained volunteers (Gallart et al., 2016)
- Participatory data collection methods (Michelsen et al., 2016)
- Crowdsourcing (Leibovici et al., 2015)
- Participatory sensing (Kotovirta et al., 2014)
- Community-based monitoring (Conrad and Hilchey, 2011)
- Volunteer Geographic Information (Klonner et al., 2016)
- Eye witnesses (Poser and Dransch, 2010)
- Non-authoritative sources (Schnebele et al., 2014)
- Human Sensor Network (Aulov et al., 2014)
- Crowdsourced Geographic Information (See et al., 2016)

Some of the terms used by the above-mentioned articles have specific definitions that are used to delineate debates on the social mechanisms of citizen participation. Others are just the best form the researcher found to characterise the contribution or the citizen (e.g. eye witnesses). Citizen Science and adjacent areas have become fields of research in themselves that, for instance, focus on understanding the motivation of citizens or its interaction with public institutions (Gharesifard and Wehn, 2016).

In this field, one of the classifications of citizen science is by level of engagement. Haklay (2013) built a model that has four levels (Fig. 1), in which the first one refers to the participation of citizens only as data collectors, passing through a second level in which citizens are asked to act as interpreters of data, going towards the participation in definition of the problem in the third level and finally, being fully involved in the scientific enterprise at hand. The aim of the review presented in this current article is focused on the contribution towards flood modelling only, coming from the two lowest levels of engagement. Further in this article, data from these levels of engagement will be termed as crowdsourced data.

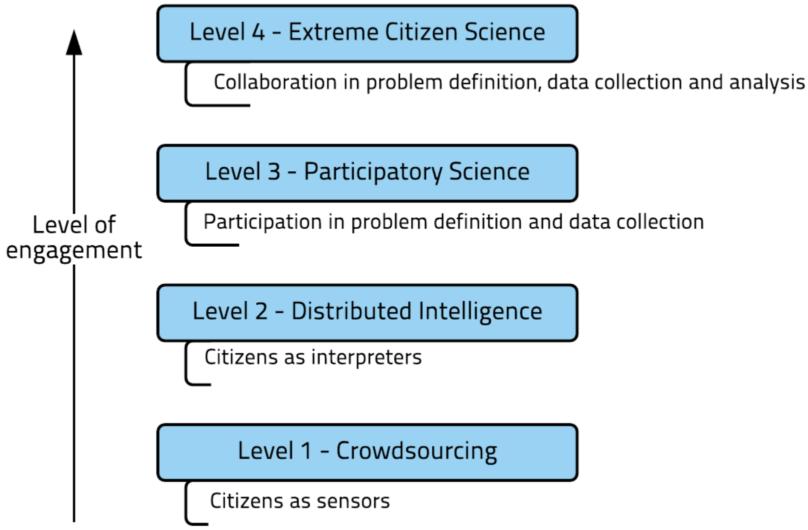

Figure 1: Levels of participation and engagement in citizen science projects. Adapted from Haklay (2013).

Another way to classify citizen science initiatives (within the context of VGI) is by setting them as implicitly/explicitly volunteered and implicitly/explicitly geographic (Craglia et al., 2012). For example, in the Degree Confluence Project (Iwao et al., 2006), citizens were oriented to go to certain locations, take pictures, make notes and deliberately make available their material on the project's website. In this case, the information is explicitly volunteered and explicitly geographic. Most land use/cover projects related to citizen science are explicitly geographic. Differently, in the study conducted by Lowry and Fienen (2013) citizens would also willingly send text messages to the researchers, in this case providing water level readings from installed water level gauges. Although explicitly volunteered, the message was non-geographic (just geo-tagged). Another type of implicitly geographic information was derived from Twitter by Smith et al. (2015) to obtain water level, velocity and flood extent estimates. As the citizens did not make the information public with the specific purpose to provide estimates, it is implicitly volunteered.

The concepts defined by Craglia et al. (2012) can be graphically represented as in Fig. 2. The SCENT project[1] (Smart Toolbox for Engaging Citizens in a People-Centric Observation Web) is one of the four Horizon 2020-funded projects focussing on citizen observatories. It lies in the middle of this quadrant as it encourages citizens to participate in gaming to collect land cover/use data, in field campaigns to collect other implicitly geographic information (e.g. water level), and also aims to obtain implicitly volunteered contributions through a CAPTCHA plugin, in which citizens tag images related to land cover/use in order to access online content.

[1] https://scent-project.eu/

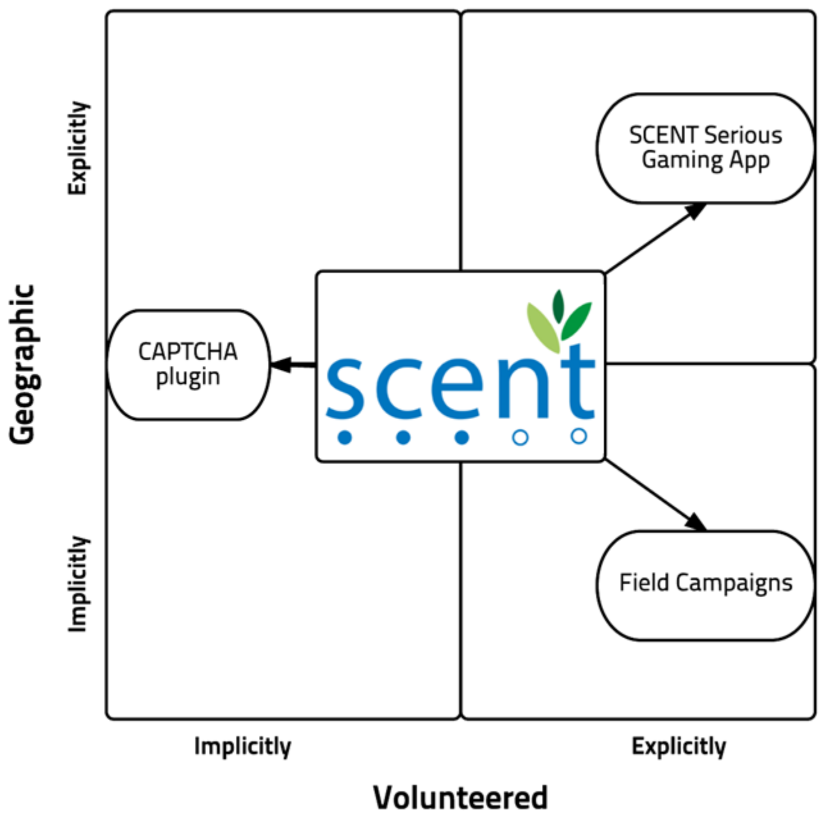

Figure 2: SCENT project represented in the typology of VGI (Volunteered Geographic Information)

1.2 Article outline

After this introduction, in Sect. 2 of the article, we overview studies on citizen contributions for flood modelling, classifying them according to the flood-related variable the contributions were made, followed by a summary of the pros and cons of measurement and analysis methods. Section 3 aggregates the studies that involve flood modelling and analyses the contributions considering the component of the modelling process where they were used, also including a discussion on the factors that affect flood modelling. Section 4 describes the challenges and opportunities of using data contributed by citizens in flood modelling, and finally, Sect. 5 presents the conclusions and recommendations.

2 Flood-related crowdsourced data

There are many types of data which relate to floods that can be collected by citizens. Likewise, there are many ways to collect, analyse and use them (for monitoring, mapping and modelling). In the next sub-sections we address how these aspects were explored in the scientific literature. Each sub-section discusses a data type corresponding to a flood modelling variable: water level, velocity, flood extent, land cover and topography. It needs to be noted that there are studies that just mention the use of crowdsourced data and do not provide more relevant information on collection, analysis and quantity of data, such as Merkuryeva et al. (2015). Some of the studies evaluate variables qualitatively, in ways that cannot be directly associated with modelling, therefore such studies are not included (Kim et al., 2011). Finally, there are articles mentioned and reviewed in more than one section because they evaluated more than one variable, as it is, for example, the case of Smith et al. (2015). It is worth mentioning that this review includes articles published up to April 2017.

2.1 Water level

Table 1 gives an overview of the articles about collection of water level data. The studies presented started to involve citizens in the collection of water level data with the explicit goal of improving flood management. This is due to the ease of collecting such data, which mostly consists of comparing the water level with a clearly defined reference. In some cases, the reference is a water level gauge, the comparison is made by the citizen, and readings are being submitted to the researchers (Alfonso et al., 2010; Degrossi et al., 2014; Fava et al., 2014; Lowry and Fienen, 2013; Walker et al., 2016). Such kind of reading practically do not require further analysis, although they entail the installation of water level gauges.

In other cases, mostly during flooding situations, citizens provide pictures (Fohringer et al., 2015; Kutija et al., 2014; Li et al., 2017; McDougall, 2011; McDougall and Temple-Watts, 2012; Smith et al., 2015; Starkey et al., 2017) or videos (Le Boursicaud et al., 2016; Le Coz et al., 2016; Michelsen et al., 2016). In the case of pictures/images, the water level is compared with objects in the images that have known or approximately known dimensions. For videos, although water level was estimated, the main goal was to obtain discharge values, via estimates of flow velocity. In two cases, texts from citizens were used, to provide directly quantitative water level values or assuming a certain value when no value was provided (Li et al., 2017; Smith et al., 2015). This sort of data (text, pictures and videos) was mostly collected through social media and public image repositories, requiring mining of the relevant material and dealing with uncertainties in the spatio-temporal characterization of the data of interest.

One aspect that varies across the studies is the level of detail in the comparison method used for determining the water level measurement. For example, McDougall (2011) and McDougall and Temple-Watts (2012) explicitly state that field visits to the selected photo locations are required in order to properly analyse the image and extract water level values. On the other hand, Fohringer et al. (2015), Smith et al. (2015) and Starkey et al. (2017) do not mention any method.

In most cases, crowdsourcing has been used to monitor water level, followed by the use of such data for modelling and lastly for mapping. In the case of Starkey et al. (2017), although hydrological modelling was done and water levels were converted into discharge to allow for comparisons, only qualitative comparisons were made.

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Table 1: Scientific literature on citizen contributions to measurement and analysis of water level

Study	Measurement/analysis methods	Type	Purpose	Case Study
Alfonso et al. (2010)	Citizen's reading of water level gauges sent by text message	1D	Monitoring	Polders in The Netherlands
Lowry and Fienen (2013)	Citizen's reading of water level gauges sent by text message	1D	Monitoring	Watersheds in the USA
DeGrossi et al. (2014)	Citizen's reading of water level gauge sent through app/webpage	1D	Monitoring	Flood Citizen Observatory in Brazil
Walker et al. (2016)	Citizen's reading of water level gauge collected and provided by the community	1D	Monitoring	Dangila *woreda* region in Ethiopia
Fava et al. (2014)	Citizen's reading of water level gauge sent through app/webpage	1D	Modelling	Flood forecasting in Brazil
Le Boursicaud et al. (2016)	LSPIV analysis of video collected from social media (YouTube)	1D	Monitoring	Flash flood in France
Le Coz et al. (2016)	LISPIV analysis of video sent through webpage	2D	Modelling	Flash flood in Argentina
Michelsen et al. (2016)	Analysis of images extracted from videos collected from social media (YouTube) and own photographs	Neither	Monitoring	Cave in Saudi Arabia
Li et al. (2017)	Analysis of texts and pictures collected from social media (Twitter)	2D	Monitoring	Flood map in the USA
Starkey et al. (2017)	Citizen's reading of water level gauge and analysis of pictures and videos collected from social media (Twitter) and crowdsourced (email, webpage and mobile app)	2D	Monitoring	Flood in the UK
McDougall (2011), McDougall and Temple-Watts (2012)	Analysis of texts and pictures collected from social media (Twitter, Facebook) and crowdsourced (email, text message, Ushahidi, Flickr and Picasa)	2D	Mapping	Flood map in Australia
Kutija et al. (2014)	Analysis of pictures collected by the University and City Council	2D	Modelling	Pluvial flood in the UK
Aulov et al. (2014)	Visual analysis of texts and pictures collected from social media (Twitter and Instagram)	2D	Modelling	Storm surge forecasting in the USA
Fohringer et al. (2015)	Visual analysis of pictures collected from social media (Twitter) and crowdsourced (Flickr)	2D	Mapping	Flood in Germany
Smith et al. (2015)	Analysis of texts and pictures collected from social media (Twitter)	2D	Modelling	Pluvial flood in the UK

2.2 Velocity

As velocities and discharges traditionally require more complex measuring methods, the collection of this type of data by citizens has not been explored on a scientific basis. However, it is common to include direct measurements of velocity in protocols to monitor the environment and water quality, as it is the case of Hoosier Riverwatch (IDEM, 2015). In these cases, the citizens perform measurements that involve more processing (e.g. definition of transects to measure flow, use of formulas).

To the best of the authors' knowledge, only three studies were found that make use of velocity data collected by citizens, all for the study of floods, as presented in Table 2. Le Boursicaud et al. (2016) evaluated the surface velocity field in a channel from a YouTube video, using the LSPIV methodology (Large Scale Particle Image Velocimetry), an established method to obtain velocity from a sequence of images. For enabling this analysis, information about the camera (model and lens type) is needed, visible, fixed elements are needed to be used as reference points and it is also required that both river banks are visible. Although the method calculates the velocity in two dimensions, in Table 2 we referred to it as 1D because it was carried out in a channel, which in a context of flood modelling is considered as a 1D domain. A complementary project was discussed by Le Coz et al. (2016), in which the same technique is applied to a video crowdsourced by a citizen, this time using the result to estimate discharge and the latter to calibrate a 1D hydraulic model. For this, a visit to the location was needed to extract cross-sectional data. In this context, Yang and Kang (2017) developed a method for crowd-based velocimetry of surface flows, based on Particle Image Velocimetry, in which citizens mark features in the picture. The method has not been tested with citizen collected data yet.

The third study, conducted by Smith et al. (2015), selected Twitter messages that include terms of semantic value related to the citizen location, water depth (e.g. knee-deep) and velocity. The terms were then associated with quantitative values/ranges. The authors did not go into detail on discussing the reliability and uncertainty in such data, even though the issue is recognised.

Table 2: Scientific literature on citizen contributions to measurement and analysis of velocity

Study	Measurement/analysis methods	Type	Purpose	Case Study
Le Boursicaud et al. (2016)	LSPIV analysis of video collected from social media (YouTube)	1D	Monitoring	Flash flood in France
Le Coz et al. (2016)	LISPIV analysis of video sent through webpage	2D	Modelling	Flash flood in Argentina
Smith et al. (2015)	Analysis of texts and pictures collected from social media (Twitter)	2D	Modelling	Pluvial flood in the UK

2.3 Flood extent

Flood extent, similarly to water level, is a variable that is simple to measure as it consists of binary values: flooded or non-flooded area. As a 2D variable, it needs a lot of spatial information and it is the main reason related studies gather flood extent estimates in data rich environments, through social media/Flickr/Picasa mining, as shown in Table 3. In some cases, the citizens act only as sensors, providing pictures to be analysed by the research team, while in other cases they also act as interpreters by providing the flooded/non-flooded information. As can be expected, all studies found were carried out in urban areas.

In some of the studies the text and images are indicating the location of their origin as being flooded (georeferenced or inferred) (Aulov et al., 2014; Smith et al., 2015; Yu et al., 2016), whilst in others (Cervone et al., 2016; Li et al., 2017; Rosser et al., 2017; Schnebele et al., 2014; Schnebele and Cervone, 2013) there is processing of the information to infer the surrounding inundated areas. Additionally, the last group of studies mentioned fused flood extent data from citizens with satellite data or with gauge data.

Table 3: Scientific literature on citizen contributions to measurement and analysis of flood extent

Study	Measurement/analysis methods	Purpose	Case Study
Cervone et al. (2016), Schnebele et al. (2014); Schnebele and Cervone (2013)	Analysis of pictures and videos collected from social media (Facebook and YouTube) and crowdsourced (Flickr)	Mapping	Flood maps in USA and Canada
Li et al. (2017)	Analysis of texts and pictures collected from social media (Twitter)	Mapping	Flood map in the USA
Rosser et al. (2017)	Analysis of crowdsourced pictures (Flickr)	Mapping*	Flood map in the UK
Aulov et al. (2014)	Visual analysis of texts and pictures collected from social media (Twitter and Instagram)	Modelling	Storm surge forecasting in the USA
Smith et al. (2015)	Analysis of texts and pictures collected from social media (Twitter)	Modelling	Pluvial flood in the UK
Yu et al. (2016)	Citizen's visual identification of flooded/non-flooded location collected by governmental Chinese website	Modelling	Flood in China
Padawangi et al. (2016)	Citizen information	Monitoring	Flood in Indonesia

* A statistical model is created, but in this study we consider only physical models in the modelling category

2.4 Land cover/Land use

Land cover is not a variable in flood-related models but we include it in this review for its importance in inferring roughness. Other valuable aspects of land use data are the information on roads and structures that can be obstacles to floods, which can be incorporated in the model structure; and the information on vulnerability (e.g. hospitals, dense residential areas, industrial zones), which can be used to obtain flood risk maps. According to Klonner et al. (2016), when reviewing the literature on VGI for natural hazard analysis, there are few studies for vulnerability analysis. The aspects of land use related to vulnerability and risk are complex and study topics on themselves, so these aspects are not discussed further in this article.
Table 4 presents the articles considered for this review. Compared to previously discussed variables, the contribution of citizens to land cover maps generation has been already proved as a concept (Albrecht et al., 2014; Fritz et al., 2012), nowadays being researched further for quality of data (Salk et al., 2016) and fusion of maps (Lesiv et al., 2016).

One of the first publications on the subject was from Iwao et al. (2006), in which they describe the Degree Confluence Project. The objective was to generate a global land cover map, which implies obtaining ground truth data from around the globe. For obvious reasons, it was unfeasible to make field campaign or analyse low-resolution images with sufficient resolution. Thus, they launched a webpage that invited citizens to visit integer coordinates (e.g. 25° W, 25°) locations, take photos from the four cardinal directions and provide comments on the region. They discovered that citizen-generated data was having quality similar to that provided by specialists.

Another significant project in the area is GeoWiki. It started in 2009 as a platform for people to validate global land cover maps, by comparing their classification to high-resolution images (Fritz et al., 2009). The project has grown since and has recently achieved its main goal: to generate a hybrid global land cover map by fusing existing maps and performing calibration and validation using the analyses made by citizens (See et al., 2015). Current initiatives in the GeoWiki project include gamification and analysis of pictures uploaded onto the platform (See et al., 2015). Many studies stemmed from the data collected, generally focused on specific land cover types. A similar approach is taken by Dong et al. (2012), that analyses pictures uploaded by citizens using a different web application. The research conducted by Dorn et al. (2014) goes one step further, as it attributes roughness values to multiple land cover maps, including Open Street Maps (a website where citizens can modify the current street and land cover map).

Table 4: Scientific literature on citizen contributions to measurement and analysis of land cover/land use

Study	Measurement/analysis methods	Purpose	Case Study
Iwao et al. (2006)	Visual interpretation of crowdsourced tagged pictures sent through app/webpage (Degree Confluence Project website)	Mapping	Global land cover map
See et al. (2015b)*	Visual interpretation of Google Earth and pictures sent through app/webpage (GeoWiki)	Mapping	Global land cover map
Dong et al. (2012)	Analysis of tagged pictures from Global Geo-Referenced Field Photo Library (DCP citizen pictures + field trip pictures)	Mapping	Forest cover map in Asia
Dorn et al. (2014)	Use of Open Street Maps	Modelling	Flood in Austria

* Many other articles related to crowdsourcing through GeoWiki

2.5 Topography

The Digital Elevation Model (DEM) is one of the most important components in flood modelling, as it generally heavily influences flood propagation. It is particularly important in urban settings, where spatial variability in refined scales has a considerable effect on the direction of water flows. Unfortunately, this is a complex variable to measure that so far relies either on fully trained professionals to go to the field, or on expensive airborne technologies. Recently, Shaad et al. (2016) studied a terrain capturing low-cost alternative to LiDAR remote sensing images and other expensive methods. The low-cost technique is the ground based close-range photogrammetry (CRP) that consists of collecting images/videos from the ground, post-processing them and obtaining terrain information. Volunteers made the videos in a designated location, where even Unmanned Aerial Vehicles (UAVs) would not be able to collect data. After comparing the results to other methods, they concluded that the result has an acceptable quality.

2.6 Summary analysis

Considering the temporal distribution of studies evaluated in this review, it is evident that there is a trend: the rise in a number of studies from 2014 onwards (Fig. 3). This relates to the initial barrier in acknowledging citizen data as having quality that is high enough for scientific studies (Buytaert et al., 2014). This resistance is reducing over time as such data has been proven useful, protocols are being designed and the data uncertainty is being better understood and quantified.

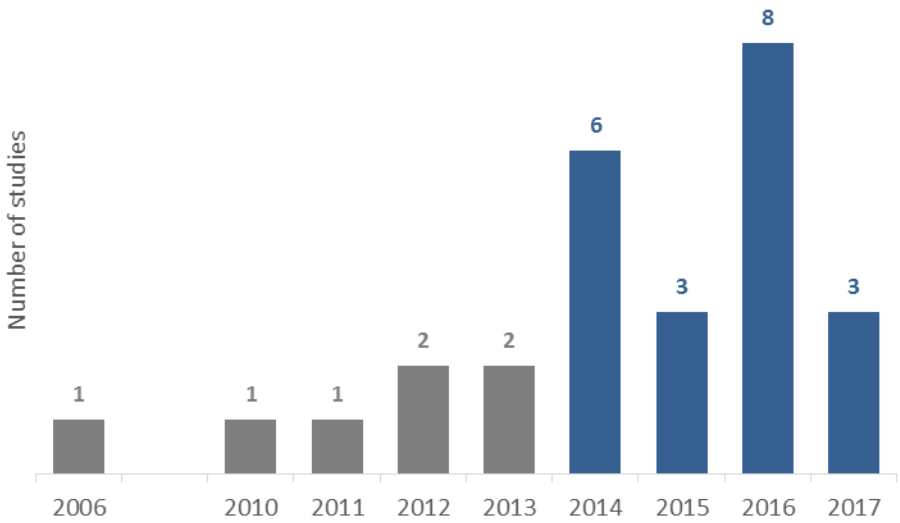

Figure 3: Number of studies analysed per year

If the analysed studies are aggregated into categories (Fig. 4), it can be seen that modelling studies amount to approximately the same quantity as monitoring ones, but they are only about a third of all studies reviewed. This is expected because to use data in models it is necessary to monitor them first. Also, monitoring and mapping applications attend to more general end uses. Specifically for land cover, there is an unexplored field in modelling (there are more mapping studies than the ones in the graph, see Sect. 2.4). The reason behind may be that modellers do not tend to validate their own land cover maps and thus will not do it with citizen science data. What can be noted though, is the lack of exploration of velocity and topography variables, which, as mentioned, can be due to the complexity in analysing and setting up the experiment.

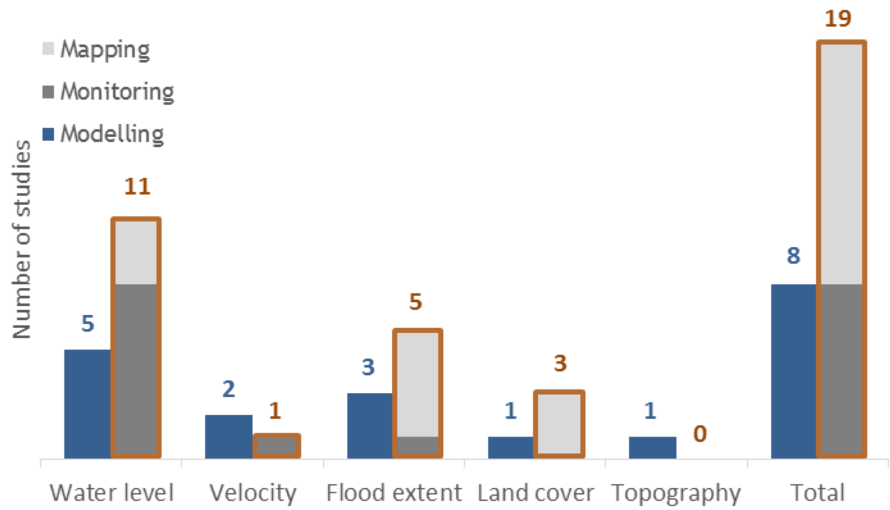

Figure 4: Number of studies analysed per flood-related variable per category: mapping, monitoring and modelling

Related to that, previous sub-sections discussed in detail the methods for collection and analysis of flood-related data obtained through crowdsourcing. For example, water level data obtained from reading a water level gauge is easy to collect and easy to analyse. On the other hand, it requires the installation of gauges (Fig. 5). In summary, whenever data is collected from the Internet, there is the disadvantage of needing social media/Flickr/Picasa mining, entailing computational efforts and dealing with a high percentage of data that is not georeferenced or time stamped. Further, in the case of water level and velocity, some studies suggest that also field visits are necessary and the methods to analyse data are complex. Considering crowdsourced data on flood extent, land cover and topography, it is straightforward to measure and analyse them, although their delivery to the interested parties requires a smartphone app or a web site to be set up and maintained (with the exception of Open Street Maps).

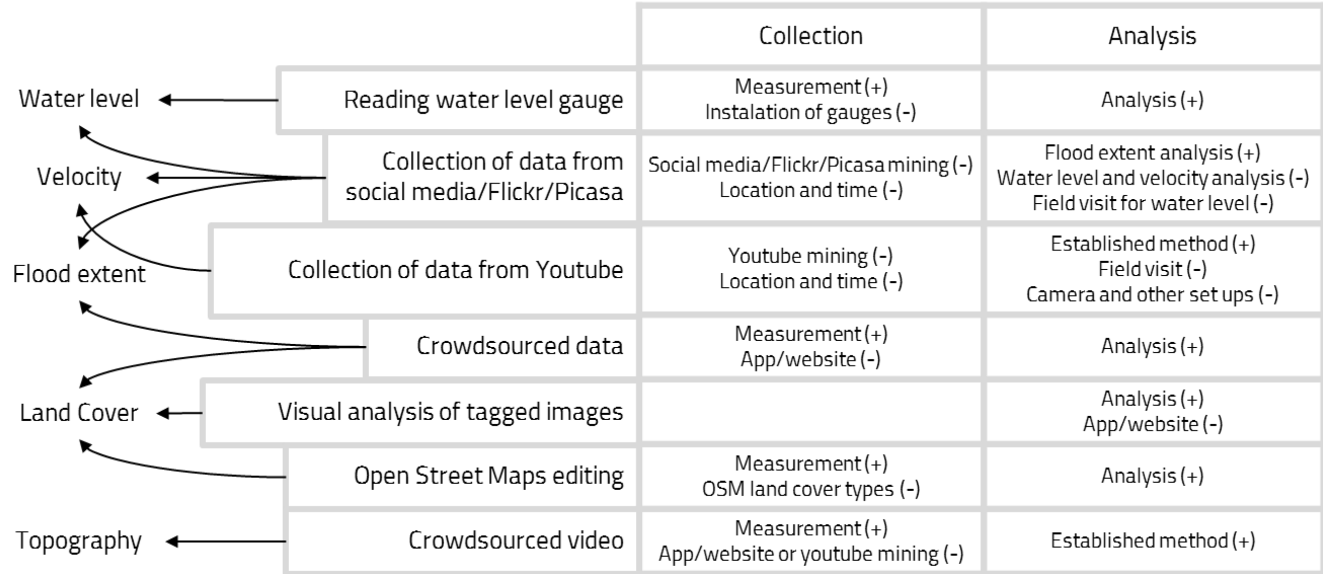

Figure 5: Pros and cons of collection and analysis methods used to collect flood-related data by citizens

3 Crowdsourced data in flood modelling

We have seen in the previous section that data related to flood modelling can be collected for many reasons, mainly monitoring, mapping and modelling. In this section we intend to explore in detail how the data was integrated into models.

The flood modelling process, typically involving hydrodynamic models, has two parts: model building, and model usage. (Fig. 6). Model building starts by defining the model setup (boundary conditions, parameters, schematization, input data), followed by calibration and validation of the water level and velocity fields (dependent variables) with observed values. Calibration and validation can be performed for both simulation and forecasting models. Once the model is ready, simulations can be run by using different boundary conditions or introducing designed measures for better flood management; or forecasts can be made by using forecasted water levels or discharges as boundaries. In a simulation setting, model parameters are assumed to be constant in time, while in a forecasting setting the parameters, inputs or states (water levels) can be updated while the model is in use, using data assimilation.

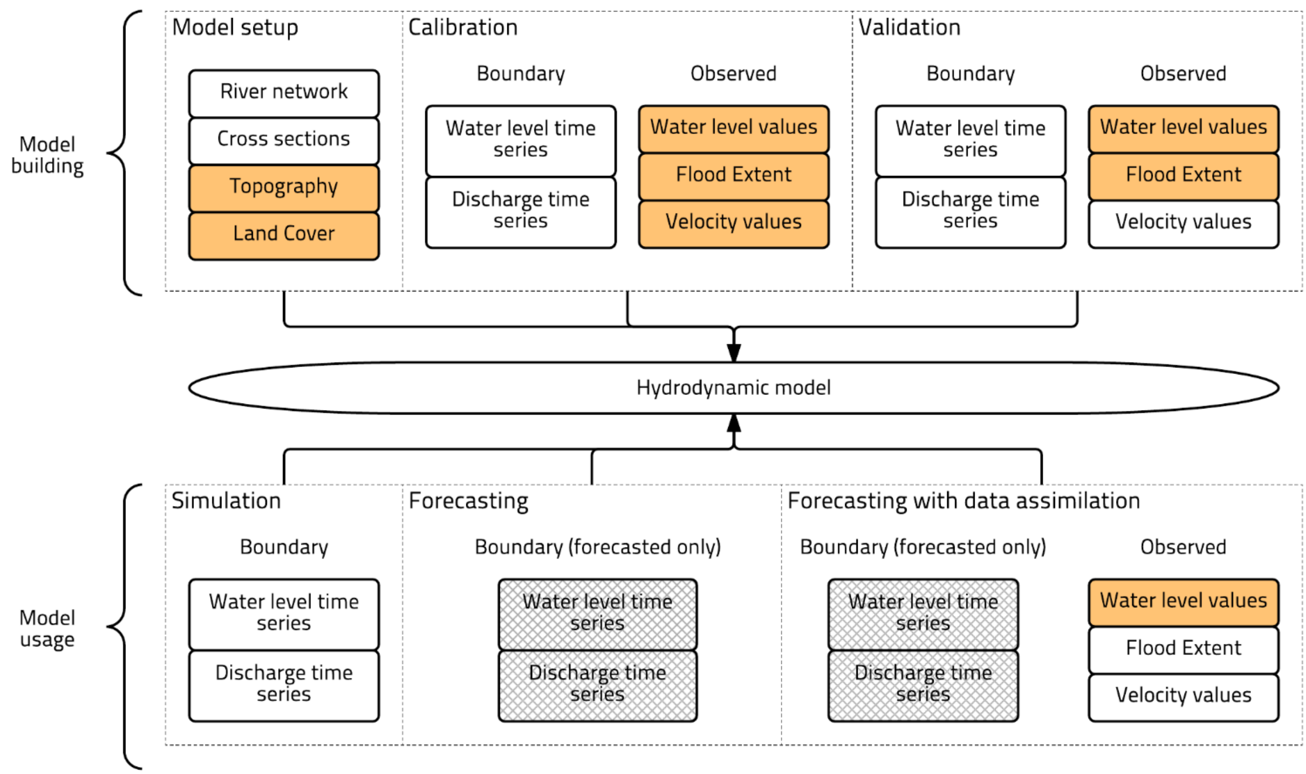

Figure 6: Flood models data requirements. Orange coloured tiles correspond to data that citizens have contributed to in a flood modelling context and gridded tiles correspond to data citizens cannot contribute to (forecasted water levels and discharges).

In view of this process, we analyse how the studies that were carried out in a modelling context included crowdsourced data into the model (Table 5). From the studies analysed, three consider 1D channels and the others worked in a 2D setting. Most of them analyse only one variable, except Smith et al. (2015) that evaluate water level and velocity. Moreover, most of them model urban floods, some in a pluvial and others in a fluvial context.

Table 5: Scientific literature on crowdsourced data used in flood modelling

Use in modelling	Study	Measurement method	Type	Variable	Case study
Model setup	Dorn et al. (2014)	Use of Open Street Maps	2D	Land cover	Flood in Austria
	Shaad et al. (2016)	Analysis of pictures captured by volunteers at selected location	2D	Topography	Flood in Indonesia
Calibration	Smith et al. (2015)*	Analysis of pictures and tweets collected from social media (Twitter)	2D	Water level and velocity	Pluvial flood in the UK
	Le Coz et al. (2016)	LISPIV analysis of videos sent through webpage	1D	Velocity	Flash flood in Argentina
	Yu et al. (2016)	Citizen's visual identification of flooded/non-flooded location provided through Chinese website	2D	Flood extent	Flood in China
Validation	Kutija et al. (2014)	Analysis of pictures collected from the University and City Council	2D	Water level	Pluvial flood in the UK
	Yu et al. (2016)	Citizen's visual identification of flooded/non-flooded location provided through Chinese website	2D	Flood extent	Flood in China
Data assimilation	Aulov et al. (2014)	Visual analysis of texts and pictures collected from social media (Twitter and Instagram)	2D	Water level and flood extent	Storm surge forecasting in the USA
	Mazzoleni et al. (2015, 2017)	Simulated citizen reading of water level gauge sent through app	1D	Water level	Flood forecasting in Italy and USA
	Fava et al. (2014)	Citizen's reading of a water level gauge sent through app or webpage	1D	Water level	Flood forecasting in Brazil

* It is classified as calibration because, in the classical sense, it improves the model according to observations. However, what actually is done is the fine-tuning selection of the precipitation field that fits the observations better.

Considering the model setup, citizens contributed to improving the datasets that are used in the model, both for Land Cover (Dorn et al., 2014) and the Digital Elevation Model (Shaad et al., 2016). The first case uses Open Street Maps, an online platform that provides maps, including land cover, which can be changed by citizens at any time. Dorn et al. (2014) do not analyse how much contribution was made by the citizens and data processing is restricted to attributing land cover classes to the features displayed in the maps. In the study of Shaad et al. (2016), which addresses topography, there is only one citizen contribution (low-cost alternative) in one selected location that is merged with an existing DEM. The objective was to compare the performance of this low-cost alternative against consolidated technologies' performance when used for hydrodynamic simulations.

Crowdsourced data has also been used to calibrate and validate flood models. We have found four studies that gather and use this information, one through social media and public image repositories mining and the others through data uploaded by citizens on specific platforms. Smith et al. (2015) aimed to do real-time urban modelling to identify possible flooded areas due to rainfall. Storm events were identified through social media, triggering shock-capturing hydrodynamic model runs with various rainfall intensities. The results were compared with social media data on water level/velocity. They defined a buffer zone around the crowdsourced observation location, built a histogram of simulated cell values within it and evaluated the overlap of the crowdsourced value/range and the histogram 70-95th percentile range. The selected simulation was the one with less rainfall, with more 'overlaps' and that would not perform better than a simulation with rainfall slightly higher. This was done because most contributions were considered as a minimum water level criterion.

Yu et al. (2016) collected flooded/non-flooded data through a Chinese website and divided it into calibration and validation data sets for a pluvial flood model verification. There is no mentioning on how this data is provided. Le Coz et al. (2016) obtained a discharge value for calibration of a hydraulic model based on the surface velocity data obtained by a video uploaded to a specific website. Kutija et al. (2014) collected pictures uploaded by citizens and extract from them water levels by comparison with reference objects, such as cars (no further detailing on the method of extraction is made). Water level data is then used to validate a pluvial flood model.

All the described approaches so far consider citizen data for model building and its possible extension for recalibration and revalidation. The studies of Mazzoleni et al. (2015, 2017) went one step further, as they incorporate crowdsourced data while the model is being used. This is done through data assimilation algorithms, adapted to deal with intermittent data. Aulov et al. (2014) and Fava et al. (2014) also used the data for simulation/data assimilation instead of setup, but the methods used are not detailed in the studies.

3.1 Crowdsourced data information content

If we aim at integrating data into model, data accuracy, volume and temporal and spatial coverage should be at a certain level. When these data properties are inadequate, data integration would not provide useful results. Although most modelling variables vary in time and space, the data does not need to cover all dimensions in all parts of the modelling process. For instance, in model setup, topographic data is not needed every 15 minutes, hourly or daily; it can be provided in a discrete time coverage, from months to years. We analyse four data properties: temporal coverage, spatial coverage, volume and uncertainty (Table 6). Although same for all parts, the last two properties vary significantly when analysing the information content of crowdsourced data and that is why these properties are included (Table 6).

Table 6: Data properties currently required in the modelling process

	Setup	**Calibration & Validation**	**Simulation**	**Data assimilation**	**Data assimilation**
	Topography *Land Cover*	*Water Level* *Velocity* *Flood Extent*	*Water Level* *Velocity*	*Water Level* *Velocity*	*Flood Extent*
Temporal coverage	Discrete	Discrete	Continuous	Variable	Variable
Spatial coverage	Distributed	Distributed	Discrete	Discrete	Unknown
Uncertainty	The lower the better				
Volume	The higher the better				

Analysing crowdsourcing studies by their information content, it is possible to draw the following conclusions:

- Model setup: for integration of topographic and land cover data, it is necessary to have spatially distributed data. While this has been achieved within land cover studies, there is only one study involving topography and the data obtained so far have discrete spatial coverage.
- Calibration and validation: through mining of water level and flood extent estimates from social media and open image repositories, spatially distributed crowdsourced data have already been acquired and integrated and that is why there are more studies related to this modelling stage.
- Simulation: traditional modelling efforts require time series of data at specific frequencies, which has only been achieved through crowdsourcing in the realm of community-based approaches, in which water levels are measured at 6 a.m. and 6 p.m. in agreement with the community (Walker et al., 2016). However, this type of data has been only monitored and not used in a modelling context so far.
- Data assimilation: it generally assimilates data provided with a fixed time frequency, but there are a few studies that consider intermittent data to be assimilated (Mazzoleni et al., 2015, 2017). However, similarly to simulation, the temporal coverage of crowdsourced data is insufficient for data assimilation efforts.

Considering uncertainty, this is highly dependent on the collection/analysis method. For example, obtaining water level values in flooded areas (2D) is uncertain, as it mostly involves the selection of what constitutes a good reference point to be made by the citizen. Flood extent, on the other hand, tends to be less uncertain, due to its binary nature. Regarding volume of data collected, this is an issue for all processes, although data mining has again been able to provide a better coverage. The challenge of data mining, however, lies in providing less uncertain data, in terms of value, geo-referencing and time stamp, and also in providing data in conditions that are not extreme, as most of the contributions are done in floods situations. Data mining is also limited to certain variables (water level, flood extent and velocity).

4 Opportunities and challenges

In the last years, the interest in citizen science and the number of citizen science studies in the water resources context has risen considerably. The main factors affecting its use in flood modelling are the degree of how difficult it is to acquire and evaluate these data and their integration into the models. Our analysis of the existing literature allows for pointing out a number of positive experiences from which we can derive opportunities to:

- Explore and improve the existing methods to obtain water velocity and topography from videos
- Explore calibration and validation employing data collected through social media in urban environments
- Explore the possibilities of setting up the models with the use of land cover maps validated with citizen science
- Make use of apps/websites already developed for citizen science

The first one is based on small scale but successful studies related to using well-developed techniques in a citizen science scenario. The relevant experience in data gathering and analysis can be updated to fit the needs of flood modelling. Also, social media and public image repositories mining has proved to be successful in calibration and validation in modelling studies, proving the concept and opening the opportunity to investigate how large this contribution is. As mentioned previously, in the field of land cover map generation citizen data has been used to validate maps and this successful example could be used to obtain new roughness maps in a modelling context. Lastly, technological development of apps, websites and techniques could be shared and put to public use, to be tested further and to avoid duplicated work.

There are aspects of interactions between citizen science and water resources that are still challenging. These are:

- Explore the use of citizens as data interpreters
- Improve methods to estimate water level from pictures
- Harmonise the time frequency and spatial distribution of models with the ones of crowdsourced data
- Deal with the uncertainty
- Increase the volume of data gathered, mainly in non-urban environments

Most of the analysed studies regard the citizen as a sensor, with the exception of studies about land cover related data, in which the citizen also acts as an interpreter. For other variables, some studies have already started evaluating the ability of citizens to provide interpreted information (Degrossi et al., 2014), but these are few. Regarding water levels, readings from rulers and extraction from pictures are described differently in the literature, with varying degrees of thoroughness, indicating a need for development and testing of water level measurement methodologies in the context of citizens' contributions. The third point brings up a challenge that concerns not only citizen science but also modelling: what is the necessary temporal and spatial distribution? Is the traditional modelling approach definitive in terms of data requirements and citizen science approaches should adapt to it, or, the modelling process can be adapted to receive citizen science data? The fourth challenge relates to the quality of data and, again, in the area of global land cover maps some articles have already discussed the subject (Foody et al., 2013), but still, when modelling is concerned, the crowdsourced data are treated as traditional data and the issue of quality is hardly addressed (albeit recognized as an issue). To which extent does this assumption hold? What is the uncertainty in citizen science data? Lastly, there is a challenge mentioned by many studies but not really addressed in itself and it is the volume of data. Although the volume of data necessary depends on the objective of the modelling effort, the volume of crowdsourced data tends to be low, lacking temporal/spatial coverage for integration into models. This leads to the question: How to increase the volume of data? Considering this limitation, it is also natural to move towards the question: How much data is needed to improve the model significantly?

Application of citizen science in modelling brings an extra challenge of interdisciplinary. Among similar technical fields (e.g. geosciences and hydrodynamic modelling) there is an issue of technology transfer to be addressed, and there are discussions on underlying assumptions and uncertainties that need to be considered. Additionally, hard and soft sciences are also very linked, as the quality and value of the citizens' observations and their temporal/spatial coverage are intrinsically related to social drivers such as why citizens engage, for how long, with which frequency and what is the role of various stakeholders.

5 Conclusions and recommendations

Citizen science has successfully made its way in many scientific domains and it is only fair that the contribution of citizens to modelling floods is also investigated, due to the related intensive data needs. Analysis of literature clearly shows an increasing number of scientific studies in this area. Successful examples of using existing measurement and analysis methods (e.g. velocity and land cover) and of modelling floods with citizen science data (e.g. social media mining) have been published and are seen as a good basis for further exploration. There is a clear need to standardise and consolidate methodologies and there are challenges involving temporal and spatial distribution of data, uncertainty and volume.

It can be observed that the role of citizen contributions is not only in providing information about the current state of the environment, in monitoring and mapping studies, but also in providing data that can be used in its modelling and forecasting. Studies reviewed in this article showed that crowdsourced data can be integrated: in model building, to improve their overall performance; and directly into models (by data assimilation), to improve immediate forecasts. These are promising studies, however still too few, and they highlight the need for further work in this direction. The integration of crowdsourced data into flood models is a viable way to help solve issues of data scarcity in both ungauged catchments and systems subject to change.

One of the challenges worth mentioning is the integration of citizen data with other more traditional data sources like gauging and remote sensing. It is also necessary to analyse cases in which citizens are involved at higher levels of engagement (e.g. participating in the problem definition, analysis of results and even in the decision-making process) and to evaluate the trade-off between model data needs and levels of engagement.

Finally, there is the challenge to make citizen contributions valuable in a time where automation in gaining increasing space. One may say that citizens are not needed because of automated sensors. At the same time, there are situations where crowdsourced data are very valuable. One of the non-technical challenges that we see here is to demonstrate such situations and increase acceptance of crowdsourced data by water managers.

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