

Opportunities for crowdsourcing in urban flood monitoring

Alysha M. Helmrich^{a,*}, Benjamin L. Ruddell^b, Kelly Bessem^b, Mikhail V. Chester^a, Nicholas Chohan^b, Eck Doerry^b, Joseph Eppinger^b, Margaret Garcia^a, Jonathan L. Goodall^c, Christopher Lowry^d, Faria T. Zahura^c

^a School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ, USA

^b School of Informatics, Computing, and Cyber Systems, Northern Arizona University, Flagstaff, AZ, USA

^c Department of Engineering Systems and Environment, University of Virginia, Charlottesville, VA, USA

^d Department of Geology, University at Buffalo, Buffalo, NY, USA

ARTICLE INFO

Keywords:

Urban hydrology
Flooding
Crowdsourced data
Data integration

ABSTRACT

Flooding is the most common natural hazard, leading to property damage, injuries, and death. Despite the potential for major consequences, urban flooding remains difficult to forecast, largely due to a lack of data availability at fine spatial scales and associated predictive capabilities. Crowdsourcing of public webcams, social media, and citizen science represent potentially important data sources for obtaining fine-scale hydrological data, but also raise novel challenges related to data reliability and consistency. We provide a review of literature and analysis of existing databases regarding the availability and quality of these unconventional sources that then drives a discussion of their potential to support fine-grained urban flood modelling and prediction. Our review and analysis suggest that crowdsourced data are increasingly available in urban contexts and have considerable potential. Integration of crowdsourced data could help ameliorate quality and completeness issues in any one source. Yet, substantial weaknesses and challenges remain to be addressed.

1. Introduction

Flooding is one of the most common, and amongst the most damaging, natural hazards in the United States (National Academies, 2019). The vast majority of flood risks to life and property are concentrated in cities (Ashley and Ashley, 2008). Cities are particularly vulnerable to pluvial flooding, which occurs when high volumes of stormwater runoff exceed drainage capacity in developed areas (National Academies, 2019). Another portion of this flood vulnerability arises when urban development expands into marshes and floodplains increasing fluvial and coastal flooding (Vidal, 2017). Further complexity is added by a non-stationary climate, meaning the future climate cannot be predicted by historical trends (Chester and Allenby, 2018; Milly et al., 2008). Extreme precipitation events are increasing in magnitude and, in some regions, increasing in frequency (Larsen et al., 2009; Minnerly and Smith, 1996; Prein et al., 2017; Schreider et al., 2000). Additionally, low magnitude, high frequency events may have consequences that exceed that of extreme precipitation events as seen with nuisance flooding (Moftakhari et al., 2017). This leads to questions regarding the adequacy of stormwater infrastructure design standards and development

approaches used to address flood vulnerability (Markolf et al., 2020; Zevenbergen et al., 2008).

Consequences of urban flooding include physical and non-physical direct impacts, indirect impacts, socioeconomic ramifications, and risks to human life and health, highlighting the interdependencies of infrastructure systems in urban spaces (Kim et al., 2017; König et al., 2002; Markolf et al., 2019; Rosenzweig et al., 2021). These compounding impacts place a higher pressure on decision-makers and emphasize the need for urban flood monitoring. We refer to this set of decision-makers as flood managers, or practitioners and researchers who monitor, model, and manage urban flooding. Despite the recognized impacts, urban flood monitoring and forecasting remains extremely limited and unreliable, largely due to a lack of water level and stream-flow data availability at the very fine spatial scales at which urban flooding occurs (Rosenzweig et al., 2021). While the majority of precipitation data are collected in cities (National Oceanic and Atmospheric Administration (NOAA), 2017), it is coarse-scale and, mostly, rural river flow observations that are used to predict flooding (United States Geological Survey, n.d.). Despite the 8,000+ streams that are currently gauged and operated by the United States Geological Survey (USGS) or

* Corresponding author.

E-mail address: ahelmric@asu.edu (A.M. Helmrich).

other local agencies, these groups do not have the capacity to cover fine-scale urban drainage systems—for instance, surface drainage (e.g., roadways) or subsurface drainage (e.g., stormwater systems)—or the nearly 400,000 named streams and the hundreds of thousands of undocumented streams throughout the United States (Wagner and Eberts, 2020) (Fig. 1). From the purely practical perspectives of size, cost, manpower, and physical access, the professional-grade gauging used by the USGS and local flood agencies to monitor streamflow could never be deployed at scale in an urban landscape. For these reasons, existing tools for urban flood monitoring, modelling, and warning are widely recognized as incomplete (National Academies, 2019). For example, the National Water Model, which simulates flooding in 2.7 million waterways at a 250 m resolution, is unable to resolve the "human-scale" urban streams, wetlands, floodplains, and stormwater basins that mitigate or exacerbate flooding in cities (Viterbo et al., 2020). Much less monitor flooding directly within the cities themselves. Decision-makers, infrastructure managers, and citizens are not connected to adequate flood monitoring and forecasting where they arguably need it most—in their backyards and streets. Alternative technologies provide a practical source for hydrological data and may have added benefits that traditional stream gauging does not.

The continuing rapid evolution of sensor network and data fusion technologies may provide a solution. What cities currently lack in formal scientific infrastructure for stream and flood monitoring, they make up for in an abundance of people and a rapidly increasing density and variety of sensor and communication systems that exist for a multitude of reasons, such as citizen cell phones, traffic cameras, private and municipal webcams, social media streams, and increasingly sophisticated on-board sensor packages in vehicles. The term crowdsourcing denotes the opportunistic collection of data from otherwise autonomous dispersed sources. For the purposes of this discussion, we will use the term to refer collectively to novel, independent data sources with a focus on public webcams, social media, and citizen science. Citizen science, an extension of crowdsourcing, is a collaborative science technique, where professional scientists can partner with amateurs to collect and, in some cases, process scientific observations (Assumpção et al., 2018). Crowdsourcing allows for near-real-time observational data to be collected in exactly the right place at the right time, i.e., in the exact locations where localized flooding occurs and creates impacts on people's activities.

To build flood monitoring and forecasting capacity in urban areas, we assert that crowdsourced data could be collected, integrated, and merged with formal hydrological observations like stream or pipe flow gauges, manual field methods, rain gauges and rain radars, or satellite remote sensing. Numerous crowdsourced data sets exist and are readily-accessible, including street-level traffic cameras, public webcams, social media posts, and citizen science approaches (Huwald et al., 2015; Lowry and Fienen, 2013; Sadler et al., 2018; Schnebele et al., 2014).

Crowdsourced data have shown potential to help identify flood events and promote preparedness and adaptation in disaster risk management (Hultquist and Cervone, 2020; Paul et al., 2017). However, the capacity of crowdsourced and citizen science data to specifically support urban flood monitoring and forecasting has not been synthesized to date. A first step towards answering this question is a comprehensive survey of literature and investigation of existing databases in respect to what crowdsourced data are available; the nature, quality, and completeness of data they each provide; and their potential for helping support a viable data foundation for urban flood monitoring.

Throughout this paper, we report on the feasibility of crowdsourced data integration in the context of our larger effort to develop a "smart city" infrastructure for managing urban flooding. The following section (Section 2) identifies twelve qualitative and quantitative metrics to assess the capabilities of crowdsourced data for urban flood monitoring and introduces the examined crowdsourced data: public webcams and traffic monitoring infrastructure, social media, and citizen science. We structure the subsequent analysis as two separate components: a literature review that expands beyond urban flood monitoring to assess the feasibility of each data source (Section 3) followed by presentation of case studies that investigate the feasibility of existing databases, ranging in spatial and temporal scales but unified through reasonable expectation to support urban flood monitoring (Section 4). For public webcam and social media databases, emphasis is placed on directories based in Arizona. Notably, cities within Arizona are representative of other modern U.S. cities in terms of infrastructure and technology, indicating that these technologies can be found across the country. In Section 5, we examine a case study beyond Arizona in Norfolk, Virginia. We extend our boundary to Norfolk due to the emphasis of public safety and integration of flood managers within the highlighted citizen science project, showcasing a key advantage of urban flood monitoring not seen in existing projects examined in Arizona. In Section 6, the opportunities and challenges for each data source are evaluated. In Sections 7 and 8, we conclude with recommendations to improve integration of the diverse crowdsourced data to provide a reliable basis for urban flood monitoring and forecasting.

2. Identifying metrics of capability of crowdsourced data for urban flood monitoring

The data types relevant and useful for flood modelling and forecasting including stage (i.e., water level), streamflow, precipitation, snowpack, soil moisture, ground temperature, topography, vegetation dynamics, soil type, and land cover data (United States Geological Survey, n.d.) are often too coarse to capture the level of heterogeneity appropriate for urban spaces, where flooding is driven by high concentrations of impervious surfaces. Furthermore, flood forecasting in

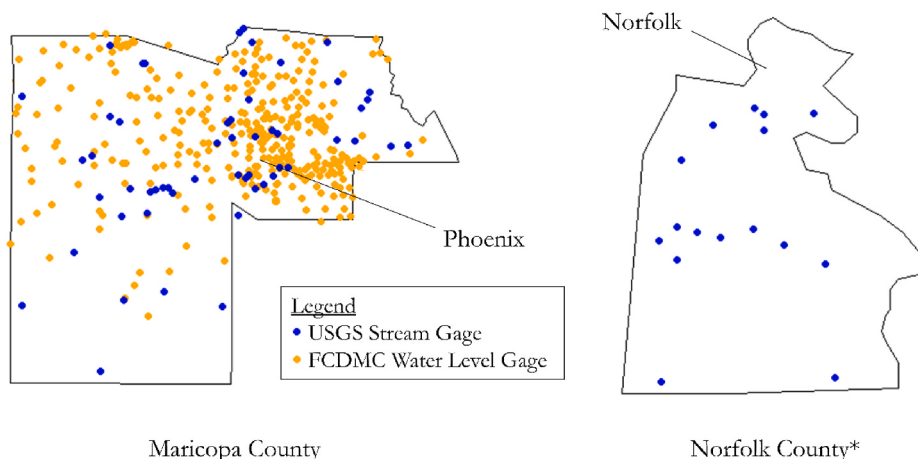


Fig. 1. Active surface-water gauges with instantaneous data available in the metropolitan regions of Maricopa County (left) and Norfolk County (right). Blue circles represent USGS stream gauges that have recorded data in the previous five years, and orange circles show operational water level gauges of the Flood Control District of Maricopa County (Flood Control District of Maricopa County, 2020; United States Geological Survey (USGS), 2020). The quantity of gauges does not provide fine-scale data for urban flood monitoring. Maps were computed using R statistical software (RStudio 1.1.383) and packages *sbtools*, *dataRetrieval*, *sf*, *readr*, and *maps*. *Norfolk County, as depicted, is comprised of multiple independent cities, including Norfolk, Portsmouth, and Chesapeake.

urban environments is not only an ecological and technological problem but a social one, where risks, vulnerabilities, and priorities must be considered (Rosenzweig et al., 2021; Uusitalo et al., 2015). Y. Wang et al. (2018) identified four primary drivers of inaccuracies in urban flood modelling:

- 1) the spatial resolution of the topographic representations of terrain and urban key features;
- 2) the lack of calibration and validation data;
- 3) the approach used to consider the effects of underground urban drainage infrastructure (drainage capacity); and
- 4) the uncertainty of accelerated land use changes in long-term modelling.

Crowdsourced data could potentially serve to address the uncertainty posed by localized topographic and land cover variations and insufficient calibration and validation data, by providing context-specific observations (Assumpção et al., 2018; Uusitalo et al., 2015; Y. Wang et al., 2018). Three data sources—public webcams, social media, and citizen science—were chosen for analysis due to their potential for providing a large volume of observational data points at a spatially-relevant, urban scale and offering accessibility for immediate implementation and integration into urban flood monitoring. These data sources can be characterized as either secondary, where data is being opportunistically harvested from a data source established for another purpose, or directed, where the data source was purposefully put in place to collect water level data. Thus, the ‘public webcams’ and ‘social media’ data sources are commonly secondary sources, while ‘citizen science,’ as explored here, is a directed data source. We identified twelve metrics to assess the practical value of novel data sources to augment urban flood modelling: accessibility, format, data type, quantity, frequency, relevance, density, urban, location, durability, real-time, and nighttime. Each metric is defined in Supplementary Materials, Appendix A, Table 1. These metrics allow us to assess the novel data sources capacity to augment urban flood monitoring. Throughout the survey of literature and investigation of existing databases, there are occasions in which the data source is not applicable to a metric, in which the metric is omitted, or does not provide enough information to calculate the metric, in which the value is omitted.

3. Crowdsourced data assessment: academic literature

3.1. Public webcams

For the purposes of our analysis, public webcams refer to any sort of video camera accessible via the internet and able to provide still images or videos of flood-prone areas or drainages. These include personal or municipal webcams freely accessible to the public, as well as restricted access networks of cameras managed by city, state, or federal agencies that are accessible through negotiated access agreements. For instance, transportation departments across the U.S. host traffic cameras to monitor traffic conditions, which can be impacted by vehicular accidents and weather events. Nearly all of these cameras capture flood-related imagery.

In general, webcam imagery combined with sophisticated automated image processing has tremendous potential as a data source, allowing extraction of a wide range of data—such as sensing turbidity (Leeuw and Boss, 2018) or determining vegetation phenology (Richardson et al., 2018). The technique has also been explored in the field of hydrology with studies quantifying the accuracy of water-level image processing. While water stage extraction from images is a proven technology, the number of studies mobilizing pre-established webcams and traffic cameras is limited. Five studies were examined that use publicly available webcams for image processing to assess the feasibility of deploying the technology to urban flood monitoring. Brief descriptions of each study are available in Supplementary Material, Appendix B, Table 1. Six

metrics of capability are evaluated: quantity, frequency, relevance, density, urban, and accuracy. Quantity is defined by the total number of cameras available to the researchers within their broader study scope. Frequency represents the refresh rate of the webcam. If an exact refresh rate is unknown, qualitative indicators in the study are listed: “Continuous” is representative of real-time feedback; “Varies” indicates that the cameras are refreshed at unique intervals as specified by the listed range; and “Consistent” indicates there was a reported minimum common refresh rate for all cameras. Relevance is the total number of webcams utilized for the study analysis. Within the literature review, a camera may be considered irrelevant if it was of low resolution, low refresh rate, or down for maintenance. Additionally, a camera was irrelevant if it did not capture the subject of interest. For example, Castelletti et al. (2016) sought to capture images of mountains; therefore, the camera needed an unobstructed view of a mountain to be considered. Density is calculated by dividing the number of relevant webcams by the area of the study region. Urban spaces are defined as having a population greater than 50,000 people (Cromartie, 2019), and the urban metric is calculated as a percentage of observations that were located in an area with a population greater than 50,000. The omitted metrics include format, accessibility, data type, location, durability, real-time, and nighttime. The format for all studies was video, and all streams were publicly accessible due to constraining our study to public webcams. The public webcams are a secondary data source that are not designed to capture data pertaining to urban flood monitoring. All webcams provided point data. The real-time metric is captured in the frequency metric (noted as “Continuous”). Durability of the cameras and nighttime data were not confirmed in the majority of studies. An assessment of the capability metrics across studies is presented in Table 1, which emphasizes the importance of webcams being properly positioned to provide relevant data.

While the presented studies expand beyond hydrology, initial research utilizing private cameras have shown an average error of 1.5 cm for reading water levels from image processing (Eltner et al., 2018; Jiang et al., 2020; Kim et al., 2008; Lin et al., 2018; Ran et al., 2016; Schoener, 2018; Shin et al., 2008; Zhang et al., 2019). Accuracy and precision values reported by each study may be found in Supplementary Materials, Appendix C, Table 1. The main limitations to improved accuracy and precision throughout these hydrological studies are attributed to camera movements, vibration in mounting structures, and abrupt movements of the water level as well as ambient noises, such as vegetation, weather, and variances in lighting and reflection.

This introduces a prevalent challenge of webcam image processing:

Table 1

Assessment of Public Webcams as Presented in Academic Literature: Public webcams, when placed in opportune areas, can provide highly relevant data.

	Quantity total # cameras available in area	Frequency image capture rate	Relevance total # relevant cameras	Density relevant camera/ km ²	Urban %
Bothmann et al. (2017)	13,988	Varies (1–60 min)	13,095	–	–
Castelletti et al. (2016)	3,500	Varies (1–60 min)	62	1.8	0
Guastella and Smith (2014)	10	Consistent (at least daily)	4	1.176 ^a	25
Morris et al. (2013)	1,800	Continuous	650	0.0049	–
Murdock et al. (2013)	2,772	Continuous	2,000	0.0002	–

^a Reported per km as project measured along beach.

nighttime data. Nighttime use of public webcams has been either deemed irrelevant (Bothmann et al., 2017) or unusable due to poor low-light performance (Murdock et al., 2013). In the Gilmore et al. (2013) study, an inexpensive wireless surveillance camera with infrared (IR) lighting for night vision was used to test an image-based water-level measurement system. This study was completed in a laboratory setting and had lower error values than the outdoor-based studies previously presented. It does provide a comparison for root mean squared error (RMSE) between day and nighttime lighting. While the nighttime observation RMSE hovered around 0.3 cm, the daytime RMSE was 0.2 cm. The study attributed most of the nighttime error to IR glare, which they deemed correctable. Though further research is needed, preliminary use of IR-capable cameras for nighttime water level appears to be plausible. The challenge may be addressed by sufficient nighttime lighting, which is available in many urban locations.

3.2. Social media

Social media are virtual platforms that allow individuals to share information with other platform members, including text messages, photos, videos, and links to other online information. Social media have two potential roles in urban flood monitoring: 1) they can serve as a directed or secondary data source to inform flood managers of flooding, and 2) the platforms can be used to notify people of potential flooding hazards. To explore the feasibility of utilizing social media to collect flood-related observations, academic articles assessing the ability of various social media platforms to gather data from flooding events around the world were reviewed. Most of these articles sampled high volumes of data from flood events in cities such as Newcastle-upon-Tyne, UK and Dresden, Germany (Fohringer et al., 2015; Smith et al., 2015). Descriptions of each article can be found in Supplementary Material, Appendix B, Table 2. Based on the information provided by the articles, we established seven metrics of data source quality and utility as a framework for our evaluation: quantity, frequency, relevance, density, urban, location, and durability. Quantity, relevance, density, urban, location, and durability are calculated following the same procedure presented for webcams but using a unit of posts where applicable. Relevancy for these articles varied by author. A few factors considered were context in which keywords (e.g., flood) were used, general location and time to explore a specific precipitation event, and georeferencing. Frequency is reported by the quantity of posts divided by the number of event days. Location is a categorical variable for spatial scale, depicting if the webcams provided point, neighborhood, or city georeferencing. Durability indicates the number of years the webcam

directory has been active. The five omitted metrics included format, accessibility, data type, real-time, and nighttime data. While the analyzed platform gives indication of format (e.g., Flickr primarily consists of image posts), the studies did not typically report a breakdown for mix-media platforms such as Twitter. The analyzed social media platforms of each study are listed in the descriptions. Due to being a secondary source, urban flood monitoring data was not intended to be captured by the platforms. Data accessibility of various social media platforms is explored in Section 4.2, and the data accessibility of these particular case studies are irrelevant. The use of nighttime data was not distinguished by the presented studies and, therefore, excluded. All studies reported real-time data availability through Twitter except for Rosser et al. (2017), which used Flickr data. Furthermore, Jongman et al. (2015) paired Twitter data with satellite data, and Fohringer et al. (2015) paired Twitter data with Flickr data. Upon reviewing these metrics in academic literature (Table 2), we see social media provides an opportunity to collect large quantities of real-time information, but georeferencing yields a significant challenge to obtain relevant data.

The use of social media as a means of quantitative data collection can introduce problems as social media users may not collect the most accurate or most quantitatively viable data (Fohringer et al., 2015). However, de Albuquerque et al. (2015) found that a social media user's physical proximity to flood-affected zones significantly increased the likelihood of flood-related social media observations on Twitter. A further obstacle to extraction of real-time flood stage data from social media of any sort is that geo-location of posts on these platforms is highly limited. Although some of the platforms provide an option for users to geo-located their posts with exact GPS coordinates, most users decline to do so, meaning that posts are, at best, roughly located by the social media platform (e.g., "North Phoenix"). In other cases, no geo-location information is accessible at all. This, in combination with the uncertain accuracy of user-reported flooding mentioned earlier, means that social media data sources may be best utilized to simply highlight areas where flooding is occurring, rather than to drive numerical simulations.

3.3. Citizen science

Citizen science projects were reviewed for applicability and feasibility by asking:

- 1) Does the project address hydrological processes in an urban region?
- 2) Is the project sustainable, in the sense that it is growing or maintaining participation over a significant span of time?

Table 2

Assessment of Social Media as Presented in Academic Literature: Social media platforms provide a high quantity of posts but with low relevancy, usually due to coarse georeferencing; however, posts typically occur in an urban setting.

	Quantity total # of posts available	Frequency quantity/# event days	Relevance total # relevant posts	Density relevant post/km ²	Urban %	Location Point (P), Neighborhood (N), City (C)	Durability years active
Herfort et al. (2014)	60,524	24,830	398	0.0011	77	P	<1
(de Bruijn et al., 2018) ^a	55,100,000	50,783	19,100,000	–	52	C	3
Rosser et al. (2017)	205	34	205	1.33	100		<1
Jongman et al. (2015)	271,792; 494,744	–	271,792; 494,744	Varies	78	C	1
Middleton et al. (2014)	597,022	119,404	4,302	–	100	C	<1
Fohringer et al. (2015)	15,853,024	880,000	5	–	100	C	<1
Smith et al. (2015)	1,834; 186	1243; 168	43; 13	0.3700; 0.1142	100	C	<1
(Arthur et al., 2018) ^a	17,828,704	44,461	12,281	0.5073	–	P	

^a Due to these studies not being specific to a singular event, frequency is calculated based on entire study length rather than number of event days.

A growing number of citizen science projects focused on hydrological data collection have been reported in the academic literature reviewed. A brief description of each of the reviewed articles can be found in Supplementary Material, [Appendix B, Table 3](#). We defined eight metrics to characterize the capability of these citizen science efforts to aid urban flood monitoring: format, quantity, frequency, relevance, density, urban, location, durability, and real-time. All metrics were measured by the same procedures used for the social media data sources. Format represents the media of data collected and is listed as either text, photo, or video. The addition of real-time classification is denoted as “Yes” (<5 min), “No” (>5 min), or “Capable,” indicating the project has the capacity to report real-time data but was not monitored in this manner (Middleton et al., 2014). The omitted metrics included accessibility, data type, and nighttime data. The challenges of accessibility and data type are further discussed later in the paper. Nighttime data was not explicitly explored by the authors. Through this review, citizen science projects showed the capacity to collect highly relevant data in urban settings on a fine spatial scale ([Table 3](#)).

Though studies evaluating the accuracy and precision of water levels reported by citizen science projects are limited (Supplementary Material, [Appendix C, Table 2](#)), they indicate promising results for flooding applications (Mazzoleni et al., 2015). More specifically, research reviewing pluvial flooding found that the success of citizen science posts to simply locate inundated areas ranged from 72 to 95% (See, 2019). The future involvement of citizen science in hydrologic studies is dependent on the further analysis and quantification of accuracy of these observations. It is also dependent upon the participation of citizens and their ability to capture precipitation events.

4. Crowdsourced data assessment: existing databases

To examine the capability of crowdsourced data, we identified, catalogued, and characterized multiple databases for each data source. We focused our inquiry to databases that 1) collected data in urban settings and 2) provided accessible data for collection. For public webcams, we examined directories on a global, national, and local (Arizona) scale. For social media, we examined major platforms and collected data for storm events in Arizona. For citizen science projects, we were able to focus our collected directories toward projects reporting stage or streamflow data, a constraint that was not feasible for the first two secondary data sources. This allowed for expansion beyond Arizona at a local level. In instances where a large number of observations were

present for a single source (e.g., Facebook, Twitter), a random sample of observations was used with a 90% confidence level and 10% margin of error to evaluate metrics. For all other data sets, metrics were evaluated through all available observations on the date accessed. The following sub-sections assess the crowdsourced data by the same metrics presented in the literature review.

4.1. Public webcams

To supplement the literature review, several webcam directories were identified to assess relevancy and feasibility of public webcams to complement urban flood monitoring (Supplementary Material, [Appendix B, Table 4](#)). The public webcam sources had to be readily accessible online and provide near real-time observations. Furthermore, the directories were assessed for either quantity (providing a high volume of spatially diverse data) or quality (high-quality data for specific regions) to be considered. Priority was given to data sources in the region of interest to our project, specifically Arizona. Directories were excluded if the majority of cameras were either inoperable or redundant with other more accessible directories.

In total, seven directories were evaluated, assessing accessibility, format, quantity, density, urban, location, durability, and lag-time. Quantity, density, and urban were calculated in the same manner as presented in the literature review for public webcams. Data accessibility was assessed by whether the source is publicly and freely available. A value of “No” in this column would not absolutely exclude a data source but indicates a negotiated data access agreement may be required. A “Varies” value indicates that accessible data is limited. Format is a categorical variable, listing whether the webcam provided photo or video. Durability indicates the number of years the webcam directory has been active from the project start date through 2018. Lastly, lag-time is a categorical variable for whether or not the directory provided real-time data. The associated numerical value indicates the time in minutes between the real-time event and posting of the image. The omitted variables include data type, relevance, and nighttime. Data type and relevance are omitted due to the secondary source nature of the directories. All webcam directories had cameras filming at night. The analysis of these metrics across directories is shown in [Table 4](#), which again emphasizes the importance of webcams being properly positioned to provide relevant data but also shows the capacity to capture real-time data.

Table 3

Assessment of Citizen Science as Presented in Academic Literature: Citizen science projects show capacity to collect highly relevant data in urban spaces, typically on a fine geospatial scale.

	Format Text (T), Photo (P), Video (V)	Quantity total # of observations	Frequency quantity/# event days	Relevance # relevant observations	Density relevant observation/km ²	Urban %	Location Point (P), Neighborhood (N), City (C)	Durability years active	Real- Time
Le Coz et al. (2016)	V	600+	600+	300	0.2102	100	P	<1	No
Shupe (2017)	T, P	750	–	748	6.503	100	P	3	Capable
(Smith and Rodriguez, 2017)^a	T	15,418	4	15,418	19.7	100	P	15	Yes
(R. Q. Wang et al., 2018)	P	5,000+	–	–	8.013	–	P	<1	Capable
(Weeser et al., 2018)^a	T	1,175	3	1,175	0.3406	0	P	1	No
Yu et al. (2016)	T	490	490	250	–	100	P, N	1	Capable
Sadler et al. (2018)	T	1,055	Varies, 1 to 159	1,055	4.23	100	P	6	No
Loftis et al. (2019)	T, P	97,446	59,718; 37,728	97,446	561.2 ^b	100	P	2	Yes
Naik (2016)	T	2,500+	2,500+	2,500+	5.8678	100	P, N	<1	Yes

^a Due to these studies not being specific to a singular event, frequency is calculated based on entire study length rather than number of event days.

^b Reported per km as projected measured along coastline.

Table 4

Assessment of Public Webcam Data toward Supplementing Urban Flood Monitoring: Public webcams provide near real-time data but at low densities.

	Accessibility	Format Photo (P), Video (V)	Quantity total # cameras	Density camera/km ²	Urban %	Location Point (P), Neighborhood (N), City (C)	Durability years active	Lag-Time minutes
EarthCam	Varies	P, V	6,310	0.00004	51.6	Varies	22.5	Varies
PhenoCam	Yes	P	491	0.0002	7.3	P	6	Varies
Weather Underground	Yes	V	250,000+	0.002	39	N	19	0
WeatherBug	No	P, V	–	–	–	P	25.5	0
USGS	Varies	P	66	0.00002	12.1	C	23	15
ADOT Traffic Cams	No	V	322	0.001	90.7	N	6	0
Mohave Flood District	No	P	15	0.0004	0	C	6	1
Weighted Average	–	–	257,200 ^a	0.002	39	–	19.0	–

^a Represents total not weighted average.

4.2. Social media

To complement the literature review, large social media platforms including Facebook, YouTube, Instagram, Google Images, Twitter, Flickr, Vimeo, and Snapchat were considered for additional analysis due to the high volume of user engagement on each platform and accessible high-quality image data (Supplementary Materials, [Appendix B](#), [Table 5](#)). Other sites—including Reddit, Yelp, Pinterest, and Tumblr—were not included in the analysis due to perceived low proportions of relevant data per keyword search, as well as minimal search tool efficiency for finding real-time, flood-related posts. Snapchat was ultimately omitted from analysis because public posts are only available for 24 h and search tool capacities are minimal. All selected sources were manually assessed through a sample of relevant posts using keywords or hashtags for “flood” and “flooding.” For social media, relevance was defined based on posts falling within the search region of Phoenix, AZ and able to provide stage data or, at very least, presence of flooding during the flood events on October 7th and 13th in 2018. If a search returned more than one hundred posts, results were filtered to the past five years and sampled. In total, seven social media platforms were evaluated, assessing quantity, frequency, relevance, density, and location. These metrics were calculated by the previously presented methods. Accessibility, data type, urban, durability, real-time, and nighttime metrics were excluded. Section 6.2 discusses the constraints of accessibility for social media platforms with an exploration of Twitter. Data type is omitted as social media is a secondary data source; however, we examined posts with stage data or presence of flooding as stated in the relevancy metric. The urban metric was excluded as all analyses were conducted in Phoenix, AZ (i.e., urban is 100% in all cases). All social media platforms are well-established and considered durable data sources. Most data were provided near real-time or had the capacity to be real-time, where the user upload was the limiting factor. Nighttime

data was not distinguished. The inspection of social media platforms conveyed similar results of the academic literature; social media provides a large quantity of posts but not fine-scale data ([Table 5](#)).

4.3. Citizen science

To further assess the potential availability of citizen science projects as data sources for large-scale hydrological monitoring efforts, we identified, catalogued, and characterized ongoing projects. Projects were identified by searching a variety of citizen science community directories, including [citizenscience.gov](#), [scistarter.org](#), [citsci.org](#), Arizona State University, and Environmental Protection Agency citizen science directories. Selected projects were then evaluated to assess the availability of hydrological data types and feasibility to supplement real-time urban flood monitoring. This query resulted in 19 citizen science projects that had: 1) stage or streamflow data readily accessible online and 2) more than two hundred observations posted (Supplementary Material, [Appendix B](#), [Table 6](#)). [Fig. 2](#) displays the thirteen hydrological data types collected across these projects. The 19 citizen science projects were evaluated on accessibility, format, quantity, frequency, urban, location, durability, real-time, and nighttime metrics. All metrics were calculated in the manners previously listed for citizen science projects. Density was omitted as the spatial scale varied significantly from cities to streams with unclear boundaries. All posts were relevant due to the constraints placed on the identified projects. The nighttime metric was calculated by the percentage of observations posted 30 min after sunset to 30 min before sunrise for the respective location. Seven of these projects (AppEAR, IseeChange, Waze, CrowdHydrology, RIFLS, AZ Water Watch, and IDAH2O) had every observation evaluated by a member of our team to assess the metrics. A random sample was used for analysis of the remaining projects. The projects are categorized by those providing real-time data, defined as within 5 min ([Table 6](#)) and those

Table 5

Assessment of Social Media Data toward Supplementing Urban Flood Monitoring: Social media platforms provide a high quantity of posts but with low relevancy, usually due to coarse georeferencing.

	Format Text (T), Photo (P), Video (V)	Quantity total # of posts available	Frequency quantity/# event days	Relevance # relevant posts	Density relevant post/km ²	Location Point (P), Neighborhood (N), City (C)
Facebook	T, P, V	6	3	6	0.0045	C, N
YouTube	T, V	22	11	20	0.0149	C, N
Instagram	T, P, V	26	13	21	0.0157	C, N
Google Images	T, P	196	98	134	0.1001	C, N
Twitter	T, P, V	9	4.5	4	0.0030	C, N
Flickr	P, T	1	1	1	0.0007	C
Vimeo	–	0	0	0	0.0000	–
Weighted Average	–	260 ^a	76.3	104.7	0.08	–

^a Represents total not weighted average.

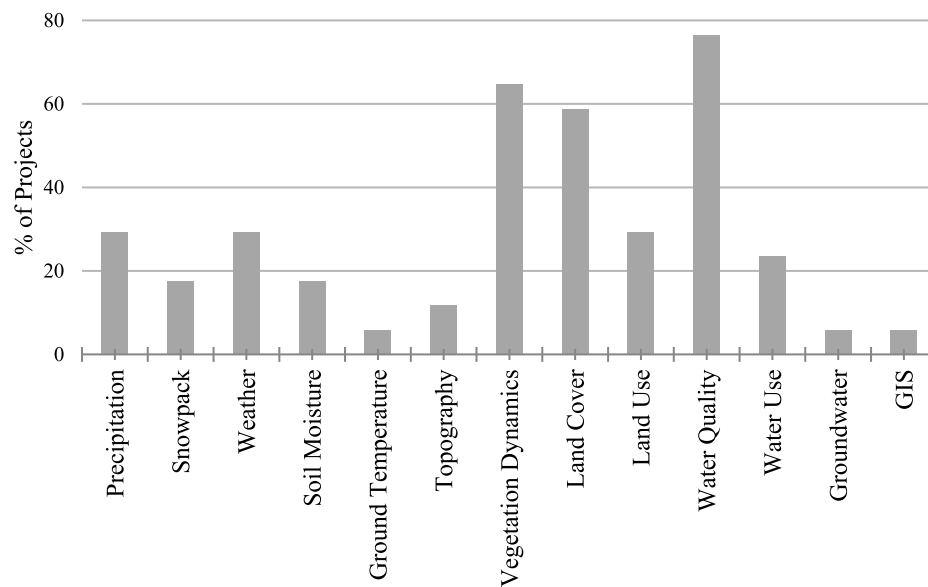


Fig. 2. Citizen Science Project Data Types: In addition to stage data, the reviewed citizen science projects included 13 other hydrological metrics.

Table 6

Assessment of Real-Time Citizen Science Project Data toward Supplementing Urban Flood Monitoring: Real-time citizen science projects provide relevant hydrological data but likely require permission to access.

	Accessibility	Format Text (T), Photo (P), Video (V)	Quantity total posts	Frequency quantity/day	Urban %	Location Point (P), Neighborhood (N), City (C)	Durability years active	Nighttime %
CrowdWater	No	P	6,234	7.08	0.80	N	2.42	–
CrowdHydrology	Yes	P, T	13,345	9.61	46.6	P	9	3.4
What's your water level?	No	P, T	1,539	3.89	3.25	N	0.92	–
DEW Picture Post ^a	No	P	6,958	1.38	0.4	P	13.75	0
AppEAR	No	P, T	218	0.91	62.4	P	0.67	–
ISeeChange	No	P	592	0.34	71.5	C	4.83	26
Waze ^b	Varies	T	1,922	2.52	100	P	2.5	–
Weighted Average	–	–	17,463*	3.40	20.73	–	6.89	0.88

^a Quantity was based on only relevant sites with waterbodies present (wet or dry), which was 39.4% of posts.

^b Based on binary data (i.e., water present or not present) rather than stage data. *Represents total not weighted average.

Table 7

Assessment of Asynchronous Citizen Science Project Data toward Supplementing Urban Flood Monitoring: Asynchronous citizen science projects provide typically accessible and relevant hydrological data, oftentimes, on a fine geospatial scale.

	Accessibility	Format Text (T), Photo (P), Video (V)	Quantity total posts	Frequency quantity/day	Urban %	Location Point (P), Neighborhood (N), City (C)	Durability years active	Nighttime %
AZT App	No	P, T	6,402	4.48	0.4	N	4	–
Stream Tracker	Yes	P, T	4,049	4.22	40.3	P	2.67	0
Mass. RIFLS	Yes	T	48,188	8.25	1.2	N	16	0
AZ Water Watch	No	P	266	0.68	11.7	N	2.17	0
Springs Online	Yes	P	14,512	4.46	0.3	P	9	0
IDAH2O	Yes	T	741	0.24	8.4	P	8.33	0
TX Stream Team	Yes	T	16,665	1.63	44.1	P	28	0.6
Utah Water Watch	Yes	P, T	3,371	3.51	16.4	P	10.5	1
Michigan VSMP	Yes	T	1,178	0.23	3.33	P	14	3.2
Missouri Stream Team	No	T	6,254	0.57	0.7	P	30	1.5
Fluker Post Project	No	P	9,107	2.34	0	P	10.67	0
STORM ¹	Yes	T	1,238	0.35	100	P	9.6	–
Weighted Average	–	–	125,316 ^a	5.52	14.3	–	15	0.57

¹Based on binary data (i.e., water present or not present) rather than stage data.

^a Represents total not weighted average.

that do not (Table 7). However, it should be noted that AZT App and Stream Tracker likely have the capacity to provide real-time data. Additionally, of the 19 projects, seven require training for citizens to participate. These include RIFLS, Springs Online, IDAH2O, Texas Stream Team, Utah Water Watch, VSMP, and Missouri Stream Team. The analysis of these metrics across directories emphasizes the degree of relevancy citizen science projects can have for urban flood monitoring with potentially high resolution.

5. Example of crowdsourced data and public safety integration

While we have focused on crowdsourced data available in Arizona, we now highlight Norfolk, Virginia, a city that has integrated urban flood monitoring and public safety. Norfolk is located in the Hampton Roads region with a metropolitan area of $\sim 250 \text{ km}^2$, housing more than 1.5 million residents and the world's largest naval station. This region experiences a humid, subtropical climate and has been experiencing an increased frequency of flooding due to low relief, regional land subsidence, and sea-level rise (Burgos et al., 2018; Sweet and Park, 2014). The City of Norfolk has been actively adopting strategies to become more resilient and was selected as one of the Rockefeller Foundation's 100 Resilient Cities in the world (100 Resilient Cities, 2019). In 2018, rain events on August 11th (9.4 cm of precipitation) and August 20th (5.2 cm of precipitation) were explored to assess the quantity and density of crowdsourced data through two citizen science projects: City of Norfolk's System to Track, Organize, Record, and Map (STORM), which is used by city employees and citizens to record incidents that occur during inclement weather, and Waze, a crowdsourced navigation application owned by Google, where Waze users can submit reports regarding real-time street conditions, including flood reports. Our analysis of the crowdsourced data returned the following results (Fig. 3):

- STORM was searched using keywords ("flooded," "flooded street," and "flooded underpass") and yielded 2.5 observations per day, equating to a density of 1 observation per 99.88 km^2 .
- For the Waze dataset, a keyword search of "HAZARD_WEATHER_FLOOD" produced 67 relevant observations per day, corresponding to a density of 1 post per 3.73 km^2 .

The STORM citizen science project observations provide high quality information reported or reviewed by trained officials at relevant sites. While STORM data reporting is restricted, Waze allows a larger group of

individuals (i.e., their users) to make instantaneous flood reports. Again, beyond density, the spatial accuracy and measurement error of the observations is critical for urban flood monitoring, and Waze users are not trained to report flood data. However, Waze holds the potential to facilitate real-time flood warnings (Prahara et al., 2021), and a partnership has been established with Norfolk through the Waze Connected Citizens program (The City of Norfolk, 2018). STORM does provide a unique characteristic that supports a core motivation behind this study: the ability to report flood hazards and damages and alert people of potential dangers in their communities. STORM observations publicly report damages such as flooded streets, flooded underpasses, debris blocked streets, downed powerlines or telephone poles, waste water issues, or damaged trees (Sadler et al., 2018; arcgis.).

6. Assessing the tradeoffs of crowdsourced data

6.1. Public webcams

The literature and database analysis revealed that the use of public webcams combined with subsequent image processing to collect data provides a number of challenges and opportunities. Images from webcams may not provide reliable data due to poor image quality; highly variable viewing angles, framing, and distance to target; unannounced downtime; or discontinuation of service (Bothmann et al., 2017; Castelletti et al., 2016; Guastella and Smith, 2014; Morris et al., 2013; Murdock et al., 2013). Because flood managers are a secondary user of the webcam stream, they do not have direct control over the positioning of the webcams for data collection (Bothmann et al., 2017; Guastella and Smith, 2014; Morris et al., 2013). For instance, many Weather Underground cameras are pointed toward the sky, which would not capture water levels, but users could potentially reposition cameras during storm events. Traffic cameras, such as found in the Arizona Department of Transportation (ADOT) database, are often pointed at interstates which are designed more robustly than local roads and may not experience the same flooding risk. There is potential for flood managers to be granted access to control traffic cameras, where the flood manager could reposition the camera during storm events to potentially monitor underpasses or redirect toward a water level gauge. Potential sources of data errors include processing errors due to noise (Bothmann et al., 2017; Castelletti et al., 2016; Murdock et al., 2013) or incorrect geo-location metadata or timestamps (Morris et al., 2013; Murdock et al., 2013). In the database analysis, many sources did not provide

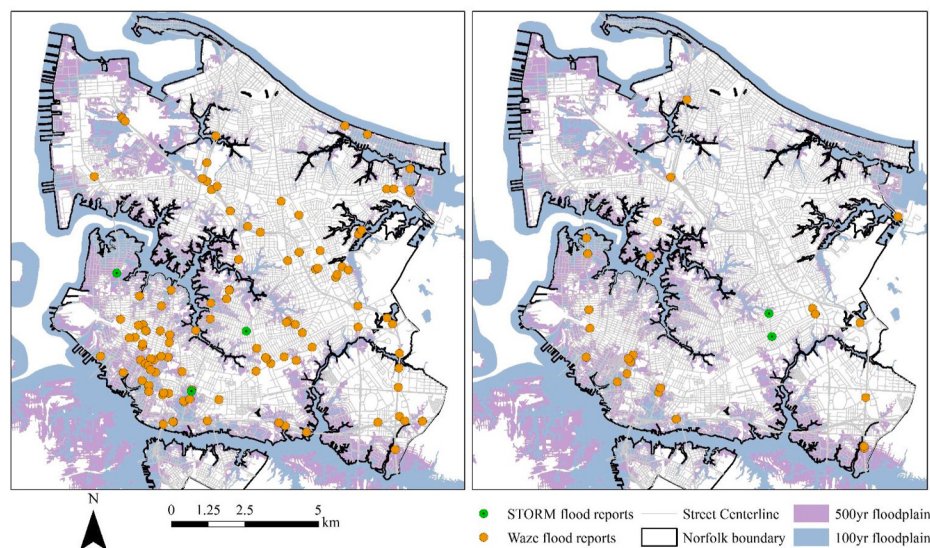


Fig. 3. Maps showing citizen science observations relevant to flooding in Norfolk, VA from two sources: City of Norfolk's STORM database (green) and Waze (gold) on 8/11/2018 (left) and 8/20/2018 (right). Citizen science projects with more participations, such as Waze, provides opportunity for more flood observations.

exact locations of webcams: EarthCam, Weather Underground, USGS, ADOT traffic cameras, Mohave Flood District. While this information could be collected manually, this would be a resource sink. Lastly, flood managers should be wary of sparsely or unevenly distributed webcams, which could lead to extrapolation errors (Murdock et al., 2013) as seen with the low density numbers reported in the existing database analysis.

However, the benefits may outweigh the challenges considering the large spatial and real-time temporal scales in which webcams are capable of operating (Bothmann et al., 2017; Castelletti et al., 2016; Guastella and Smith, 2014; Morris et al., 2013; Murdock et al., 2013) and access to large datasets can minimize the impacts of such errors (Murdock et al., 2013). Every database examined operated in real-time, although there may be a slight posting delay. Furthermore, there are now individual cities with millions of webcams, so a large dataset is a realistic possibility. The two sources highlighted prior, for potentially high accessibility (Weather Underground and ADOT traffic cameras), showed higher density and urban applicability than other databases examined, indicating strong contenders for pilot programs. When relevant webcams are identified, they provide an objective and consistent data source that relies on little human involvement (Guastella and Smith, 2014; Morris et al., 2013) and can be processed with high accuracy (Bothmann et al., 2017; Castelletti et al., 2016; Morris et al., 2013). The analyzed databases also showed promising durability, with the minimum active years reported as six. In short, public webcam directories provide low-cost or free resources to supplement traditional monitoring networks, which are currently strained (Castelletti et al., 2016; Guastella and Smith, 2014; Morris et al., 2013).

6.2. Social media

Social media platforms deliver both opportunities and challenges for urban flood monitoring. While social media provides a high-volume stream of low cost, real-time data that may complement other data sources. Social media also provides an opportunity to capture a flood of any size as well as provide a communication tool in emergency situations that is readily accessible to people (Jongman et al., 2015; Middleton et al., 2014; Smith et al., 2015). This accessibility is a notable advantage compared to citizen science projects, such as STORM, that may lack awareness or adequate mobile compatibility. Machine-processed validation techniques provide an opportunity for scalability that is not possible through manual validation techniques (de Bruijn et al., 2018; Herfort et al., 2014), but this requires posts to have quality data attached (Fohringer et al., 2015; Smith et al., 2015). Due to the individuality of social media posting, the data quality also varies widely as seen in the database investigation which reported text, photo, and video posts across platforms. Therefore, it may be worthwhile to weight the knowledge of a user or number of post shares (Jongman et al., 2015; Smith et al., 2015). For instance, a city water department's post may be more valuable than an average citizen. Sophisticated algorithms and queries are needed to filter posts according to language and identify spatial scale based on location names (Arthur et al., 2018; de Bruijn et al., 2018; Fohringer et al., 2015; Herfort et al., 2014; Jongman et al., 2015; Middleton et al., 2014; Rosser et al., 2017; Smith et al., 2015).

To elaborate, many social media posts lack high-resolution georeferencing. In our existing database analysis, none of the posts were able to be pinned to a point location. Examining the various social media platforms, the Twitter application programming interface (API) is perhaps the most useful and accessible, allowing extensive searching and filtering of results using one of three access tiers offering differing levels of search functionality: a "standard" access tier that is free, and "premium" and "enterprise" levels of paid access. Free access is limited to searching the last seven days of activity at rates up to 180 queries per 15-min window. Premium level allows searching both 30-day and complete archives of tweets, as well as higher query rates. Enterprise access adds more powerful search criteria specification. In practice, we found the standard (free) API to be adequate for our exploration of

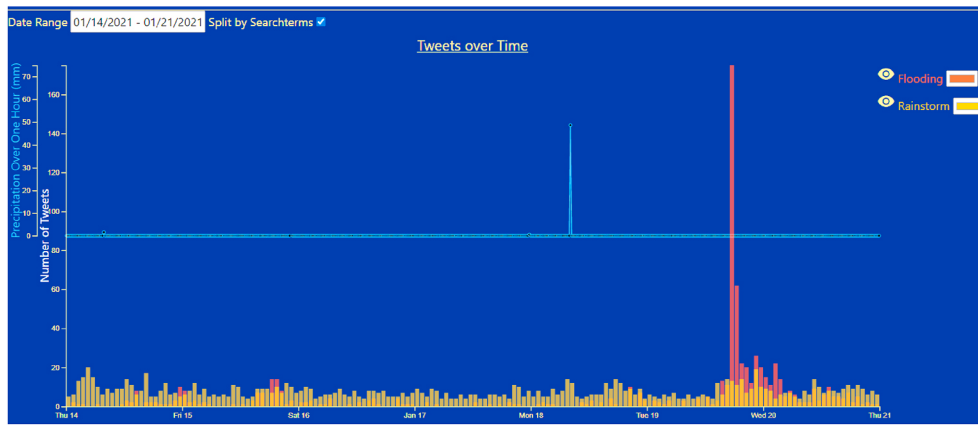
tracking flood-related Twitter activity in real-time, where very high query rates and searching of historical tweet archives are not relevant. Queries could be organized and spaced out temporally to avoid exceeding access rate limits while still providing a stream of near real-time data. Twitter allows complex logical queries to be formulated to retrieve and filter posts from specified geographic regions. For instance, one could search for tweets mentioning "flooding" but also having other keywords like "water" and "storm," to eliminate metaphorical uses of the worded "flooding" or "flooded." Thus, some careful effort could likely lead to development of effective query probes that do, indeed, relate to flooding. As noted for all social media earlier, Twitter users rarely allow their posts to be tagged with detailed geo-locations. For instance, we found that less than 1% of tweets found containing the words "flood," "flooding," or "inundation" have location data attached. Thus, tweets can be geo-located only to the city level or, for larger cities, to a general region of the city. Even so, tweets might be useful as a general indicator of flooding activity, to complement sparse public webcams coverage of an area, or to help understand overall flooding dynamics in planning placement of webcams.

A preliminary analysis examined Twitter activity around sixteen cities between November 15, 2019 through January 20, 2020 to explore how tweets may or may not correspond with storm and flooding activity and potential correlation was indicated. To better understand these initial findings, we built a software tool to mine Twitter for targeted cities and to graph the resulting tweets in a "tweetograph," a social media analogy to a hydrograph (Fig. 4). The methods of this preliminary analysis may be viewed in more detail in Supplementary Materials, Appendix D as Phase 1 and Phase 2, respectively. We present the tweetographs below specifically to 1) provide proof of concept of social media data mining algorithms and 2) illustrate potential temporal correlation between social media activity and flooding from the preliminary analysis. This utility highlights a pathway to integrate social media data into urban flood monitoring.

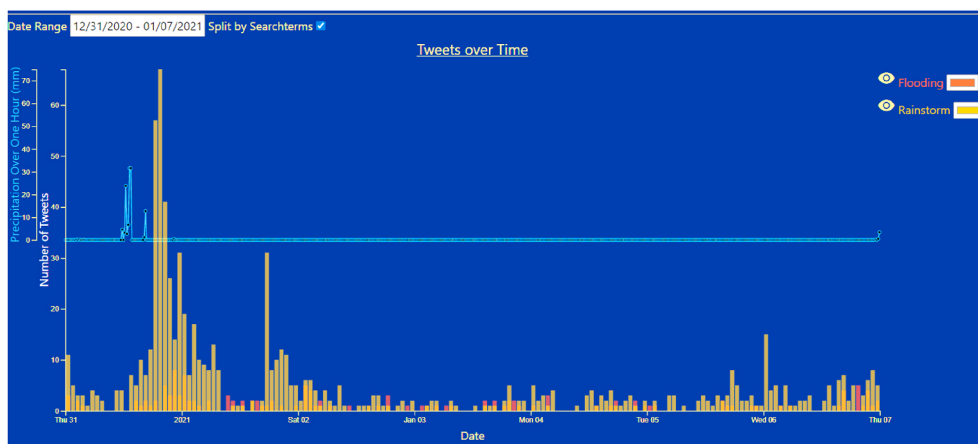
6.3. Citizen science

Integrating citizen science data sources into hydrological monitoring and modelling efforts holds promise due to the nature of direct data sources but also presents significant challenges in terms of accuracy, reliability, and coverage. If citizen scientists are not trained, there may be issues of quality due to unidentifiable observations (e.g., shorthand, blurry images, etc.) or poor technique in taking hydrologic measurements (Le Coz et al., 2016; Shupe, 2017; Smith and Rodriguez, 2017; R. Q. Wang et al., 2018; Weeser et al., 2018; Yu et al., 2016). Less than half of the examined citizen science projects trained users on data collection techniques. Coverage and reliability are often problematic, as citizen science projects typically lack large networks, leading to a low volume of irregular participation (Le Coz et al., 2016; Shupe, 2017; Smith and Rodriguez, 2017). Additionally, inclement weather reasonably causes citizen scientists to stay indoors and away from active hydrological situations at the precise time when they are needed most. Asking citizen scientists to venture out in potentially unsafe flood conditions raises ethical and liability concerns (Le Coz et al., 2016). As mentioned in the Norfolk case study, training requirements also create an entry barrier, which may reduce observations. Awkward data formats, constraints on mobile data access, and a limited feedback of high-value information to contributing citizen scientists can limit interest and long-term community engagement (Le Coz et al., 2016; Smith and Rodriguez, 2017; R. Q. Wang et al., 2018; Yu et al., 2016). These barriers will need to be addressed to adopt citizen science data into urban flood monitoring.

Despite these challenges, citizen science can offer tremendous opportunity for citizen engagement (Le Coz et al., 2016; Shupe, 2017; Weeser et al., 2018). Observations can be reported real-time and supported with text, photos, and videos, providing low-cost data. The database analysis also showed that observations were often detailed, reporting fine spatial scale and occasionally nighttime data.



(a)



(b)

Fig. 4. Tweetographs for week-long monitoring periods in (a) Miami, FL and (b) New Orleans, LA. Bar graph displays tweets returned from two different probes called “Flooding” and “Rainstorm,” respectively, at 1-h intervals. The blue line superimposes NOAA precipitation data. An increase of total tweets can be seen following the storm events for both locations, paralleling the rainfall event, but following based on a time lag. The actual inundation and flooding are unknown and unmeasured, but presumably that inundation and flooding correlates to the tweets.

Furthermore, citizen science projects allow the community to co-generate knowledge in high-traffic areas, or spaces that are a priority to the community (Le Coz et al., 2016; Naik, 2016; Shupe, 2017; Smith and Rodriguez, 2017; R. Q. Wang et al., 2018; Weeser et al., 2018). Projects with fixed gauges placed at key points within the cityscape (e.g., CrowdHydrology) can provide long-term data for a fixed reference point (Le Coz et al., 2016; Lowry et al., 2019; Lowry and Fienen, 2013; R. Q. Wang et al., 2018; Weeser et al., 2018). A couple databases, Missouri Stream Team and TX Stream Team, have existed for 30 and 28 years respectively, emphasizing the long-term data source potential. The integration of social media with citizen science can increase participation and awareness while further supplementing data gaps (Le Coz et al., 2016; R. Q. Wang et al., 2018). Projects based around events—whether sampling blitzes or coastal tides—typically have higher number of observations (Loftis et al., 2019). Despite its limits, the public engagement of citizen science provides a notable opportunity to further educate and empower residents, while potentially increasing project observations.

6.4. Crowdsourced data

A summary of qualitative and quantitative metrics across academic literature and established databases for the three established data sources (Table 8) reveals the potential for integrating observational data from crowdsourcing and citizen science projects into urban flooding monitoring. Public webcam networks have been around the longest (1990s), while citizen science networks and social media sources primarily started within the following decade (2000s). In general, all three

Table 8

Summary of Data Sources from Academic Literature and Existing Databases: Social media produces a significantly higher quantity of observations than public webcams or citizen science projects; however, social media observations are likely to be irrelevant to urban flooding. The highest density of relevant observations was found in real-time citizen science projects.

	Public Webcams	Social Media	Citizen Science (real-time ^a)	Citizen Science (not real-time)
Quantity total # of observations	279,274	91,085,822	139,067	128,146
Frequency total # of observations per day	Varies	196,758	40,326	8.4
Relevance %	71.6	21.9	95.1	99.6
Density relevant observation/km ²	0.03	0.08	454.53	0.04
Urban %	39	51.2	90.1	15.3
Location Point, Neighborhood, City	P, N, C	P, N, C	P, N, C	P, N
Durability years active	19.0	—	4.0	14.7
Lag-Time minutes	Varies	—	—	—
Nighttime %	—	—	0.1	0.6

^a Projects in the literature review that had capacity for real-time data were placed in this category.

sources are relatively well established and could be described as durable over time, indicating they are viable for long-term data collection. Furthermore, all three sources provide a wide variety of data that could supplement ongoing monitoring efforts. With the continuous improvement of video and image processing, utilizing public webcam and social media sources is becoming more plausible for relevant flood data such as stage, streamflow, precipitation, snowpack, weather, topography, vegetation dynamics, land cover, land use, water use, and informing GIS data. It remains necessary to have specialized camera setups, or citizen science projects, for anything more difficult to extrapolate beyond the visuals of videos and images, such as soil moisture, ground temperature, water quality, and groundwater data. Lastly, there is concern about a lack of useful nighttime data across the data sources. Though specialized camera setups with nighttime lighting or infrared capabilities can provide nighttime data, most public webcam networks do not have these capabilities. While some citizen science projects reported nighttime data, most did not. Notably, the ISeeChange project yielded roughly a quarter of observations overnight but these were typically not reported until the following day. Social media is the most promising avenue for crowdsourcing nighttime flooding data as individuals may report local flooding.

7. Discussion

Each of the three data sources have unique opportunities and challenges to support urban flood monitoring. Social media and public webcams produce a large quantity of observations across a widespread area, providing a frequent, real-time snapshot of water levels during urban flooding that is not captured by citizen science projects. Citizen science projects have an advantage of nearly all observations being relevant for water-level measurements, leading citizen science projects to provide better baseline data than event data for urban flood monitoring. Social media and public webcams may serve better providing real-time data for flood events; however, both data sources have a high number of non-relevant observations. To address this, multiple query probes could be configured to explore different filtering criteria. Recalling the Twitter example (Fig. 4), these queries could be used to discover (a) to what extent Twitter activity tracks precipitation and associated urban flooding and, if so, (b) which content-based logical filters yielded tweetographs with the best correlations to precipitation and flooding. As might be expected, our initial trials suggest that success will hinge on development of finely-tuned query probes that accurately return tweets truly related to flooding activity. At that point, further analysis can determine how reliably tweeting does or does not, fundamentally, signal flooding events. Despite existing weaknesses across data sources, these crowdsourced data provide a chance to augment urban flood monitoring using data fusion to exploit their combined and relative strengths. The integration of primary observations into traditional urban flood modelling allows data to be collected where it is needed most—at flooded locations in cities. We propose an integrated flood stage observation network that fuses crowdsourced and professional hydrology data in real-time to feed that data to modelers and communicate flood status and risk to community members and decision makers.

Appendix A

Table 1

Crowdsourcing and Citizen Science Data Source Assessment Metrics: 12 metrics are identified to assess the capability of the novel data sources to augment urban flood modelling.

Metric	Description	Unit
Accessibility	Can the observation be publicly downloaded for free?	Binary; Classified as either 'Yes' or 'No'
Format	In what format is the observation communicated?	Classified as either 'Text,' 'Photo,' or 'Video'
Data Type	What data types do sources provide?	

(continued on next page)

8. Conclusion

Opportunities and challenges exist for integration of each data source (public webcams, social media, and citizen science) into urban flood monitoring. Public webcams have the highest potential when located at frequently flooded or high-risk locations. Webcams provide an opportunity for low-cost, reliable, real-time data and house potential for reasonably accurate nighttime observations through IR-capable cameras. Public webcams are limited by difficult directory navigation and fixed locations. Camera views may be impaired by poor angles, long distances, obstructions, and network problems. When aided by a streetlight, the webcam may be able to provide nighttime data. Next, the greatest asset of social media is the high quantity of observations that provide free, real-time data that are typically not constrained to a specific location. The drawbacks are the low number of relevant posts, low quality media, and lack of georeferenced observations. Social media provides ample opportunity for easy integration with other data collection methods to supplement observations. Lastly, citizen science delivers detailed, quality data through community engagement with low-cost technologies such as smartphones. However, engagement is generally low outside of campaigned events, and participation falls further during inclement weather, such as flooding events. There are barriers to data collection as not all projects publicly post data, or the data may be in difficult formats. Citizen science's largest strength is the detail of information provided for each observation. Crowdsourced data introduces a layer of uncertainty of measurement errors. It remains difficult to organize data gathered via crowdsourcing into real-time monitoring systems due to inconsistent metrics, uncoordinated efforts, and to get enough georeferenced, ground-based observations to calibrate models. Despite the presented challenges, each data source holds potential to enhance urban flood monitoring by providing access to real-time, localized flood reports, especially if fused together to exploit their relative and combined strengths and to create a more complete and up-to-date data source for urban flooding.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mikhail Chester reports financial support was provided by National Science Foundation Award No. 1831475. Jonathan L. Goodall reports financial support was provided by National Science Foundation Award No. 1735587. All authors are part of the NSF Award No. 1831475, but Mikhail is the lead PI. Jonathan and Faria are associated with NSF Award No. 1735587, with Jon having the seniority of the two.

Acknowledgments

This project is funded by the National Science Foundation's Smart and Connected Communities program (1831475) and Critical Resilient Interdependent Infrastructure Systems and Processes program (1735587).

Table 1 (continued)

Metric	Description	Unit
		Percent of the data source with stage, streamflow, precipitation, snowpack, weather, soil moisture, ground temperature, topography, vegetation dynamics, land cover, land use, water quality, water use, groundwater (quality, level), and GIS data
Quantity	How many total observations?	Total number of posts
Frequency	How many observations per a temporal boundary?	Posts/day or event
Relevance	What percentage of sources or posts are relevant for informing flood modelling and decision-making?	Number of posts that depict flooding within the spatial and temporal boundaries
Density	How many observations per a spatial boundary?	Posts/km ²
Urban	Are urban observations supported?	Percent of observations in locations that have a population $\geq 50,000$ people (Cromartie, 2019)
Location ¹	Is the location of the observation provided? If so, are accuracy and precision maintained?	Classified as 'Point' (has latitude and longitude or the precise building/location name), 'Neighborhood' (tagged by neighborhood name, or to an area approximately the size of a neighborhood), or 'City'
Durability	How long have observations been hosted?	Total number of active years rounded up; if less than one year, input one year
Real-time	Are real-time observations supported? If so, are accuracy and precision is precision maintained?	Binary; Classified as either 'Yes' or 'No' by whether the posting delay exceeds 5 min. If available, lag time is noted
Nighttime	Are nighttime observations supported? If so, are accuracy and precision maintained?	Percent of observations that provided stage data between 30 min after sunset and 30 min before sunrise

¹The locations of observations are either directly geotagged, visualized (displayed on a map), or described (with text).

Appendix B

Data sources

Table 1
Brief Summaries of Academic Literature regarding Public Webcams

Article	Description
Bothmann et al. (2017)	Webcams from AMOS were used for vegetation greenness levels: USA & Europe
Castelletti et al. (2016)	Touristic webcams (complemented with data from Flickr) used for flood prediction of a snow catchment: Lake Como, Italy
Guastella and Smith (2014)	Touristic webcams used for assessing changes in coastal morphology: KwaZulu-Natal, South Africa
Morris et al. (2013)	Traffic webcams used for vegetation greenness levels: England, UK
Murdock et al. (2013)	Outdoor webcams from the AMOS collection used to create cloud maps for weather forecasting: USA

Table 2
Brief Summaries of Academic Literature regarding Social Media

Article	Description
Herfort et al. (2014)	Observational flooding data recorded between June 8th (1:30 p.m.) to June 10th, 2013 (midnight) from geo-referenced Twitter data from River Elbe Flood: Germany, 2013
de Bruijn et al. (2018)	Used an event-based algorithm to sort through location ambiguity of Tweets for flooding disasters between July 29, 2014 and July 18, 2017: Global
Rosser et al. (2017)	Collected geotagged social media (Flickr) flood data for a series of storms between January 5th to 11th in 2014 to create a flooding model: UK
Jongman et al. (2015)	Analyzed Twitter and satellite source data to determine how they are used to support flood responses to a tropical depression and typhoon, respectively: Pakistan (single day event) and the Philippines (multiple day event)
Middleton et al. (2014)	Review and case study of social media's use in response data: Hurricane Sandy (monitored for five days in October 2012)
Fohringer et al. (2015)	Case study of flood patterns and depths data collected through photos on Twitter and Flickr from May 5 to June 21, 2013 flood: Dresden, Germany
Smith et al. (2015)	Modeled and assessed two flooding events in 2012 on June 28th and August 5th: Newcastle-upon-Tyne, UK
Arthur et al. (2018)	Examined Twitter data from floods in 2015 from October 22 to November 25: UK

Table 3
Brief Summaries of Academic Literature regarding Citizen Science Projects

Article	Description
Le Coz et al. (2016)	Flood photo project RiskScape by the National Institute of Water and Atmospheric Research (NIWA): Christchurch, New Zealand
Shupe (2017)	Water quality data and hydrologic observations collected via a smartphone app: Vancouver, Canada
Smith and Rodriguez (2017)	Flood observations recorded by New York City 311, online or with the non-emergency city telephone line: New York City, New York, USA
(R. Q. Wang et al., 2018)	Study of the web and mobile crowd-sourcing platform MyCoast that collects photos of coastal, urban flooding: Charleston, SC, USA
Weeser et al. (2018)	Analysis of numerical text-message water level data collected from thirteen sites: Kenya
Yu et al. (2016)	Comparison of crowdsourced and model-predicted flood inundation for an extreme, one-day storm event: Shanghai, China
Sadler et al. (2018)	Developed flood severity model using crowdsourced flood reports for coastal city: Norfolk, Virginia, USA
Loftis et al. (2019)	Crowdsourced flood mapping was used to identify the inundation extent during king tide events and validate flood forecast model: Hampton Roads, Virginia, USA
Naik (2016)	Precipitation event paralyzed a city, resulting in the creation of an impromptu, crowdsourced flood map: Chennai, India

Table 4

Public Webcam Resources: A summary of each public webcam directory examined.

Resource	Description
<i>Global</i>	
EarthCam	A global, commercial network of live-stream webcams for online tourism.
PhenoCam	A database of landscape images in North America for phenological research.
Weather Underground	A global, commercial service that provides real-time weather data derived from the National Weather Service and personal weather stations.
WeatherBug	A global, web and mobile application that provides hyper-local weather data from private weather stations and sensors.
<i>National</i>	
United States Geological Survey (USGS)	A national multimedia gallery, including webcams, which provides near real-time conditions to monitor extreme weather events.
<i>Local</i>	
Arizona Department of Transportation	A state-wide database of traffic cameras that provide near real-time road and traffic conditions.
Arizona Mohave Flood District	A county-specific database of real-time weather cameras to provide flood warnings.

Table 5

Social Media Resources: A summary of each social media platform examined.

Resource	Description
Facebook	A global social networking site where users may post text, photos, and video to a 'story' (i.e., content posted up to 24 h) or to their 'feed' (e.g., content posted until deleted). Users may also interact with content through reactions, sharing, or comments.
Flickr	A global image and video hosting service where users may caption, react, and comment on uploads.
Google Images*	A global image searching service.
Instagram	A global social networking site where users may post images or videos to a story or feed with the ability to caption, react, share, and comment on uploads.
Twitter	A global social networking site where users may post text, photos, and videos to a feed. Users may interact with content by replying, sharing, or reacting.
Vimeo	A global video hosting service where users may caption, react, and comment on uploads.
YouTube	A global video hosting service and social networking site where users may post text, photos, and video to a story or feed. Users may interact with content through reactions and comments.

*To comply with permissions, Google Images was limited to results labeled for noncommercial reuse.

Table 6

Citizen Science Resources: A summary of each citizen science project examined.

Resource	Description
<i>Global</i>	
AppEAR	A global, mobile and web-based application that crowdsources environmental data for freshwater aquatic environments for research and education.
CrowdWater	A global, mobile application which crowdsources water level, streamflow, soil moisture, plastic pollution data of water bodies to improve forecasting of hydrological events.
Digital Earth Watch Picture Post	A global, mobile and web-based database which crowdsources images of landscapes for environmental monitoring.
The Fluker Post Project	A global, mobile application which crowdsources images of landscapes for long-term natural resource management.
IseeChange	A global, mobile and web-based application that crowdsources examples of climate change mitigation and adaptation.
Stream Tracker Project	A global, mobile application that crowdsources when and where water is flowing to monitor intermittent streams.
Waze	A global, mobile application that crowdsources road and traffic conditions to provide trip navigation.
<i>National</i>	
CrowdHydrology	A national, web-based application which crowdsources water level data, primarily in or near urban locations, through text messaging to collect hydrologic data.
Springs Online	A national, web-based database that crowdsources ecosystem characteristics and processes to promote healthy environments.
What's your water level?	A national, web-based application that crowdsources water level data focused on coastal flood management.
<i>Local</i>	
Arizona Trail Water Report	A state-level, web-based database that crowdsources availability of water sources across Arizona trails.
Arizona Water Watch	A state-level, mobile application which crowdsources water, wildlife, and pollution data of water bodies in Arizona.
IDAH2O	A state-level, web-based database that crowdsources habitat, biological, chemical, and physical data of Idaho's streams.
Michigan Clean Water Corps Volunteer Stream Monitoring Program (VSMP)	A state-level, web-based database that crowdsources water quality data in Michigan's wadeable streams and rivers for water resources management and protection.
Missouri Stream Team	A state-level, mobile and web-based database that crowdsources water quality data in Missouri for river conservation.
Massachusetts River Instream Flow Stewards (RIFLS)	A state-level, web-based database which crowdsources streamflow of ungauged rivers in Massachusetts.
STORM	A city-level, web-based application that crowdsources flooded streets in Norfolk, VA.
Texas Stream Team	A state-level, web-based database that crowdsources water and environmental quality of over 400 Texas waterways for scientific research and environmental stewardship.
Utah Water Watch	A state-level, web-based database which crowdsources water quality data of lakes and streams in Utah for watershed management and education.

Appendix C

Reported Water Level Errors across Data sources

Table 1

Accuracy and Precision of Water Level Derived from Webcam Image and Video: Studies of cameras indicate webcams hold potential to accurately measure water level data.

Source	Error (cm)	Error (%)	Error Method*	Precision (cm)
Jiang et al. (2020)	2.6	20	RMSE	–
Zhang et al. (2019)	≤0.4	–	RMSE	±1
Lin et al. (2018)	1.1	1	RMSE	–
Eltner et al. (2018)	0.6	–	MAE	±1.5
Schoener (2018)	1.4	–	MAE	±3
Ran et al. (2016)	2	–	RMSE	–
Kim et al. (2008)	2.5	8	MAE	–
Shin et al. (2008)	–	2.3	MAE	–
Average	1.5			

*RMSE = root mean square error; MAE = mean absolute error.

Table 2

Accuracy of Water Level Derived from Citizen Science Sources: Studies regarding citizen science projects are limited but indicate potential for retrieving accurate water level data.

Source	Error (cm)	Error (%)	Error Method*
Dauids et al. (2017)	–	1.9%	MAE
Le Coz et al. (2016)	–	15–20%	MAE
Lowry and Fienen (2013)	0.6	–	RMSE
Average	0.6	9.7%	–

*RMSE = root mean square error; MAE = mean absolute error.

Appendix D

Detailed methods for twitter analysis

Our analysis of Twitter as a potential near-real-time indicator of urban flooding activity was conducted in two phases. First, a simple initial pilot effort was manually conducted to get an initial assessment of potential utility. Second, a more in-depth analysis (ongoing) for which we constructed a specialized software “twitter scraper” tool with significant automation that could be targeted to monitor flood-related twitter activity in any targeted locale over either specific timeframes or on an ongoing basis.

Phase 1: Pilot evaluation of Twitter as an indicator of urban flooding.

Using the public, free Twitter API, searches were made using the keywords “flood,” “flooding,” and “inundation.” These searches were made from November 15, 2019 to January 20, 2020 and were localized to several locations in the United States which were known to be at risk for flooding to reduce noise. The following locations were used:

- o Pahrump, Nevada
- o Jersey City, New Jersey
- o Plano, Texas
- o Peachtree Corners, Georgia
- o Miramar Beach, Florida
- o Raleigh, North Carolina
- o Rogers City, Arkansas
- o Carmel, Indiana
- o St. Augustine, Florida
- o The Woodlands, Texas
- o Round Rock, Texas
- o Denton, Texas
- o Kissimmee, Florida
- o San Marcos, Texas
- o Sugar Land, Texas
- o Queens, New York

Searches were made for tweets which were geo-located within the boundaries of these locations, or for tweets where the author states their location in their profile to be within one of these locations.

Events were closely monitored then verified through local news outlets. The following events were captured:

- o Pahrump, Nevada

- o December 12, 2019 to December 15, 2019
- o Plano, Texas
- o January 16, 2020
- o Peachtree Corners, Georgia
- o January 12, 2020 to January 16, 2020
- o Raleigh North Carolina
- o December 5, 2019 to December 6, 2019
- o December 13, 2019 to December 15, 2019
- o December 18, 2019 to December 20, 2019
- o Rogers City, Arkansas
- o January 9, 2020 to January 14, 2020
- o Carmel, Indiana
- o January 9, 2020 to January 12, 2020
- o Denton Texas
- o January 10, 2020 to January 13, 2020
- o Queens, New York
- o January 2, 2020 to January 5, 2020

Events analyzed in this way showed an increase of up to four times the number of tweets that matched search criteria during and shortly after flooding events. These preliminary results were deemed promising enough to warrant initiating a deeper analysis of the reliability of Twitter as a flooding indicator.

Phase 2: Software for Automation: Large-scale analysis of Twitter as reliable indicator of urban flooding.

To provide a basis for a larger statistical analysis of the reliability of Twitter activity as an indicator of urban flooding events, we constructed an automated “Twitter scraper” software product to use as a research tool, capable of monitoring and capturing Twitter activity and precipitation in flood-prone cities across the United States. The tool is embodied in a web-application that allows researchers to easily configure monitoring of any city, either continuously or within specified time windows. This allows continuous long-term monitoring to provide a strong record of “baseline” Twitter activity in various regions, as well as targeted monitoring of specific events, e.g., when a large storm is forecast for a given region. Some specific features include:

- User can create and deploy an unlimited number of monitoring tasks targeted to specified geographic regions.
- User can specify an unlimited set of “search term sets”, which are essentially complex constructed logical queries aimed at filtering out “flood-related” tweets from the stream of tweets.
- o The probes used in the provided examples used:
 - Flooding: (flood OR flooded OR flooding) – “flood with” – “flooded with” – “flood of”
 - Rainstorm: monsoon OR rain OR rainstorm OR thunderstorm
 - For a given monitoring task, user can attach one or more search term sets to use in monitoring that region.
 - Monitoring tasks also query NOAA in 15-min intervals to collect a timeline of current precipitation data for the targeted region.
 - A graphical interface is provided to visualize Twitter activity. In other words, the number of tweets returned for each of the specified search term sets, along with precipitation data, can be generated.

Screenshots of the tool in action are given in Fig. 4 in the main body of the paper. We note that, while the tool can technically support unlimited monitoring tasks and search term sets, a practical limit is set by the API access level used to access Twitter, as outlined in the main paper. Thus, for example, the “standard” (free) access level is limited to 180 queries per 15-min rolling window with this quota spread across all active monitoring tasks and their respective search term sets.

The web application is based on the Django v2.1.7 application framework. This application and the various backend modules that do the actual web scraping are written in Python v3.6.9. The tool is supported by a PostgreSQL v10.12 database. The webapp stores all monitoring tasks and logs status information to the database and the results of all Twitter queries returned by all monitoring tasks are stored in the database as well. This approach overcomes the limitations to archival tweets imposed by Twitter. We collect all relevant tweets in real-time and essentially create our own historical archive in the database. The script uses the Tweepy v3.9 Python package to access the Twitter API, and directly accesses the OpenWeatherMap v2.5 API to collect precipitation data.

At the time of this writing, long-term data collection is still running for a number of U.S. cities. We are also setting targeted monitoring of select cities where heavy precipitation and/or flood warnings are issued. Although detailed results await completion of data collection and more careful statistical analysis, our early observations suggest that Twitter may not be as reliable as our pilot effort led us to hope as an early indicator of urban flooding. Correlations between precipitation/flooding and flood-related tweets do often appear but are often obscured or confused by variations in baseline Twitter activity in some locales. More work is also required to discover more reliable filtering queries that separate tweets truly related to flooding from those that mention flooding and rain in unrelated mundane contexts. A more complete report will be provided in an upcoming publication focused specifically on this topic.

References

100 Resilient Cities, 2019. *Resilient Cities, Resilient Lives: Learning from the 100RC Network*.
 arcgis STORM Map [WWW Document], n.d. URL <https://orf.maps.arcgis.com/apps/webappviewer/index.html?id=5f602e6b500c4e159568dc560371088d> (accessed 4.22.21).

Arthur, R., Boulton, C.A., Shotton, H., Williams, H.T.P., 2018. Social sensing of floods in the UK. *PLoS One*. <https://doi.org/10.1371/journal.pone.0189327>.
 Ashley, S.T., Ashley, W.S., 2008. Flood fatalities in the United States. *J. Appl. Meteorol. Climatol.* 47, 805–818. <https://doi.org/10.1175/2007JAMC1611.1>.
 Assumpção, T.H., Popescu, I., Jonoski, A., Solomatine, D.P., 2018. Citizen observations contributing to flood modelling: opportunities and challenges. *Hydrol. Earth Syst. Sci.* 22, 1473–1489. <https://doi.org/10.5194/hess-22-1473-2018>.

- Bothmann, L., Menzel, A., Menze, B.H., Schunk, C., Kauermann, G., 2017. Automated processing of webcam images for phenological classification. *PLoS One* 12. <https://doi.org/10.1371/journal.pone.0171918> e0171918.
- Burgos, A.G., Hamlington, B.D., Thompson, P.R., Ray, R.D., 2018. Future nuisance flooding in Norfolk, VA, from astronomical tides and annual to decadal internal climate variability. *Geophys. Res. Lett.* 45 (12), 432. <https://doi.org/10.1029/2018GL079572>, 12, 439.
- Castelletti, A., Fedorov, R., Fraternali, P., Giuliani, M., 2016. Multimedia on the mountaintop: using public snow images to improve water systems operation. In: *Proceedings of the 24th ACM International Conference on Multimedia*. ACM, pp. 948–957. <https://doi.org/10.1145/2964284.2976759>.
- Chester, M.V., Allenby, B., 2018. Toward adaptive infrastructure: flexibility and agility in a non-stationarity age. *Sustain. Resilient Infrastruct* 4, 173–191. <https://doi.org/10.1080/23789689.2017.1416846>.
- Cromartie, J., 2019. What is Rural? [WWW Document]. United States Dep. Agric. <https://www.ers.usda.gov/topics/rural-economy-population/rural-classifications/what-is-rural.aspx>. accessed 9.26.20.
- Davids, J.C., van de Giesen, N., Rutten, M., 2017. Continuity vs. the crowd—tradeoffs between continuous and intermittent citizen hydrology streamflow observations. *Environ. Manag.* 60, 12–29. <https://doi.org/10.1007/s00267-017-0872-x>.
- de Albuquerque, J.P., Herfort, B., Brenning, A., Zipf, A., 2015. A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management. *Int. J. Geogr. Inf. Sci.* 29, 667–689. <https://doi.org/10.1080/13658816.2014.996567>.
- de Bruijn, J.A., de Moel, H., Jongman, B., Wagemaker, J., Aerts, J.C.J.H., 2018. TAGGS: grouping tweets to improve global geoparsing for disaster response. *J. Geovisualization Spat. Anal.* 2, 1–14. <https://doi.org/10.1007/s41651-017-0010-6>.
- Eltner, A., Elias, M., Sardemann, H., Spieler, D., 2018. Automatic image-based water stage measurement for long-term observations in ungauged catchments. *Water Resour. Res.* 54 (10), 362. <https://doi.org/10.1029/2018WR023913>, 10, 371.
- Flood Control District of Maricopa County, 2020. ALERT Data Map [WWW Document]. URL: <http://alert.fcd.maricopa.gov/alert/Google/v3/gmap.html>. accessed 11.25.20.
- Fohringer, J., Dransch, D., Kreibich, H., Schröter, K., 2015. Social media as an information source for rapid flood inundation mapping. *Hazards Earth Syst. Sci.* 15, 2725–2738. <https://doi.org/10.5194/nhess-15-2725-2015>.
- Gilmore, T.E., Birgand, F., Chapman, K.W., 2013. Source and magnitude of error in an inexpensive image-based water level measurement system. *J. Hydrol.* 496, 178–186. <https://doi.org/10.1016/j.jhydrol.2013.05.011>.
- Guastella, L.A., Smith, A.M., 2014. Coastal dynamics on a soft coastline from serendipitous webcams: KwaZulu-Natal, South Africa. *Estuar. Coast Shelf Sci.* 150, 76–85. <https://doi.org/10.1016/j.ecss.2013.12.009>.
- Herfort, B., De Albuquerque, J.P., Schelhorn, S.J., Zipf, A., 2014. Does the spatiotemporal distribution of tweets match the spatiotemporal distribution of flood phenomena? A study about the River Elbe Flood in June 2013. In: *ISCRAM 2014 Conf. Proc. - 11th Int. Conf. Inf. Syst. Crisis. Response Manag.*, pp. 747–751.
- Hultquist, C., Cervone, G., 2020. Integration of crowdsourced images, USGS networks, remote sensing, and a model to assess flood depth during hurricane florence. *Rem. Sens.* 12 <https://doi.org/10.3390/rs12050834>.
- Huwald, H., Brauchli, T.J., Chen, Z., Weijs, S., 2015. Stream flow velocity measurement with smartphones: a technique for citizen observatories, decision-making, and water management. In: *26th General Assembly International Union of Geodesy and Geophysics (IUGG)*. <http://infoscience.epfl.ch/record/215091>.
- Jiang, X., Li, Jun, Li, Z., Xue, Y., Di, D., Wang, P., Li, Jinglong, 2020. Evaluation of environmental moisture from NWPModels with measurements from AdvancedGeostationary satellite imager—a case study. *Rem. Sens.* 12 <https://doi.org/10.3390/rs12040670>.
- Jongman, B., Wagemaker, J., Romero, B., de Perez, E., 2015. Early flood detection for rapid humanitarian response: harnessing near real-time satellite and twitter signals. *ISPRS Int. J. Geo-Inf.* 4, 2246–2266. <https://doi.org/10.3390/ijgi4042246>.
- Kim, Y., Muste, M., Hauet, A., Krajewski, W.F., Kruger, A., Bradley, A., 2008. Stream discharge using mobile large-scale particle image velocimetry: a proof of concept. *Water Resour. Res.* 44 <https://doi.org/10.1029/2006WR005441>.
- Kim, Y., Eisenberg, D.A., Bondank, E.N., Chester, M.V., Mascaro, G., Underwood, B.S., 2017. Fail-safe and safe-to-fail adaptation: decision-making for urban flooding under climate change. *Climatic Change* 145, 397–412. <https://doi.org/10.1007/s10584-017-2090-1>.
- König, A., Særgrov, S., Schilling, W., 2002. Damage Assessment for Urban Flooding, in: *Global Solutions for Urban Drainage*. American Society of Civil Engineers, Reston, VA, pp. 1–11. [https://doi.org/10.1061/40644\(2002\)273](https://doi.org/10.1061/40644(2002)273).
- Larsen, A.N., Gregersen, I.B., Christensen, O.B., Linde, J.J., Mikkelsen, P.S., 2009. Potential future increase in extreme one-hour precipitation events over Europe due to climate change. *Water Sci. Technol.* 60, 2205–2216. <https://doi.org/10.2166/wst.2009.650>.
- Le Coz, J., Patalano, A., Collins, D., Guillén, N.F., García, C.M., Smart, G.M., Bind, J., Chiaverini, A., Le Boursicaud, R., Dramais, G., Braud, I., 2016. Crowdsourced data for flood hydrology: feedback from recent citizen science projects in Argentina, France and New Zealand. *J. Hydrol.* 541, 766–777. <https://doi.org/10.1016/j.jhydrol.2016.07.036>.
- Leeuw, T., Boss, E., 2018. The HydroColor App: above water measurements of remote sensing reflectance and turbidity using a smartphone camera. *Sensors* 18. <https://doi.org/10.3390/s18010256>.
- Lin, Y.T., Lin, Y.C., Han, J.Y., 2018. Automatic water-level detection using single-camera images with varied poses. *Meas. J. Int. Meas. Confed.* 127, 167–174. <https://doi.org/10.1016/j.measurement.2018.05.100>.
- Loftis, J.D., Mitchell, M., Schatt, D., Forrest, D.R., Wang, H.V., Mayfield, D., Stiles, W.A., 2019. Validating an operational flood forecast model using citizen science in Hampton roads, VA, USA. *J. Mar. Sci. Eng.* 7, 242. <https://doi.org/10.3390/jmse7080242>.
- Lowry, C.S., Fienen, M.N., 2013. CrowdHydrology: crowdsourcing hydrologic data and engaging citizen scientists. *Ground Water* 51, 151–156. <https://doi.org/10.1111/j.1745-6584.2012.00956.x>.
- Lowry, C.S., Fienen, M.N., Hall, D.M., Stepenuck, K.F., 2019. Growing pains of crowdsourced stream stage monitoring using mobile phones: the development of CrowdHydrology. *Front. Earth Sci.* 7, 128. <https://doi.org/10.3389/feart.2019.00128>.
- Markolf, S.A., Hoehne, C., Fraser, A., Chester, M.V., Underwood, B.S., 2019. Transportation resilience to climate change and extreme weather events – beyond risk and robustness. *Transport Pol.* 74, 174–186. <https://doi.org/10.1016/j.tranpol.2018.11.003>.
- Markolf, S.A., Chester, M.V., Helmrich, A.M., Shannon, K., 2020. Re-imagining design storm criteria for the challenges of the 21st century. <https://doi.org/10.1016/j.cities.2020.102981>.
- Mazzoleni, M., Verlaan, M., Alfonso, L., Monego, M., Norbiato, D., Ferri, M., Solomatine, D.P., 2015. Can assimilation of crowdsourced data in hydrological modelling improve flood prediction? *Hydrol. Earth Syst. Sci.* 21, 839–861. <https://doi.org/10.5194/hess-21-839-2017>.
- Middleton, S.E., Middleton, L., Modafferi, S., 2014. Real-time crisis mapping of natural disasters using social media. *IEEE Intell. Syst.* 29, 9–17. <https://doi.org/10.1109/MIS.2013.126>.
- Milly, P., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., Stouffer, R.J., 2008. Stationarity is dead: whither water management? *Science* 319 (80), 573–574. <https://doi.org/10.1126/science.1151915>.
- Minnery, J.R., Smith, D.I., 1996. Climate change, flooding and urban infrastructure. In: *Greenhouse: Coping with Climate Change*, pp. 235–247.
- Moftakhari, H.R., AghaKouchak, A., Sanders, B.F., Matthew, R.A., 2017. Cumulative hazard: the case of nuisance flooding. *Earth's Futur* 5, 214–223. <https://doi.org/10.1002/2016EF000494>.
- Morris, D., Boyd, D., Crowe, J., Johnson, C., Smith, K., 2013. Exploring the potential for automatic extraction of vegetation phenological metrics from traffic webcams. *Rem. Sens.* 5, 2200–2218. <https://doi.org/10.3390/rs5052200>.
- Murdock, C., Jacobs, N., Pless, R., 2013. Webcam2Satellite: estimating cloud maps from webcam imagery. In: *Proceedings of IEEE Workshop on Applications of Computer Vision*, pp. 214–221. <https://doi.org/10.1109/WACV.2013.6475021>.
- Naik, N., 2016. Flooded streets-A crowdsourced sensing system for disaster response: a case study. In: *ISSE 2016 - 2016 International Symposium on Systems Engineering - Proceedings Papers*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/SysEng.2016.7753186>.
- National Academies, 2019. Framing the challenge of urban flooding in the United States. Washington, D.C. <https://doi.org/10.17226/25381>.
- National Oceanic and Atmospheric Administration (NOAA), 2017. NOAA ATLAS 14 Point Precipitation Frequency Estimates: Arizona. NOAA.
- Paul, J.D., Buytaert, W., Allen, S., Ballesteros-Cánovas, J.A., Bhusal, J., Cieslik, K., Clark, J., Dugar, S., Hannah, D.M., Stoffel, M., Dewulf, A., Dhital, M.R., Liu, W., Nayaya, J.L., Neupane, B., Schiller, A., Smith, P.J., Supper, R., 2017. Citizen Science for Hydrological Risk Reduction and Resilience Building, vol. 5. Wiley Interdiscip. Rev. Water. <https://doi.org/10.1002/wat2.1262> e1262.
- Praharaj, S., Chen, T.D., Zahura, F.T., Behl, M., Goodall, J.L., 2021. Estimating impacts of recurring flooding on roadway networks: a Norfolk, Virginia case study. *Nat. Hazards* 1–25. <https://doi.org/10.1007/s11069-020-04427-5>.
- Prein, A.F., Rasmussen, R.M., Ikeda, K., Liu, C., Clark, M.P., Holland, G.J., 2017. The future intensification of hourly precipitation extremes. *Nat. Clim. Change* 7, 48–52. <https://doi.org/10.1038/nclimate3168>.
- Ran, Q.H., Li, W., Liao, Q., Tang, H.L., Wang, M.Y., 2016. Application of an automated LSPV system in a mountainous stream for continuous flood flow measurements. *Hydrol. Process.* 30, 3014–3029. <https://doi.org/10.1002/hyp.10836>.
- Richardson, A.D., Hufkens, K., Milliman, T., Aubrecht, D.M., Chen, M., Gray, J.M., Johnston, M.R., Keenan, T.F., Klosterman, S.T., Kosmala, M., Melaas, E.K., Friedl, M. A., Frokling, S., 2018. Tracking vegetation phenology across diverse North American biomes using PhenoCam imagery. *Sci. Data* 5, 1–24. <https://doi.org/10.1038/sdata.2018.28>.
- Rosenzweig, B.R., Herreros Cantis, P., Kim, Y., Cohn, A., Grove, K., Brock, J., Yesuf, J., Mistry, P., Wely, C., McPhearson, T., Sauer, J., Chang, H., 2021. The value of urban flood modeling. *Earth's Futur* 9. <https://doi.org/10.1029/2020EF001739> e2020EF001739.
- Rosser, J.F., Leibovici, D.G., Jackson, M.J., 2017. Rapid flood inundation mapping using social media, remote sensing and topographic data. *Nat. Hazards* 87, 103–120. <https://doi.org/10.1007/s11069-017-2755-0>.
- Sadler, J.M., Goodall, J.L., Morsy, M.M., Spencer, K., 2018. Modeling urban coastal flood severity from crowd-sourced flood reports using Poisson regression and Random Forest. *J. Hydrol.* 559, 43–55. <https://doi.org/10.1016/j.jhydrol.2018.01.044>.
- Schnebele, E., Cervone, G., Waters, N., 2014. Road assessment after flood events using non-authoritative data. *Hazards Earth Syst. Sci.* 14, 1007–1015. <https://doi.org/10.5194/nhess-14-1007-2014>.
- Schoener, J.F., 2018. Time-lapse photography: low-cost, low-tech alternative for monitoring flow depth. *J. Hydrol. Eng.* 23 [https://doi.org/10.1061/\(ASCE\)HE.1943](https://doi.org/10.1061/(ASCE)HE.1943).
- Schreider, S.Y., Smith, D.I., Jakeman, A.J., 2000. Climate change impacts on urban flooding. *Climatic Change* 47, 91–115. <https://doi.org/10.1023/a:1005621523177>.
- See, L., 2019. A review of citizen science and crowdsourcing in applications of pluvial flooding. *Front. Earth Sci.* 7, 44. <https://doi.org/10.3389/feart.2019.00044>.

- Shin, I., Kim, J., Lee, S.-G., 2008. Development of an internet-based water-level monitoring and measuring system using CCD camera. In: Sasaki, M., Choi Sang, G., Li, Z., Ikeura, R., Kim, H., Xue, F. (Eds.), ICMIT 2007: Mechatronics, MEMS, and Smart Materials. SPIE. <https://doi.org/10.1117/12.784102>, 67944Q.
- Shupe, S.M., 2017. High resolution stream water quality assessment in the Vancouver, British Columbia region: a citizen science study. *Sci. Total Environ.* 603–604, 745–759. <https://doi.org/10.1016/j.scitotenv.2017.02.195>.
- Smith, B., Rodriguez, S., 2017. Spatial analysis of high-resolution radar rainfall and citizen-reported flash flood data in ultra-urban New York city. *Water* 9, 736. <https://doi.org/10.3390/w9100736>.
- Smith, L., Liang, Q., James, P., Lin, W., 2015. Assessing the utility of social media as a data source for flood risk management using a real-time modelling framework. *J. Flood Risk Manag.* 10, 370–380. <https://doi.org/10.1111/jfr3.12154>.
- Sweet, W.V., Park, J., 2014. From the extreme to the mean: acceleration and tipping points of coastal inundation from sea level rise. *Earth's Futur* 579–600. <https://doi.org/10.1002/2014EF000272>.
- The City of Norfolk, 2018. Norfolk joins waze connected citizens program [WWW Document]. URL <https://www.norfolk.gov/CivicAlerts.aspx?AID=3706&ARC=7515>.
- United States Geological Survey, n.d. How are floods predicted? [WWW Document]. United States Geol. Surv. URL https://www.usgs.gov/faqs/how-are-floods-predicted?qt-news_science_products=0#qt-news_science_products (accessed 9.26.20).
- United States Geological Survey (USGS), 2020. National water information system (NWIS). Mapper [WWW Document]. URL <https://maps.waterdata.usgs.gov/mapper/index.html>. accessed 10.13.20.
- Uusitalo, L., Lehtikoinen, A., Helle, I., Myrberg, K., 2015. An overview of methods to evaluate uncertainty of deterministic models in decision support. *Environ. Model. Software*. <https://doi.org/10.1016/j.envsoft.2014.09.017>.
- Vidal, J., 2017. As flood waters rise, is urban sprawl as much to blame as climate change? World news | The Guardian [WWW Document]. Guard. URL <https://www.theguardian.com/world/2017/sep/02/flood-waters-rising-urban-development-climate-change>. accessed 9.26.20.
- Viterbo, F., Mahoney, K., Read, L., Salas, F., Bates, B., Elliott, J., Cosgrove, B., Dugger, A., Gochis, D., Cifelli, R., 2020. A multiscale, hydrometeorological forecast evaluation of national water model forecasts of the may 2018 Ellicott City, Maryland, Flood. *J. Hydrometeorol.* 21, 475–499. <https://doi.org/10.1175/JHM-D-19-0125.1>.
- Wagner, C., Eberts, S., 2020. USGS streamgaging network [WWW Document]. United States Geol. Surv. URL https://www.usgs.gov/mission-areas/water-resources/science/usgs-streamgaging-network?qt-science_center_objects=0#qt-science_center_objects. accessed 9.26.20).
- Wang, R.Q., Mao, H., Wang, Y., Rae, C., Shaw, W., 2018a. Hyper-resolution monitoring of urban flooding with social media and crowdsourcing data. *Comput. Geosci.* 111, 139–147. <https://doi.org/10.1016/j.cageo.2017.11.008>.
- Wang, Y., Chen, A.S., Fu, G., Djordjević, S., Zhang, C., Savić, D.A., 2018b. An integrated framework for high-resolution urban flood modelling considering multiple information sources and urban features. *Environ. Model. Software* 107, 85–95. <https://doi.org/10.1016/j.envsoft.2018.06.010>.
- Weeser, B., Stenfort Kroese, J., Jacobs, S.R., Njue, N., Kemboi, Z., Ran, A., Rufino, M.C., Breuer, L., 2018. Citizen science pioneers in Kenya – a crowdsourced approach for hydrological monitoring. *Sci. Total Environ.* 631–632, 1590–1599. <https://doi.org/10.1016/j.scitotenv.2018.03.130>.
- Yu, D., Yin, J., Liu, M., 2016. Validating city-scale surface water flood modelling using crowd-sourced data. *Environ. Res. Lett.* 11 <https://doi.org/10.1088/1748-9326/11/12/124011>, 124011.
- Zevenbergen, C., Veerbeek, W., Gersonius, B., Van Herk, S., 2008. Challenges in urban flood management: travelling across spatial and temporal scales. *J. Flood Risk Manag.* 1, 81–88. <https://doi.org/10.1111/j.1753-318x.2008.00010.x>.
- Zhang, Z., Zhou, Y., Liu, H., Gao, H., 2019. In-situ water level measurement using NIR-imaging video camera. *Flow Meas. Instrum.* 67, 95–106. <https://doi.org/10.1016/j.flowmeasinst.2019.04.004>.