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Review Article

How computer vision can facilitate flood management: A systematic review

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ABSTRACT

Better prediction and monitoring of flood events are key factors contributing to the reduction of their impact on local communities and infrastructure assets. Flood management involves successive phases characterized by specific types of assessments and interventions. Due to technological advances, computer vision plays an increasing role in flood monitoring, modeling and awareness. However, there is a lack of systemic analysis of computer vision's relative adequacy to specific needs associated with successive flood management phases. This article presents a systematic review of relevant literature and proposes a need-based evaluation of these use-cases. Finally, the article highlights future areas of research in this domain.

1. Introduction

Floods are one of the most frequent, widespread and costly natural disasters in the world [1–10]. According to the United Nations (UN), floods result in the highest number of casualties in comparison to any other disaster [3,11]. It is expected that floods will become even more frequent and devastating because of global warming [1,12]. Flood events can be categorized into three groups: (a) flash floods, usually occurring within 6h of heavy rainfall (b) rive plain inundations, caused by sustained precipitations over large catchment areas, and (c) coastal floods, caused by coastal storms or cyclones and often reinforced by tidal cycles [6].

Flood management aims to reduce the impact of flood events on local communities and infrastructure assets. Flood management follows a four-step cycle including prevention, preparedness, response and recovery phases [9,13]. Approaches to flood management include structural and non-structural measures. Structural measures aim to create artificial structures such as dams, water diversions, embankments and channel improvements; non-structural measures involve flood plain zoning, early warning systems, flood proofing and evacuation plans [13,14]. Early warning systems rely upon access to relevant, timely and accurate data [15,16]. Therefore, remote data collection and automated interpretation have become essential instruments of modern flood management [17].

Automated Computer Vision is a field of Artificial Intelligence (AI) developing theories and algorithms for computer to automatically interpret and understand the content of visual information. This technology is becoming increasingly useful for different flood management phases. Activities utilizing computer vision algorithms include land use classification for flood risk assessment [18,19], real-time flood monitoring [7,20–23], flood surface water velocity measurement [24–39], flood modeling [40,41], flood detection and inundation mapping [8,42–55], flood debris management [56–58], and post flood damage assessments [59]. Despite these successful efforts, progress in using computer vision to its full strength is relatively slow compared to other domains of application. Thus, it is particularly relevant to analyze the potential advantages of computer vision approaches over the conventional monitoring ones in order to establish their proper use for flood management.

Conventional flood monitoring uses point source and mono-dimensional data, such as rainfall and water level measurements, to calibrate and validate hydrological models. However, conventional synoptic networks are often costly to install and maintain [7]. Non-intrusive camera based monitoring (e.g., Gauge-Cams) of river flow for possible flood detection and water related measurements is one of the common approaches used in flood management. Gauge-Cams are permanently installed overhead cameras used to record the river flow using computer vision algorithms [24,28]. One application of Gauge-Cams is to measure the surface water velocity using computer vision and image analytic [27,29,31,60]. The non-intrusive nature of Gauge-Cams make them a suitable option during extreme flood conditions compared to conventional measurement approaches [25,28].

Satellite imagery has provided crucial spatially explicit visual information to analyze interactions between land use, run-off and inundation. Amongst emerging technologies, satellite microwave remote sensing is a promising solution for mapping hydrodynamic ecosystems.

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In particular, Synthetic Aperture Radar (SAR) can cope with challenging environments such as urban areas and dense vegetation covers [7]. However, given the limited orbital frequencies and inter-track spacing, satellite imagery and remote sensing are of limited use for real-time monitoring applications [7].

To overcome these limitations, airborne remote sensing has benefited from the rapid technological advances of civilian Unmanned Aerial Vehicles (UAVs). UAVs can be deployed on-demand and under heavy cloud cover, with low operational costs [61,62]. They have demonstrated their value for high resolution and rapid mapping of inundations, especially in urban landscapes [2]. Ground cameras are also used in critical locations where people's safety (visual detection of endangered individuals during a flood) or security of infrastructure (visual detection of submersion or structural damage) are at risk [22,63]. Although computer vision based solutions can monitor larger areas and collect multi-dimensional information associated with inundations [63], examples of fully-integrated applications are still rare. FloodX is an example of such an integrated monitoring system for urban flash flood [15].

Recent technological advances in mobile devices and access to crowdsourced data have made it possible to engage the community in explicitly collecting data for flood risk management and raising awareness [64–66]. Citizen science is the process of engaging the community in a collaborative effort to track, monitor and respond to common community issues [67,68]. Crowdsourcing or citizen science is actively used for facilitating during flood events (e.g., street flooding detection using social media, web and mobile applications for flood reporting) and post flood events (e.g., damage assessments) [69]. CrowdWater [70,71], CrowdHydrology [72], CityHyd [73], WeSenseIt [74], PetaJakarta [75], SCENT [76], Smartphones4Water [77], mPING [78] and GroundTruth2.0 [79] are few highlighted initiatives which used citizen science for flood detection, modeling and mapping by making use of mobile and web-based applications. From computer vision perspective, research in this domain can be categorized into (a) mobile and web applications where visual data is used for flood monitoring, modeling and mapping [80–84] (b) social media visual Big Data for flood related measurements and detection (e.g., flood detection, water depth estimation) [85–96].

Despite an increasing number of scientific articles describing the use of various computer vision technologies in specific contexts [17,97], there is a need for a comprehensive review of these technologies, using a flood management perspective. Presented systematic review aims to create a common taxonomy linking assessment requirements for flood management and capabilities offered by various computer vision technologies. Followings are the main contributions of the presented review:

(a) Study highlights the lack of systematic analysis of various computer vision technologies specific to needs associated with successive flood management phases and proposes a common taxonomy to establish the link.
(b) Study presents a comprehensive need-based analysis of literature. Furthermore, it highlights future directions with potential computer vision technologies as a possible solution and corresponding challenges.

This article is organized as follows: Section 2 presents the methodology adopted to perform the presented systematic review; Section 3 presents a detailed taxonomy of functionalities required by each flood management phase and provided by each computer vision technology; Section 4 presents a structured review of the selected articles using our proposed taxonomy; Section 5 presents a need-based analysis of the selected articles and identifies several opportunities to enhance the role of computer vision for flood management; Section 6 presents the future directions of computer vision technologies and corresponding challenges.

2. Review methodology

This systematic review is performed using the Preferred Reporting Items for Systematic Reviews and Meta-analyzes (PRISMA) [98], and guidelines reported by Kitchenham et al. [99,100] and Kankanamge et al. [101]. Review protocol included formulation of research questions, selection of pertinent keywords, selection of search databases, the definition of exclusion/inclusion criteria, descriptive analysis of selected literature, detailed review of the literature and need-based analysis.

A set of research questions were formulated to perform the systematic review with the aim to explore the state of the art computer vision technologies in flood management. Listed are three main research questions explored in the presented systematic review:

(a) *What is the current status of computer vision technologies in the flood management domain?*
(b) *What are various computer vision technologies used to address flood management requirements/problems?*
(c) *What is the future scope of computer vision in flood management?*

A list of relevant keywords was composed to extract the literature related to formulated research questions from academic databases. Search keywords included "computer vision" AND "flood", "drone" AND "flood", "UAV" and "flood", "optical remote sensing" AND "flood", "visual sensing" AND "flood", "deep learning" AND "flood", "CNN" AND "flood", "Citizen Science" AND "flood", "Crowdsourcing" AND "flood" and "image processing" AND "flood". Three academic databases including Science Direct, IEEE Xplore and Scopus were searched against the defined keywords and pertinent literature was acquired. In total, 8174 articles were obtained from all three databases with the individual distribution of 6403 from Science Direct, 680 from IEEE Xplore and 1091 from Scopus.

Extracted literature was refined and filtered based on defined inclusion/exclusion criteria. Presented systematic review only included journal articles, conference articles, technical reports, thesis and books published in the English language between 1998 and 2020. Furthermore, duplicate entries among the three databases were removed. Literature filtered through initial inclusion/exclusion criteria was further screened at three stages (a) title screening (b) abstract screening (c) full-text assessment. As a result, 103 unique entries were finalized and included in the presented review. Fig. 1 shows the PRISMA flow diagram for the systematic literature review.

The selected use-cases were subjected to exploratory analysis for highlighting the trends in distribution across various categories. Fig. 2 (a) presents the year-wise distribution of selected literature. It is evident from the bar graph that the volume of research in flood management using computer vision technologies has increased notably from 2015 onward. Fig. 2(b) shows the pie-chart highlighting proportions of published research using different visual sensing technologies. From the pie-chart, it can be noticed that fixed ground camera based solutions were examined the most. In contrast, the potential of hybrid approaches has not been investigated in detail. Fig. 2(c) presents the distribution of literature across different flood management phases. From the pie-chart, it is apparent that computer vision technologies were predominantly used at the response phase in comparison to other phases. In contrast, to the best of authors knowledge, no published evidence was found for the use of computer vision at the recovery phase. Finally, Fig. 2(d) shows the distribution across different types of literature presented in the systematic review. 91.1% of total literature was collectively from journals and conferences, 3.9% was from arXiv repository for unpublished research and 5% from other sources (thesis, technical reports, letters). Literature was not assessed for quality because of a relatively small number of records, therefore, all relevant published writings were included in the review.

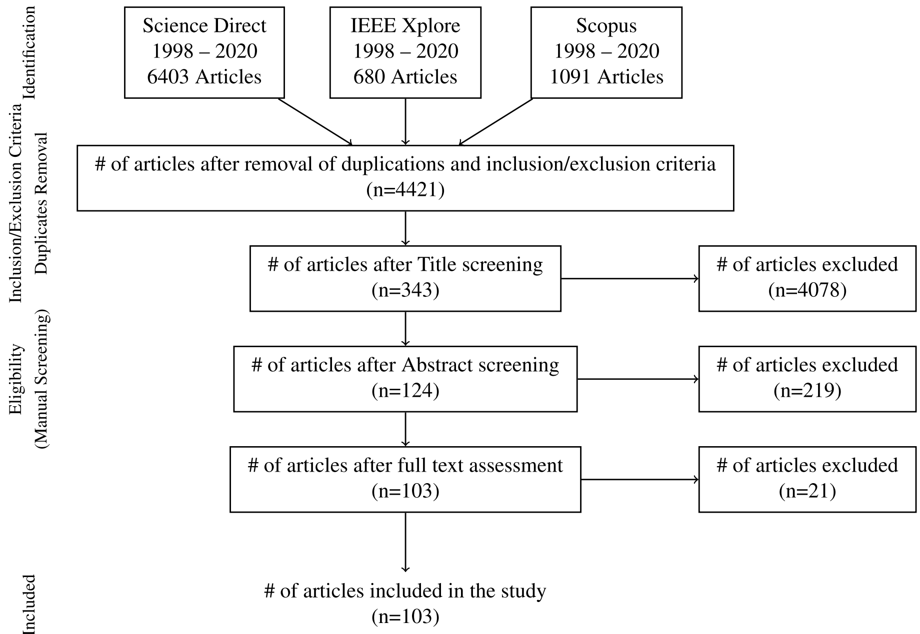
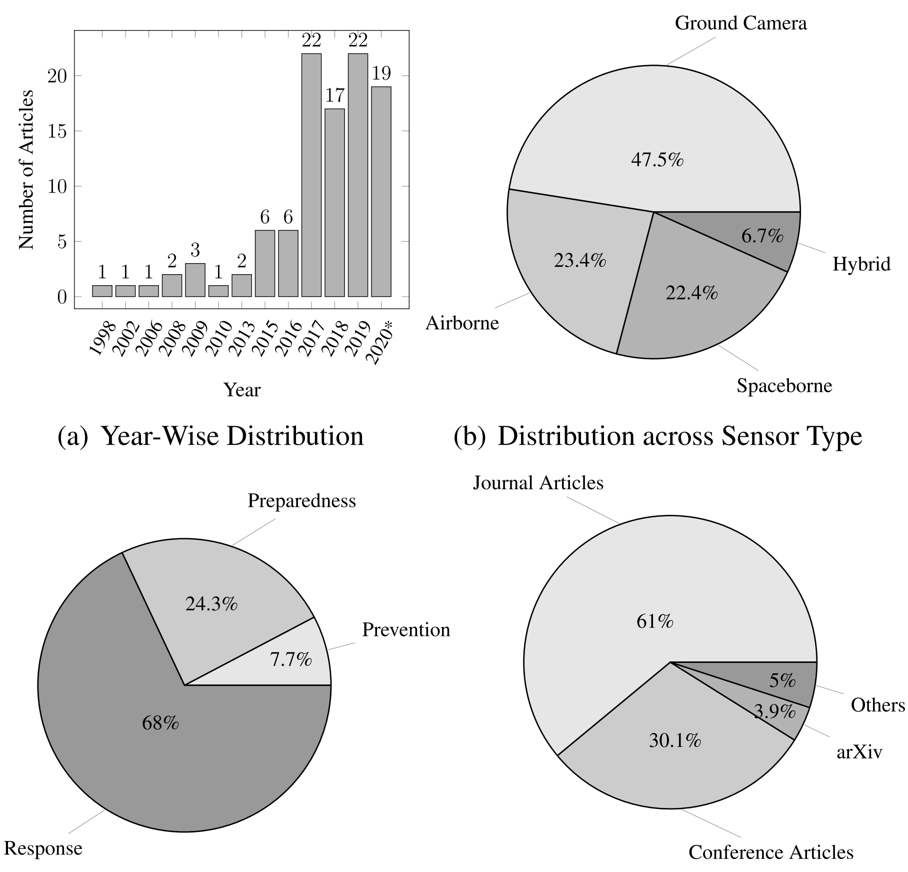


Fig. 1. Prisma flow diagram for presented systematic review.



(a) Year-Wise Distribution (b) Distribution across Sensor Type

(c) Distribution across Flood Phase (d) Distribution across Type of Literature

Fig. 2. Exploratory analysis of selected literature.

3. Review taxonomy

This section proposes and defines a detailed taxonomy based on (1) specific needs associated with each phase of a flood management process and (2) capabilities offered by various computer vision technologies. In the following section, defined taxonomy is used to review selected articles. A broader objective for defined taxonomy is to serve as a foundation to an analytical framework for readers to review future scientific articles on the topic or for authors to categorize their research clearly.

Each phase of a flood management process includes a series of assessment activities characterized by their intended functionality. For example, during the 'prevention' phase, the 'flood risk estimation' activity often uses a 'land use management' assessment, which intended functionalities include a land cover and human activity mapping of the target area. Table 1 summarizes functionalities associated with the most common assessment techniques used at each phase of flood management process.

Capabilities associated with computer vision technologies fall into four categories: classification, detection, tracking and forecasting. Thus, our next step is to map the aforementioned required functionalities over these technological capabilities. For example, computer vision capabilities needed by a 'land use management' assessment will broadly fall into a 'classification' category. Table 2 shows how already identified functionalities (Table 1) can be associated with specific computer vision capabilities.

Finally, we need to evaluate capabilities offered by computer vision sensing technologies (satellite imagery sensing, airborne remote sensing and ground cameras) against requirements associated with specific assessment activities. We have limited these requirements to three broad categories: coverage area, visual precision and real-time response. Table 3 presents a list of the most common flood related assessments and their particular requirements. Based on these assumptions, Table 4 shows the suitability of computer vision sensing technologies for these flood related assessments. For example, 'land use management' assessment requires large area coverage at a low resolution without the need for real-time response. Satellite imagery is the most suitable solution for this use-case.

Table 1
List of different functionalities involved in flood management related assessments.

	Functionalities		
Socio-Economic Assessment	land cover classification	classification of human related activities	land use classification
Baseline Data Collection	visual data collection	questionnaires and surveys	interviews
Flood Monitoring and Early Warning System	water level measurement	surface water detection/surface water velocity	forecasting and prediction of future floods
Flood modeling	hydrological flow behiours estimation	hydrological structures design and modeling	–
Flood Inundation Mapping	surface water detection	water depth estimations	–
Flood Debris Management	debris flow estimation	debris recognition	debris blockage detection
Post Flood Damage Assessment	detection of damaged infrastructures	total flood damage estimations	structural health monitoring
Search and Rescue	victim identification	crowd detection	–
Reconstruction and Debris Removal Monitoring	change detection in infrastructures development	–	–

4. Taxonomy-based review of computer vision technologies in flood management

This section reviews successively use-cases associated with ground camera technology (4.1), spaceborne satellite imagery (4.2), airborne remote sensing (4.3) and hybrid approaches (4.4). A review of the literature is presented in chronological order to highlight the different stages of development.

4.1. Ground camera approaches

Fixed ground camera sensors equipped with edge-computing hardware and computer vision algorithms are used for facilitating flood management processes in the local scope. An abridgment of selected use-cases from literature where ground camera sensors are used for flood management is presented.

In 1998, Fujita et al. [36] proposed Large Scale Particle Image Velocimetry (LSPIV) as an extension to the PIV approach for measuring surface water velocity. The LSPIV approach was improved in comparison to conventional PIV for illumination conditions, seeding procedures and pre-processing. The Proposed LSPIV approach was based on computing the cross co-relation of features between two consecutive frames and calculating the flow vectors to determine the flow characteristics. The evaluation was performed for three different flow cases and a mean error of 3%–5% was reported for surface water velocity measurements. In 2008, Udomsiri and Iwahashi [20] developed a computer vision based water level detection system using a horizontal edge detector and Finite Impulse Response (FIR) filter. Conventional edge detection and the FIR filter were used to identify the water-ground boundary and enhance performance in assorted lighting conditions, respectively. The proposed approach was validated for a custom collected dataset of 15 video sequences with encouraging results. No comparison with existing literature was made to highlight the scope of the study. Later on, Yu and Hahn [102] adopted a similar approach to using conventional image processing techniques to detect the water level. The proposed algorithm used image subtraction, image registration, reference marking and edge detection techniques. Furthermore, to compensate for the camera viewpoint variations, a camera calibration approach was used. Results of the proposed method were compared with ultrasonic water level measurements and were found relatively close indicating the high accuracy of the computer vision approach. Park et al. [21] proposed a solution for flood water depth detection at the response phase by using a fixed camera. The water level was determined by identifying the level at the reference measuring scale using an accumulated histogram and bandpass filter approaches. The developed solution was not validated for generalized data and results were not compared with existing literature to determine the scope.

In 2010, Rankin and Mathies [43] used the saturation-to-brightness ratio as a key factor for semantic segmentation of the water body from other terrain types. Color, saturation and texture information of water was efficiently used in the designed approach. However, no validation metric was defined to evaluate the performance of the developed algorithm. Three years later, Kao et al. [57] introduced a real-time computer vision based debris flow monitoring system using background subtraction and spatial filtering techniques. The developed algorithm was validated comprehensively for three datasets; however, no comparison to existing literature was made to highlight the scope of the study. In 2013, Li et al. [37] implemented a multi-channel Large Scale Particle Velocimetry (LSPTV) approach to measure the surface velocity for unsteady flow conditions. Most critical issues of flow seeding, illumination, tracer identification and particle matching were addressed. The

Table 2
Categorization of flood management related functionalities as standard computer vision problem.

	Standard Computer Vision Problem			
	Classification	**Detection/Segmentation**	**Tracking**	**Forecasting**
Functionalities	classification of land cover	debris recognition	hydrological flow behavior estimation	forecasting and prediction of future floods
	classification of human related activities	debris blockage detection	debris flow behavior	hydrological flow behavior estimation
	flood detection	total flood damage estimation	change detection in infrastructure development	total flood damage estimation
	surface water detection	victim identification	water level variation	future blockage risk estimation
	victim identification	classification of land cover	surface water velocity	surface water velocity
	Debris blockage detection	water level detection	–	–
	detection of damaged infrastructures	water depth estimation	–	–
	crowd detection	–	–	–

Table 3
Flood management related requirements for each assessment.

		Flood Management Related Requirements		
		Coverage Area	**Visual Precision**	**Real-Time Response**
Assessments in Flood Management	Land use management	Large/ Global	Low	No
	Baseline data collection	Both Local and Global	Moderate to High	No
	Flood monitoring and early warning	Local	High	Yes
	Flood inundation mapping	Large/ Global	Low	No
	Flood forecasting	Local	High	No
	Flood debris management	Local	Moderate to High	Yes
	Post flood damage	Both Local and Global	Moderate to High	No
	Search and rescue	Local	High	Yes

Table 4
Relation between computer vision sensing technologies and flood management related assessments based on requirements.

	Ground Camera	**Airborne**	**Spaceborne**
Land use management	×	✓	✓
Baseline data collection	✓	✓	✓
Flood monitoring and early warning	✓	✓	×
Flood inundation mapping	×	×	✓
Flood forecasting	✓	✓	×
Flood debris management	✓	✓	×
Post flood damage assessment	×	✓	✓
Search and rescue	×	✓	✓

approach was evaluated for a test case and encouraging results were reported. In 2015, Lo et al. [7] addressed the early flood warning problem at the preparedness stage by proposing a Closed-Circuit Television (CCTV) camera based solution. The water body from images was extracted using computer vision techniques and a virtual marker was used to determine the water level. A continuous water elevation was plotted and a threshold on water elevation was set to issue flood warnings. The designed method was extensively assessed for its real-time functionality. However, no proper evaluation metric was defined to measure its generalized performance.

In 2016, San Miguel et al. [42] used conventional image processing techniques including background subtraction, histogram equalization and object detection to extract surface water bodies from the video feed. Extensive testing of the developed method for a diverse dataset was not reported. The same year, Hiroi and Kawaguchi [103] used conventional image processing techniques to detect the water level in rivers for early flood warning. Accurate water level measurements were reported for use-case; however, the generalized performance was not investigated. Later, Yeum [104] proposed the use of Convolutional Neural Network (CNN) based object classification and detection algorithms for steel and concrete structural damage assessments. The proposed method was validated on custom collected data from a use-case and admissible results were reported. In 2016, Tauro et al. [25] emphasized the need for a non-intrusive fully autonomous mechanism to measure surface water velocity during extreme flood conditions. The LSPIV approach was used to measure the velocity for a case study on the Tiber River flood event. The performance was assessed for challenging environmental conditions (e.g., peak flood, variable illumination, variable weather). The use of the LSPIV approach for extreme flood conditions was suggested because of its non-intrusive nature and comparable accuracy to conventional approaches. However, a possible degraded performance may exist under reduced visibility conditions (e.g., extreme rain, bad lighting, fog).

In 2017, Tauro et al. [31] compared the performance of LSPIV and PTV image velocimetry approaches for custom collected videos of high flows. Dataset consisted of 12 videos with artificial seeds distributed homogeneously to improve the measurement accuracy. From the experimental results, the modified PTV approach was found in close agreement with ground truth, while the LSPIV approach underestimated the velocity measurements. In 2017, Lopez-Fuentes et al. [44] used existing CNN based semantic segmentation algorithms to extract water from images. High segmentation precision was achieved; however, the dataset was relatively small from deep learning perspective to generalize the performance. Harjoko et al. [56] investigated computer vision based detection technique for debris flow rate estimation for a use-case. The optical flow approach and Lucas-Kanade algorithm were used to detect the motion of flood debris and to estimate the speed, respectively. The proposed algorithm was validated only for limited scope and no quantifiable results were reported. Teng et al. [105] proposed a novel approach of using semantics and CNN based multi-label classification to detect flooding event from images. A three-stage pipeline comprising of the semantic model, classification model and event discrimination model was used to classify an image as flooded or non-flooded. The proposed method was assessed for a custom collected dataset and compared with other CNN models with improved performance.

In 2017, Wang et al. [85] proposed the use of computer vision technologies for collecting hyper-resolution data to support urban flooding. MyCoast crowdsourcing platform was used to collect flooding images from social media. A CNN based image classification algorithm was used to detect the flood in a given image. Although promising results were achieved, but the investigation of more state of the art computer vision techniques was not done. In the same year, Alam et al. [86] proposed an end-to-end system called Image4Act to process social media images for disaster response. The system mainly consisted of image collector, image filtering, image denoising and finally, image classification. VGG16 deep architecture was used to classify the collected image into one of the defined flood response classes. Encouraging results were reported; however, a detailed investigation of the proposed system was not performed. Later, Geetha et al. [87] proposed a computer vision based approach to automatically estimate the flooding extent from random crowdsourced images. Color-based segmentation of the water body from the image was used as the main idea in the proposed algorithm. The Flood level in the image was estimated by segmenting the human body (e.g., face and body regions) and determining the average relative height. A reasonable performance was achieved for the concept; however, investigation of the state of the art algorithms was not performed. Yang and Ng [80] proposed the use of crowdsourcing approach as an alternative to conventional sensors towards monitoring urban rainfall. Smartphones, surveillance cameras and other mobile devices were proposed to be used as precipitation sensors. From the series of simulation based experiments, it was reported that rainfall data generated through crowdsourcing lead to better stormwater flow modeling in comparison to conventional rain gauge data. However, all the data used in the simulations was generated statistically based on assumptions and challenges in the development of rainfall reporting/monitoring tools for mobile devices were not addressed.

In 2018, Strobl et al. [81] assessed the accuracy of crowdsourced streamflow observations towards using citizen science in water management. Observations from approximately 500 citizens were taken using field surveys and virtual-gauge functionality of the CrowdWater mobile application for ten streams in Switzerland. From the results, it has been reported that stream level observations were more accurate in comparison to streamflow estimates. In the same year, Giannakeris et al. [88] proposed a warning system to detect the vehicles and people in danger during a disaster from crowdsourced images. The proposed system consisted of image classification (if there is an emergency situation in the image), emergency localization (identify the region of emergency), object detection (detect person and vehicles) and severity level estimation. VGG16 was used for classification, DeepLab for localization and Faster R–CNN for object segmentation. Encouraging results were reported to demonstrate the scope of the proposed approach. Witherow et al. [89] proposed an image processing pipeline to detect the extent of floodwater on roads from the crowdsourced collected images (images from mobile devices). A custom collected dataset from the actual flooding event was used to demonstrate functionality of the proposed system. Edge detection, Region Based CNN (R–CNN), image inpainting and contract correction methods were used towards extracting the flood extent information from the crowdsourced images. Encouraging results were reported; however, challenges regarding the variation of data in terms of image resolution, lighting condition and environmental conditions were also highlighted. In 2018, Feng and Sester [90] proposed a deep learning based approach to extract flood related Volunteered Geographic Information (VGI) from social media texts and photos. A dataset of 7600 images was used for the classifier training in the pipeline. Logistic regression, random forest, multilayer perceptron, gradient boosted trees and XGBoost classifiers were trained and compared for their performance. From the analysis, XGBoost was reported best in terms of classification accuracy. Later, Krohnert and Eltner [91] proposed a low-cost camera based system for hydrological measurements. Smartphones were highlighted as the main source of data to be processed for hydrology related measurements and observations. Android based application called “Open Water Levels” was used to collect the water level information from smartphones. Encouraging results were reported; however, a detailed investigation was not performed.

In 2018, Tauro et al. [38] proposed Optical Tracking Velocimetry (OTV) approach to measure the surface water velocity. The proposed approach enabled automatic detection of features, tracking in Lucas-Kanade algorithm and Region of Interest (ROI) filtering to discard the un-realistic trajectories. The OTV approach was validated for varied flow conditions and was found insensitive to image resolution. Furthermore, the OTV was reported to be less sensitive to noise and surface seeding in comparison to other cross co-relation based velocimetry approaches. A significant impact of acquisition frequency was reported for the values lower than 7HZ. Furthermore, the performance of multiple feature detectors was compared and the Features from Accelerated Segment Test (FAST) algorithm was reported best among studied. In the same year, Leitao et al. [34] used the Surface Structure Image Velocimetry (SSIV) approach for runoff velocity measurements using consumer-grade surveillance cameras. The proposed SSIV approach was based on the conventional LSPIV with improvements for (a) glare and shadows on water surface (b) lack of traceable feature. Among other contributions, investigation of the proposed approach for variable illumination conditions was most critical from image processing perspective. From the results, it was reported that the proposed approach accurately measured surface water velocity as low as $0.1ms^{-1}$ in the day while $0.5ms^{-1}$ at the night. Lin et al. [22] developed a single camera based system for detecting water level at a reservoir. Conventional image processing techniques including line detection, camera transformation and camera calibration were used to identify the water level from a water gauge. Although the proposed algorithm efficiently compensated for camera movement, camera tilt and noise issues; however, it was not assessed for comprehensive visual data for generalized performance. Lohumi and Roy [106] introduced a deep learning based approach to estimate flood severity from the video. Gated Recurrent Unit (GRU) with VGGNet was used to classify the video sequence. The proposed system was tested on a custom collected dataset with considerable accuracy. Layek et al. [107] proposed a CNN-based approach to detect flood images from social media. CNN classification model and color based filtering were used to detect the flooded and non-flooded images. Encouraging results were reported when validated for a custom collected dataset.

In 2019, Pouyanfar et al. [108] used an adversarial data augmentation approach to address the problem of real-world weather conditions in flood detection. CycleGAN data augmentation approach with the ResNet50 CNN model for classification was used to categorize social media collected images into flooded and non-flooded. A custom dataset of approximately 10,000 images was developed and the performance of different algorithm configurations was compared to highlight the advantage of the proposed algorithm. Later on, Rubio et al. [109] introduced deep learning for accurate state estimation of infrastructure damage. Semantic segmentation was used to extract the delamination and rebar damage for a custom dataset of approximately 700 images. Dataset was relatively small from deep learning perspective to address generalization. Ackere et al. [110] emphasized on inclusion of flood-prone buildings into socio-economic impact assessment and proposed the idea of using computer vision technologies as a potential solution. Location and dimension of doors, windows and basement ventilation holes were proposed to be detected using some image segmentation algorithms towards generating information useful for flood risk management. Zhang et al. [111] proposed a novel approach to detect the water level under complex illumination conditions using image processing techniques. The water line was detected using the position of Maximum Mean Difference (MMD) of horizontal projections. The proposed method was evaluated for two sites under a variety of natural and artificial illumination conditions with encouraging results.

In 2019, Etter et al. [83] proposed the use of crowdsourced water level class observations towards calibrating the hydrological model. A Bucket-Type runoff model (HBV) was calibrated for four catchments in Switzerland using crowdsourced water level values collected via virtual gauge functionality of CrowdWater mobile application. Effects of temporal resolution and magnitudes of errors in the crowdsourced water level observations were studied on the validation performance of the hydrological model. From the results, it was reported that one observation per week for one year could significantly improve the performance of the hydrological model. Furthermore, a minimal effect of typical citizen science based errors was observed on the performance of the hydrological model. In the same year, Seibert et al. [82] proposed the use of virtual staff gauge under the CrowdWater mobile application platform towards collecting accurate crowdsourced stream water levels. Virtual staff gauge allowed to avoid the installation of physical gauges and enabled citizens to easily capture the water level data. Although the idea was encouraged by the community; however, problems in placement, virtual gauge size and unsuited location were highlighted to be improved.

More recently, Meng et al. [112] developed computer vision algorithms based pipeline to estimate the flood depth from web images. The Mask R–CNN model was used for the semantic segmentation of humans from web image and extraction of body key points. Face++ Application Programming Interface (API) was used to determine the sex, age and ethnicity information. The proposed approach was assessed for a relatively small dataset of only 155 web images. In 2020, Mishra et al. [113, 114] developed a deep learning based pipeline to classify the drains as different blockage classes. Semantic segmentation and VGG16 classification models were used in the pipeline to focus on the drain and classify it into one of the defined blockage classes. The proposed methodology was evaluated for a custom dataset and admissible results were reported. Huang et al. [115] introduced a novel image segmentation based approach to estimate the flood water depth from images. The tyre of the vehicle was used as a reference object and was segmented from the image using the Mask R–CNN model for estimation of water depth. Admissible results were reported for the proposed approach when validated against a custom collected dataset. Liang et al. [116] developed a novel WaterNet CNN model for segmenting the water body from a given image. The volatile and dynamic appearance of water was used as a key feature in the developed CNN model. A dataset of 2388 images and 20 videos with segmentation labeling named "WaterDataset" was developed. A proper evaluation metric was defined and the results of the proposed algorithm were compared with existing algorithms in the literature for the introduced dataset.

In one of the most recent publications, Feng et al. [93] proposed a three-stage pipeline for mapping flood severity using VGI, also referred to as social media information. Flood related images from social media were extracted at the first stage, interpreted for flood severity at the second stage and a flood severity map was generated based on social media post location at the final stage. Mask R–CNN, OpenPose and DeepLabv3+ models were used for human detection, body keypoint detection and semantic segmentation, respectively, at the second stage. A comprehensive analysis of the performance of the proposed method was made for a selected use-case. Muhadi et al. [117] performed a comparative study of different image segmentation approaches to extract water body from a given image to determine the flooding. Image segmentation approaches were compared qualitatively and quantitatively for a custom test case. The hybrid approach was reported as the best in comparison to region growing and threshold based approaches. Evaluation for a more generalized dataset was not addressed and state of the art semantic segmentation algorithms (e.g., Mask R–CNN) were not included in the comparative study.

Pereira et al. [94] used flood related social media images dataset to identify the flood and determine its severity. A custom dataset was developed taking images from European Flood 2013 dataset and the Multimedia Satellite Task from MediaEval. DenseNet and EfficientNet CNN models were used with reasonable accuracy to demonstrate the potential of using deep learning techniques for flood event detection. However, limitations of an extensive dataset and generalized performance were not discussed. Quan et al. [95] used human pose information from social media images to determine the flood extent. Pipeline included classification of flood related images, detection of humans in the image, detection of body key points and determination of flood severity based on the extracted information. The proposed approach was validated on the MediaEval19 challenge public dataset and was ranked first in the competition. Chaudhary et al. [96] proposed a multi-task deep learning approach to estimate water depth from the social media images for flood mapping. The idea of training the model for a small set of annotated water levels (regression task) and a larger set of weak annotated dataset (ranking task) was used effectively towards saving annotation effort. An annotated dataset named "DeepFlood" was introduced with 8145 images. The water level with less than 11 cm Root Mean Square (RMS) error was estimated using a multi-task approach with the VGG16 CNN model. In a recent research, Tosi et al. [26] developed a low-power edge computing hardware for streamflow velocity measurement in Situ River. The OTV approach based on the FAST features detection and Lucas-Kanade algorithm was used to measure surface water velocity. For the deployment on edge computing hardware (Raspberry PI 3 B), baseline OTV was optimized for search area, pyramid levels, number of tracked features, frame rate and image resolution. From the analysis, improved performance for the optimized OTV approach was reported; however, dependence on visual quality degrading factors (e.g., lighting conditions, extreme weather, lower image resolution) was not addressed.

Most recently, Etter et al. [84] assessed the quality of water level class observations collected using the virtual staff gauge functionality of CrowdWater mobile application. Crowdsourced observations were compared with real surveyed values for 12 different locations under different flow conditions. From the results, crowdsourced observations were reported better in comparison to the real observations. The use of virtual staff gauge and interactive mobile application to record hydrology related data was encouraged. In 2020, Ning et al. [92] proposed a screening system based on deep learning algorithms to identify floods related images. The proposed system mainly consisted of image downloading from social media, detecting flooding in images and finally a web based application for human verification. A custom collected dataset of 4800 images was used to train the CNNs and classification accuracy of 93% was reported for VGG16 among others.

Fixed ground camera based approaches were reported to be used across a variety of flood management related activities including water level detection, surface water detection, surface water velocity measurement, flood severity determination, socio-economic impact assessment, flood early warning systems and flood debris detection. Implementation of computer vision technologies evolved over the years from conventional image processing techniques (e.g., line detection, edge detection, transformations, filters, color transforms, LSPIV, LSPTV, SSIV, OTV) towards CNN based approaches (e.g., ResNet50, CycleGAN, WaterNet, Mask R–CNN, DenseNet, EfficientNet, VGG16). However, the limitation of not having comprehensive visual annotated datasets was consistently observed in the presented literature. Furthermore, crowdsourcing or citizen science has shown significant potential in flood management related activities. All the reported solutions were proposed for a specific local utility under the limited scope and no generalized performance was addressed mainly because of the unavailability of standard visual datasets. Furthermore, except for a few use-cases, there was no comparison between the proposed approach and existing algorithms made to highlight the scope of the study. Some studies were not performed in the direct scope of flood management, such as Rubio et al. [109]; however, included in the review because similar approaches can potentially be used for flood management in the future.

4.2. Spaceborne optical imagery approaches

Spaceborne or satellite images interpreted using computer vision algorithms are used in the global scope for flood management. A summary of selected use-cases where satellite optical images are used to address flood management activities is presented.

In 2006, Ip et al. [47] introduced an autonomous spacecraft using Autonomous Sciencecraft Experiment (ASE) software for flood monitoring. On-board capabilities of spacecraft were used to automatically detect and react to a flooding event without human intervention. A reduced react time of 6 h was achieved from preliminary tests. In 2015, Castelluccio et al. [18] performed CNN based classification on satellite captured images dataset called “UC Merced Land Use Dataset” to identify the land use based on visual features. GoogleNet and CaffeNet CNN models were validated for the UC Merced dataset with 97% and 95% classification accuracy, respectively. In 2017, Liu et al. [45] proposed a novel spatiotemporal context learning method with a modest AdaBoost classifier to automatically generate the flood inundation maps. The proposed method was validated on two different flood cases with admissible results. Isikdogan et al. [46] developed a novel DeepWaterMap CNN model to specifically classify water bodies from satellite images. High accuracy was achieved for custom Landsat images; however, integration of other sources of information to compensate revisit limitations of the satellite was not addressed. Later that year, Helber et al. [19] proposed a comprehensive novel land use classification dataset called “EuroSAT”. GoogleNet and ResNet50 CNN models were implemented for classification and achieved over 98% accuracy.

In an effort to address flood management using state of the art computer vision approaches, MediaEval introduced a challenge in 2017 called “Multimedia Satellite Task: Emergency Response for Flooding” to detect the flood from the social media textual and satellite visual information [118]. Teams from academic institutions around the world were invited to propose corresponding solutions. Few highlighted solutions [48–55] are presented in this review where CNNs, random forest classifier and regression approaches were used. Teams were provided with the dataset, and results of the challenge indicated that visual information could be efficiently used for flood detection. Although the state of the art vision algorithms were deployed over a relatively small but standard satellite images dataset; however, proposed solutions were not comprehensively explored for their real-time implementation and were not tested in real-world events for more challenging conditions.

In 2018, Weng et al. [119,120] proposed the combination of CNN and Constrained Extreme Learning Machine (CELM) for land use classification. Features were extracted using a pre-trained CNN model, while classification at the fully connected layer was done using the CELM classifier to improve the performance. The proposed algorithm demonstrated improved performance in comparison to literature when applied to standard UC Merced and AID datasets. Yang et al. [121] developed CNN models SegNet and LiteNet for the land cover and land use classification, respectively. Different variants of CNN models were used for custom-defined satellite dataset and accuracy of around 80% was achieved. However, a more generalized performance of the proposed algorithm was not addressed. Nogueira et al. [8] proposed a computer vision based solution for threshold and atmospheric variations in reflectance based surface water mapping. Existing CNN models were used to classify satellite images as flooded or non-flooded. High accuracy was achieved over a custom dataset; however, the generalized performance was not investigated. Zhang et al. [122] developed novel multi-scale deep learning models, named ASPP-Unet and ResASPP-Unet for urban land cover classification. ASPP-Unet model was introduced to extract high-level features while ResASPP-Unet to improve the model architecture by replacing layers with residual links. In comparison to existing literature, proposed models were reported better when applied on a custom dataset collected from a use-case.

In 2019, Potnis et al. [123] proposed a novel Efficient Residual Factorized Convnet (ERFNet) deep learning model to segment the flooded regions in the satellite images. The markGT annotation tool was developed to facilitate the end-to-end annotation of the custom satellite image dataset. The proposed algorithm demonstrated acceptable performance for the custom dataset highlighting the future potential of deep learning for such applications. In 2020, Weber and Kan [124] developed a deep learning based damage detection pipeline for xBD satellite dataset [125]. ResNet50 model was used as a backbone, while Mask R–CNN semantic segmentation was used at the final step to visualize the damage map of a given region. The improved performance was reported when compared with the base model proposed in the literature. Gupta and Shah [126] proposed a novel RescueNet CNN model for building damage assessment from satellite images. Localization aware loss function comprising of Binary Classification Loss for building detection while Categorical Cross-Entropy Loss for damage detection was used to achieve improved results. The proposed algorithm was compared with existing literature for a standardized xBD satellite dataset [125] and improved results were reported. More recently, Shao et al. [127] developed a novel Building Damage Detection Network (BDD-Net) to map the post disaster structural damage from satellite images. The proposed end-to-end pixel classification model was used to classify each pixel of satellite image as damaged, undamaged, or other background class. Encouraging results were reported for the proposed model when validated on a custom dataset.

Spaceborne optical images were reported to be used for flood management activities including flood inundation mapping, land use classification, land cover classification, and structural damage assessment. Computer vision technologies have emerged from the use of existing pre-trained CNN models (e.g., GoogleNet, CaffeNet, ResNet) towards the development of problem-specific CNN models (e.g., DeepWaterMap, SegNet, LiteNet, ASPP-Unet, ResASPP-Unet, ERFNet, RescueNet, BDD-Net) for achieving better performance. For land use classification, land cover classification and flood detection, standard visual dataset have been developed over the years including UC Merced Land Use Dataset, EuroSAT and MediaEval. However, there is potential of incorporating UAV captured data for on-demand and quick land use classification. Although water mapping and flood inundation mapping using the reflectance information from the satellites is a more accessible and accurate approach in comparison to vision based mapping [128–130]; however, comes with the limitation of cost.

4.3. Airborne optical imagery approaches

Airborne images usually captured by UAVs equipped with edge-computing hardware are used for addressing flood management activities. Generally, UAVs based setup provides the functionality of on-demand analysis and discusses the gaps between the satellite imaging and ground imaging by providing better spatial resolution and temporal coverage [23,131]. A summary of selected use-cases where airborne optical approaches are used for flood management is presented.

In 2008, Lewis and Rhoads [30] proposed the use of the LSPIV approach with Unmanned Aerial System (UAS) for measuring flow patterns in rivers. The performance was assessed by comparing the LSPIV-UAS results with LSPIV-Stationary and conventionally measured velocity values for two case sites. From the results, UAS mounted LSPIV was reported more accurate in comparison to LSPIV-Stationary and conventional measurements. In 2009, Robertson and Chan [132] used a color-based image segmentation approach for flood risk analysis from aerial images. Image classification via entropy and image gradients were used to differentiate between different land use classes. Admissible accuracy for the proposed approach was reported on a custom dataset. In 2015, Sumalan et al. [133] proposed the use of a computer vision approach to detect the surface water from UAV captured images. Local Binary Patterns (LBP) were used to detect the water in images based on color variations. A comprehensive evaluation of the proposed algorithm in terms of generalization and scope was not presented. In 2015, Tauro et al. [39] proposed the use of the LSPIV velocimetry approach for UAVs in an effort to increase the measurement area and access to locations. Video sequences were captured using a custom developed quadcopter. Captured videos were processed using the LSPIV approach to measure the surface water velocity. Gimbal setup was used to prevent the image orthorectification. The proposed approach was validated for lab scenarios and real-world sites with encouraging results for velocity measurements.

Feng et al. [2] proposed a vision based algorithm to identify flooded areas from airborne images captured using a mini UAV. Grey level derived texture features were extracted from aerial images and were classified as flooded or non-flooded using random forest classifier. High classification accuracy was achieved for a custom and relatively small dataset; however, the generalized performance was not addressed. Sullivan et al. [58] developed a novel approach to detect the cross drainage structures more vulnerable to debris blockage from UAV captured images. The proposed idea was to automate the process of detecting the large woody piles and classifying into one of three defined categories; small pile (1–2 trees), medium pile (3–6 trees), and large pile (more than 6 trees). No computer vision algorithm was developed or implemented for the detection and classification of debris; instead, a manual survey-based approach was used to identify the risk.

In 2016, Perks et al. [134] developed a computer vision based approach to track flood related features and determine surface water velocity from UAV captured images. Transformations were used to compensate for the camera orientations and Kande-Lucas-Tomasi (KLT) algorithm was implemented for water surface features tracking. Furthermore, velocity vectors were achieved using a vector correction method. In the same year, Tauro et al. [35] proposed the use of recreational drone and LSPIV approach to precisely measure surface water velocities. Natural and artificial tracers were used to enhance the performance of the image velocimetry approach. From the results, it was reported that the deployed quadcopter platform was able to capture stable videos and there was no significant effect on velocity measurements. Although encouraging results were reported; however, generalized performance and dependence on lighting conditions were not investigated.

In 2017, Zhu et al. [135] investigated the significance of data collection using UAVs to better monitor and mitigate flood events. It was reported that UAV data, in combination with Geographic Information System (GIS), provides more accurate and quick information about flood events in comparison to conventional approaches. In 2018, Rahnemoonfar et al. [136] introduced the use of densely connected CNN and Recurrent Neural Network (RNN) models to accurately segment out the flood related regions from aerial images. A custom collected dataset from Houston, Texas use-case was used to assess the performance and over 90% accuracy was reported for the proposed approach. However, details about the dataset were not comprehensively presented and generalized performance was not addressed. Kamilaris and Prenafeta-Boldu [12] proposed a deep learning based algorithm to classify the small dataset of airborne images into disaster and non-disaster categories and identified the type of disaster. The proposed approach was validated for a custom collected small dataset and admissible performance was reported; however, the generalized performance was not discussed.

In 2018, Ridolfi [23] used the idea of detecting water level in the reservoir from UAV captured images. The conventional edge detection approach was used and implemented on use-case with an error of only 0.02 m. However, no discussion on compensating camera viewpoints, vibrations and noise was included. Furthermore, the generalized performance was not addressed since the visual dataset was relatively small. In 2019, Kyrkou and Theocharides [137] used multiple CNN models on a custom developed dataset to classify disaster from aerial images. Aerial Image Database for Emergency Response (AIDER) containing around 300 flood related images was developed and classified using CNN algorithms including MobileNet, ResNet50, VGG16 and SCNet. Gao et al. [138] proposed computer vision based water level detection from UAV captured images. Conventional image processing techniques were used to draw a water line in the image and fluctuations were measured using a parametric approach. A correction factor was used to compensate for the UAV drift factor and favorable results were achieved from preliminary tests for a use-case. Gebrehiwot et al. [139] introduced the use of the VGG-based CNN model to extract the flooded regions from a UAV captured image. A custom dataset of only 100 images was used to train the CNN model and highlighted as an advantage of the proposed approach; however, justification of the claim was not provided. The proposed algorithm might drastically fail for more generalized datasets as the learning curve indicated the overfitting.

In 2019, Yang and Cervone [140] developed a deep learning and machine learning based pipeline to automatically classify a given aerial image as flooded or non-flooded. For training the CNN model, manually annotated 1000 images were used. A max voting classifier was used to classify the extracted features and performance of approximately 90% accurate classification was reported. However, the potential of more advanced CNN models with generalized performance was not explored. Stulic et al. [141] proposed a novel visual attention based approach to detect a person from aerial images. The idea of reducing the search space by training a CNN based visual attention algorithm was used. A database of around 70,000 images called “HERIDAL” was used and the accuracy of 88.9% was achieved for the proposed algorithm. Reported results were compared with the existing literature and found improved in terms of performance. Lygouras et al. [142] used an unsupervised deep learning-based human detection algorithm to facilitate the search and rescue operations. A CNN model pre-trained on the COCO dataset was fine-tuned and transfer learned using a custom swimmers dataset. The proposed algorithm was also implemented on hardware and admissible accuracy was achieved from preliminary tests. Ichim and Popescu [143] developed a UAV to map the flooded region by using the CNN model. The idea of splitting the images into small patches and classifying each patch as flooded or non-flooded was used for flood mapping. The proposed approach was tested on a custom dataset and admissible results were achieved.

In 2019, Pi et al. [144] proposed the use of CNN algorithms on images captured by UAV for identifying flood related damages. You Only Look Once (YOLO) object detection model-based algorithms were used for the detection of damage in the images. A detailed comparison of different models was carried out for a custom annotated dataset. In the same year, Koutalakis et al. [29] performed a comparative study to investigate the performance of three commonly used image velocimetry approaches (i.e., PIVlab, PTVlab, KU-STIV) on drone captured videos of Aggitis River. Comparable results were reported for all three approaches with the capability of measuring surface water velocity within the 0.02–3.99 ms^{-1} range. However, performance for diverse flow conditions and variable lighting conditions was not studied. In 2020, Mishra et al. [145] introduced a visual dataset for search and rescue purposes to facilitate the implementation of deep learning based algorithms. The proposed detection and action recognition dataset consisted of around 2000 images with 30,000 human instances of different actions. A deep CNN model was proposed for detection purposes and performance was compared with R–CNN and R–FCN models from literature to demonstrate the advantage. More recently, Fung et al. [146] used a deep learning based object detection and segmentation approach to detect the disaster victims in a cluttered urban environment.

In a recent publication, Pearce et al. [27] performed comparative sensitivity analysis for five common image velocimetry approaches on UAS captured videos of Kolubara River under low river flow conditions. Artificial seeding material was distributed homogeneously across the river to improve the performance of image velocimetry approaches.

Sensitivity analyses were performed mainly for particle identification area and feature extraction rate parameters. From the analysis, it was observed that KLT and SSIV approaches were sensitive to change in feature extraction rate while the change in particle identification area had a negligible impact. Converse behavior was observed for the OTV and LSPTV approaches. LSPIV approach was reported sensitive to change in any of both features. From the results, it was reported that optical image velocimetry approaches were able to measure surface water velocity of as low as 0.12 ms^{-1}. However, dependence on lighting conditions and flow variations was not comprehensively investigated.

Airborne optical images captured using UAV and interpreted by computer vision algorithms were reported in the literature to address flood management activities including flood detection, water level detection, surface water velocity measurement, baseline data collection, flood debris detection, flood damage assessment and search and rescue missions. Computer vision technologies in this domain have emerged over the years from conventional techniques (e.g., LBP, random forest classifier, KLT, Image transformations, line detection, LSPIV, LSPTV, SSIV, OTV) towards deep learning based techniques (e.g., densely connected CNN and RNN, VGG-based CNN, max voting classifier, YOLO). Although the magnitude of research has been observed as increased after 2015; however, lack of comprehensive datasets, investigation of generalized performance and comparison with existing literature were found consistent limitations of presented literature. Studies performed by Stulic et al. [141], Mishra et al. [145] and Fung et al. [146] were not in the direct scope of floods, however, a similar approach can be used for flood management using UAVs in future.

4.4. Hybrid approaches

Hybrid approaches (i.e., a combination of two or more visual sensing techniques) were used to compensate for the limitations of a single visual platform. A summary of selected use-cases where a hybrid approach was used to address flood management is presented as follows.

In 2002, Zhang et al. [147] highlighted the use of both spaceborne and airborne sensing to monitor floods in China. A system called "NPOIS" was proposed to effectively monitor and evaluate the flooding events in China. Although the system is claimed to be already functional; however, no information about the evaluation metric or performance of the proposed system was presented. In 2015, Balkaya et al. [59] proposed an open access vision tool based analysis of the spaceborne optical image to detect the damages caused by the floods. To overcome the limitation of the only top view, a multiview camera was integrated along with the satellite captured images. In 2017, Popescu et al. [148] developed a flood estimation system using a combination of ground visual sensors and UAV captured airborne images. Deep neural networks were used for feature extraction and identification of flooded regions. High classification accuracy was achieved for the proposed algorithm; however, the generalized performance was not studied. In 2019, Munawar et al. [149] proposed a machine learning and image processing based flood detection pipeline to classify a given image as flooded or non-flooded. Conventional image processing approaches including edge detection, image transformations and landmark detection were used as pre-processing before training a Support Vector Machine (SVM) classifier. Both satellite and aerial visual data were used to train the classifier. Accuracy of 90% was achieved for the proposed approach; however, there was no standard dataset used to assess the generalized performance.

In 2019, Bhola et al. [150] introduced the idea of using visual data as validation for the inundation maps. Determination of water levels using state of the art image processing algorithms can provide a forecast for flood inundation. In 2020, Lin et al. [151] proposed the idea of using VGI for flood detection. Image processing and photogrammetric method were used collectively for water level determination. Random forest classification and Canny edge detector were used for flood level detection from images. The proposed algorithm was applied on a use-case and admissible results were reported. In 2020, Jimenez-Jimenez et al. [152] proposed the use of satellite images and aerial images along with Digital Elevation Model (DEM) and object-based image analysis to determine the damage caused to structures by the floods. Image segmentation analysis was used to classify houses from satellite images while vegetation and houses from UAV images. The difference between house objects detected from satellite images and aerial images was used to determine the washed away houses by floods. In general, satellite images were used as ground truth or reference. No comprehensive analysis and details on the detection of houses using UAV and dealing with challenges related to UAV data were addressed.

Hybrid approaches were reported to be used for addressing flood management related activities including flood monitoring, flood damage assessments, flood inundation mapping and water level detection. Although the trend of incorporating UAV images into ground and satellite images is increasing; however, a more comprehensive investigation is found consistently missing in the reported literature.

5. Need-based analysis

Need-based analysis of the literature is propounded to highlight the contributions in the flood management domain from the slant of a solution provider. As proposed by Iqbal et al. [17], a need-oriented analysis of literature renders an intact picture regarding technologies being used for specific assessments at each phase of flood management. Moreover, it underlines the trends and distribution of efforts being made for certain assessments. In addition to need-based analysis, the presented literature is subjectively assessed for consideration of flood management related requirements as proposed by Iqbal et al. [17]. Each flood management phase and assessment involves a number of constraints and a set of requirements to be addressed for providing effective solutions. Presented literature is evaluated for comprehensiveness to which common flood management related requirements (accuracy, responsiveness, generalization) are considered. Assessment criteria is defined as follows:

- **Accuracy** determines the extent of precision to which the proposed method addressed one of the flood management related problems. For this review, the following scoring criteria is used to assess the accuracy:
  - (+) if the authors minimally evaluated the proposed method for accuracy by using at least one standard measure.
  - (++) if the authors extensively evaluated the proposed method for accuracy by using multiple measures.
  - (+++) if the authors extensively evaluated the proposed method and compared it with existing literature to highlight the scope.
- **Responsiveness** determines the response times of the proposed approach to address one of flood management related problems. The following criteria is used in this review score to the literature:
  - (+) if the authors minimally evaluated the proposed method for response time and processing speed using at least one standard measure.
  - (++) if the authors extensively investigated the proposed approach for responsiveness using more than one standard measure.
  - (+++) if the authors extensively evaluated the proposed method and compared it with existing literature to highlight the scope.
- **Generalization** determines the extent of variability to which the proposed approach is assessed to address one of the flood management related problems. Following scoring criteria is used for this review to evaluate literature:
  - (+) if the authors validated the proposed method for a relatively small dataset collected from at least two different sites.
  - (++) if the authors validated the proposed method for a comprehensive and diverse custom collected dataset.

Table 5
Need-based analysis of literature for ground camera approaches in flood management – part a.

Article	Phase	Assessment	Proposed Technology	Scope	Addressed Requirements		
					Accuracy	Responsiveness	Generalization
Fujita et al. [36]	Preparedness	Surface Water Velocity	LSPIV	Real-World	+	Not Addressed	+
Udomsiri and Iwahashi [20]	Preparedness	Water Level Detection	horizontal edge detector and FIR filter	In-Lab Experiment	+ +	Not Addressed	Not Addressed
Yu and Hahn [102]	Preparedness	Water Level Detection	image subtraction, registration and edge detection	Real-World	+ +	+	Not Addressed
Park et al. [21]	Response	Water Depth Detection	accumulated histogram and bandpass filter	In-Lab Experiment	Not Addressed	Not Addressed	Not Addressed
Rankin and Mathies [43]	Response	Surface Water Detection	saturation-to-brightness and color information	Real-World	+ +	+	Not Addressed
Kao et al. [57]	Response	Flood Debris Detection	background subtraction and spatial filtering	Real-World	+ +	+ +	+
Li et al. [37]	Preparedness	Surface Water Velocity	multi-channel LSPTV	Real-World	+	Not Addressed	+
Lo et al. [7]	Preparedness	Water Level Detection	conventional image segmentation	Real-World	Not Addressed	+ +	Not Addressed
San Miguel et al. [42]	Response	Surface Water Detection	background subtraction and histogram equalization	Real-World	Not Addressed	Not Addressed	Not Addressed
Hiroi and Kawaguchi [103]	Preparedness	Water Level Measurement	conventional image processing	Real-World	+	Not Addressed	Not Addressed
Yeum [104]	Response	Structural Damage Assessment	CNN based classification and detection algorithms	Real-World	+ +	+	+ +
Tauro et al. [25]	Preparedness	Surface Water Velocity	LSPIV	Real-World	+ +	Not Addressed	+
Tauro et al. [31]	Preparedness	Surface Water Velocity	LSPIV, PTV	Real-World	+ + +	Not Addressed	+ +
Lopez-Fuentes et al. [44]	Response	Surface Water Detection	CNN based semantic segmentation algorithms	Real-World	+ +	Not Addressed	+
Harjoko et al. [56]	Response	Flood Debris Detection	optical flow and edge detection	Real-World	Not Addressed	Not Addressed	Not Addressed
Teng et al. [105]	Response	Flood Detection	semantic mode, multilabel classification and discrimination model	Real-World	+ +	Not Addressed	+ +
Wang et al. [85]	Response	Flood Monitoring	MyCoast, CNN	Real-World	+ +	Not Addressed	+
Alam et al. [86]	Response	Flood Detection	VGG16	Real-World	+	Not Addressed	+
Geetha et al. [87]	Response	Flood Detection	color segmentation and face detection	Real-World	+	Not Addressed	+
Yang and Ng [80]	Preparedness	Rainfall Monitoring	crowdsourced data	Real-World	+ +	Not Addressed	+
Strobl et al. [81]	Preparedness	Streamflow Monitoring	crowdsourced Observations	Real-World	+ +	Not Addressed	+ +
Giannakeris et al. [88]	Response	Flood Detection	VGG16, DeepLab and Faster R–CNN	Real-World	+ + +	Not Addressed	+

(+) = Minimally Addressed, (++) = Moderately Addressed, (+++) = Comprehensively Addressed.

- (+++) if the authors validated the proposed method for a benchmark dataset and compared it with existing literature.

Tables 5–9 provide the need-based analysis of literature for ground camera, airborne, spaceborne and hybrid approaches, respectively. From the analysis, the following important observations can be evidently reported:

(1) Assessments at the response phase of flood management are targeted the most while the recovery phase is completely neglected. Most aided assessments reported include water level detection, surface water detection, structural damage assessment and flood depth estimation.
(2) Use of computer vision technologies has emerged from conventional techniques (line detection, edge detection, filtering, transformations, LSPIV, LSPTV, SSIV, OTV) to existing CNN models (ResNet50, VGG16, GoogleNet, CaffeNet, Faster R–CNN, Mask R–CNN) to assessment specific designed CNN models (RescueNet, DeepWaterMap, WaterNet, SegNet, BDD-Net).
(3) Availability of benchmark visual datasets is found lacking and mostly case-based solutions are provided. For the same reason, the generalized performance of proposed approaches is not addressed comprehensively.
(4) Flood management related requirements are found not to be comprehensively addressed in most of the presented literature. This might be because of a lack of proper requirement formulation and lack of collaboration among the flood management officials and technology providers.

6. Future applications and challenges

The presented systematic review demonstrates the potential of visual information and computer vision technologies within the flood management domain. Our critical analysis of literature reported various limitations of existing approaches and highlighted the future scope of computer vision technologies. A brief summary of future applications of computer vision technologies and corresponding challenges in flood management is presented.

Lack of proper requirement formulation and unavailability of comprehensive visual datasets are major limitations observed universally from reported computer vision based solutions. For land use classification task at the prevention stage of flood management, computer vision approaches using CNN have already achieved success at satellite images dataset [18,19]. To achieve real-time on-demand classification maps for local regions, UAVs can be utilized; however, edge computing, image stitching and camera viewpoints are the challenging factors. Monitoring the performance of flood prevention structures (e.g., dams) can utilize computer vision technologies in damage detection and water level measurement [23] activities. A combination of classical image processing techniques (e.g., edge detection) and learning-based approaches (e.g., deep learning) can prove helpful. Howbeit, dealing with variable lighting conditions, on-board processing and generalization are

Table 6
Need-based analysis of literature for ground camera approaches in flood management – part B.

Article	Phase	Assessment	Proposed Technology	Scope	Addressed Requirements		
					Accuracy	Responsiveness	Generalization
Witherow et al. [89]	Response	Flood Detection	R–CNN, image inpainting and contrast correction	Real-World	+ +	Not Addressed	+ +
Feng and Sester [90]	Response	Flood Information Extraction	XGBoost	Real-World	+ +	+	+ +
Krohnert and Eltner [91]	Preparedness	Hydrological Measurements	crowdsourcing	Real-World	+	Not Addressed	+
Tauro et al. [38]	Preparedness	Surface Water Velocity	OTV	Real-World	+ + +	+ +	+ +
Leitao et al. [34]	Preparedness	Surface Water Velocity	SSIV	In-Lab Experiment	+ +	Not Addressed	+ +
Lin et al. [22]	Prevention	Water Level Detection	line detection and image transformation	In-Lab Experiment	+	Not Addressed	Not Addressed
Lohumi and Roy [106]	Response	Flood Severity Estimation	GRU and VGGNet	Real-World	+ +	Not Addressed	+ +
Layek et al. [107]	Response	Flood Detection	CNN model and color filtering	Real-World	+ +	Not Addressed	+ +
Pouyanfar et al. [108]	Response	Flood Detection	CycleGAN and ResNet50 CNN	Real-World	+ + +	Not Addressed	+ +
Rubio et al. [109]	Response	Structural Damage Detection	VGG16 based FCN model	Real-World	+ +	Not Addressed	+ +
Ackere et al. [110]	Prevention	Flood Impact Assessment	segmentation and detection algorithms	Real-World	Not Addressed	Not Addressed	Not Addressed
Zhang et al. [111]	Preparedness	Water Level Detection	Maximum Mean Difference (MMD)	Real-World	+ +	Not Addressed	+ +
Etter et al. [83]	Preparedness	Water Level Detection	crowdsourcing	Real-World	+ +	Not Addressed	+ +
Seibert et al. [82]	Preparedness	Water Level Detection	virtual staff gauge	Real-World	Not Adressed	Not Addressed	+ +
Meng et al. [112]	Response	Flood Depth Estimation	Mask R–CNN and Fcae++ API	Real-World	+	Not Addressed	Not Addressed
Mishra et al. [113, 114]	Response	Drain Blockage Detection	segmentation and VGG16	Real-World	+ +	Not Addressed	+ +
Huang et al. [115]	Response	Water Depth Estimation	MasK R–CNN	Real-World	+ +	Not Addressed	+ +
Liang et al. [116]	Response	Surface Water Detection	WaterNet CNN	Real-World	+ + +	Not Addressed	+ +
Feng et al. [93]	Response	Flood Severity Estimation	Mask R–CNN, OpenPose and DeepLabv3+	Real-World	+ + +	Not Addressed	+ + +
Muhadi et al. [117]	Response	Surface Water Detection	region growing and threshold	Real-World	+	Not Addressed	Not Addressed
Pereira et al. [94]	Response	Flood Severity Estimation	DenseNet and EfficientNet	Real-World	+ +	Not Addressed	+ + +
Quan et al. [95]	Response	Flood Severity Estimation	Mask R–CNN, OpenPose Resnet50 and Faster R–CNN	Real-World	+ + +	Not Addressed	+ +
Chaudhary et al. [96]	Response	Flood Mapping	VGG16 CNN	Real-World	+ +	Not Addressed	+ +
Tosi et al. [26]	Preparedness	Surface Water Velocity	optimized OTV	Real-World	+ +	+ +	+
Etter et al. [84]	Preparedness	Water Level Detection	virtual staff gauge	Real-World	+ +	Not Addressed	+ +
Ning et al. [92]	Response	Flood Detection	VGG16, CNN	Real-World	+ +	Not Addressed	+ +

(+) = Minimally Addressed, (++) = Moderately Addressed, (+++) = Comprehensively Addressed.

the possible research domains.

In early flood warning systems, conventionally, water level measurements from multiple gauge stations are used as core information. But, water level sensors are expensive to install and maintain. Water level measurement using computer vision approaches is propounded as a potential solution to this shortcoming [7,20–22]; however, a comprehensive and accurate solution is yet to be developed. Variable lighting conditions, time-series monitoring and on-board processing are some strenuous tasks to be addressed. Image velocimetry approaches to measure surface water velocity have already demonstrated their ability to precisely measure the velocity in real-world scenarios. However, it is still an active area of research where the potential of machine learning, advanced computer vision and AI algorithms is yet to be explored. In flood forecasting, neural networks based learning algorithms are already used to interpret the time-series rainfall data to predict future floods. Howbeit, the idea of using visual data for forecasting future floods and correcting the existing numerical models is yet to be explored. Collection of extensive visual data from floods and incorporation of self-correcting functionality in existing flood forecasting models are the capable future areas for research. Gaming technology and gaming physics engines (e.g., Unity, Unreal Engine, Voxel) are interesting areas to explore as a potential tool in investigating flood dynamics (modeling, monitoring and mapping) given the implementation of precise physics based water simulations [153–155]. Furthermore, customized and realistic 3D applications can be developed to generate synthetic visual (image and video) datasets for flood related assessments [156].

Flood inundation mapping at the early response phase predominantly comprises the detection of water flooded areas and depth of water. The use of computer vision to detect water bodies from satellite images has already been promulgated with admissible accuracy [8, 45–55]. Having said that, the use of the airborne platform for real-time and on-demand inundation maps for local regions is not comprehensively investigated. Segmentation of water bodies from aerial images and the distinction between normal and flooded water are demanding tasks. Furthermore, the capacity of a hybrid model including space-borne, airborne and ground sensors is not scrutinized. Victim identification during the search and rescue phase can be addressed using a UAV equipped with state of the art object detection algorithm. However, detecting victims under shelters from the air is a challenging task from computer vision perspective. Structural damage assessment at the late response phase is an encyclopedic procedure and involves enormous technical resources. Computer vision technologies can be efficiently

Table 7
Need-based analysis of literature for airborne approaches in flood management.

Article	Phase	Assessment	Proposed Technology	Scope	Addressed Requirements		
					Accuracy	Responsiveness	Generalization
Lewis and Rhoads [30]	Preparedness	Surface Water Velocity	LSPIV	Real-World	+ + +	Not Addressed	+
Robertson and Chan [132]	Prevention	Flood Risk Analysis	color based segmentation	Real-World	+	Not Addressed	+
Sumalan et al. [133]	Response	Surface Water Detection	Local Binary Patterns (LBP) and color variations	Real-World	+	Not Addressed	Not Addressed
Tauro et al. [39]	Preparedness	Surface Water Velocity	LSPIV	Real-World	+ +	Not Addressed	+ +
Feng et al. [2]	Response	Flood Detection	grey level texture features and random forest classifier	Real-World	+ +	Not Addressed	+
Sullivan et al. [58]	Response	Flood Debris Detection	manual Surveys	Real-World	Not Addressed	Not Addressed	Not Addressed
Perks et al. [134]	Response	Flood Detection	image transformations and Kande-Lucas-Tomasi (KLT)	Real-World	+ +	Not Addressed	Not Addressed
Tauro et al. [35]	Preparedness	Surface Water Velocity	LSPIV	Real-World	+ + +	Not Addressed	+
Zhu et al. [135]	Prevention	Baseline Data Collection	UAV equipped with camera	Real-World	Not Addressed	Not Addressed	Not Addressed
Rahnemoonfar et al. [136]	Response	Surface Water Detection	densely connected CNN and RNN	Real-World	+	Not Addressed	Not Addressed
Kamilaris and Prenafeta-Boldu [12]	Response	Flood Detection	VGG CNN model	Real-World	+	Not Addressed	+
Ridolfi [23]	Response	Water Level Detection	edge detection	Real-World	+	Not Addressed	Not Addressed
Kyrkou and Theocharides [137]	Response	Flood Detection	MobileNet, ResNet50, VGG16 and SCNet CNN models	Real-World	+ + +	+ + +	+ + +
Gao et al. [138]	Preparedness	Water Level Detection	line detection and parametric approach	Real-World	+ +	Not Addressed	Not Addressed
Gebrehiwot et al. [139]	Response	Surface Water Detection	VGG-based CNN model	Real-World	+ +	Not Addressed	+
Yang and Cervone [140]	Response	Flood Detection	CNN and max voting classifier	Real-World	+ +	+	+ +
Stulic et al. [141]	Response	Search and Rescue	CNN-based visual attention algorithm	Real-World	+ + +	+	+ +
Lygouras et al. [142]	Response	Search and Rescue	DarkNet and SSDMobileNet	Real-World	+ +	+	+ +
Ichim and Popescu [143]	Response	Flood Mapping	CNN model	Real-World	+	Not Addressed	Not Addressed
Pi et al. [144]	Response	Flood Damage Detection	DarkNet, YOLO	Real-World	+ +	+	+ + +
Koutalakis et al. [29]	Preparedness	Surface Water Velocity	PIVlab, PTVlab KU-STIV	Real-World	+	Not Addressed	+
Mishra et al. [145]	Response	Search and Rescue	SSD-based CNN model	Real-World	+ + +	Not Addressed	+ +
Fung et al. [146]	Response	Search and Rescue	detection and segmentation CNN	Real-World	+ + +	Not Addressed	+ +
Pearce et al. [27]	Preparedness	Surface Water Velocity	LSPIV, LSPTV, OTV KLT, SSIV	Real-World	+ + +	+	+

(+) = Minimally Addressed, (++) = Moderately Addressed, (+++) = Comprehensively Addressed.

used to accommodate experts in remotely accessing hazardous regions and explicate damage of structures. But, the collaboration between damage assessment experts and computer vision technology developers is lacking. The blockage of cross drainage structures by debris is customary in urban areas and originates flooding in the region. Real-time monitoring of hydraulic structures and interpretation of blockage is a potential future computer vision utility. Having said that, the unforeseeable and erratic nature of debris accumulation at hydraulic structures makes it an arduous task to accurately interpret the blockage of hydraulic structures. Finally, at the recovery phase, computer vision technologies can be used for reconstruction monitoring, debris removal monitoring, historic structures restoration monitoring and vegetation growth monitoring in the same scope as for structural damage assessment at the response phase.

Based on observation (4) in the need-based analysis section, a detailed qualitative case study can be planned to bring the opinion of flood management officials into the loop and highlight what is essential from the flood management perspective.

7. Conclusion

Presented systematic review highlighted the use of various computer vision technologies across variety of flood management related activities including land use classification, water level measurement, surface water detection, water depth estimation, victim identification, structural damage assessment and early flood warning system. Review in this paper established the link between flood management and computer vision by proposing a common taxonomy for mapping flood management activities as computer vision problem in a systematic way. The need-based analysis of selected literature underlined some important trends. The use of computer vision technologies has evolved from conventional techniques towards CNN based approaches significantly from 2015 onward. However, the availability of benchmark visual datasets have been consistently found lacking. In addition, selected literature failed to comprehensively formulate and address flood management related requirements while proposing solutions, which suggests a lack of collaboration among flood management officials and technology providers. Finally, future applications of computer vision technologies across different phases of flood management and corresponding real-

Table 8
Need-based analysis of literature for spaceborne approaches in flood management.

Article	Phase	Assessment	Proposed Technology	Scope	Addressed Requirements		
					Accuracy	Responsiveness	Generalization
Ip et al. [47]	Preparedness	Flood Monitoring	comparative analysis	Real-World	+ +	Not Addressed	+
Castelluccio et al. [18]	Prevention	Land Use Classification	GoogleNet and CaffeNet	Real-World	+ + +	Not Addressed	+ + +
Liu et al. [45]	Response	Flood Inundation Mapping	spatiotemporal context learning with AdaBoost classifier	Real-World	+ +	Not Addressed	+ +
Isikdogan et al. [46]	Response	Surface Water Detection	DeepWaterMap	Real-World	+ +	+	+ +
Helber et al [19].	Prevention	Land Use Classification	GoogleNet and ResNet50	Real-World	+ +	Not Addressed	+ + +
MediaEval [48–55, 118]	Response	Flood Detection	CNN models and classifiers	Real-World	+ + +	Not Addressed	+ + +
Weng et al. [119, 120]	Prevention	Land Use Classification	CNN model and CELM classifier	Real-World	+ + +	+	+ + +
Yang et al. [121]	Prevention	Land Use Classification	SegNet and LiteNet	Real-World	+ +	Not Addressed	+ +
Nogueira et al. [8]	Response	Surface Water Detection	ConvNets	Real-World	+ + +	Not Addressed	+ +
Zhang et al. [122]	Prevention	Land Cover Classification	CASPP-Unet and ResASPP-Unet	Real-World	+ + +	Not Addressed	+ +
Potnis et al. [123]	Response	Surface Water Detection	ERFNet and markGT	Real-World	+	+	+ +
Weber and Kan [124]	Response	Structural Damage Detection	ResNet50 and Mask R–CNN	Real-World	+ +	Not Addressed	+ + +
Gupta and Shah [126]	Response	Structural Damage Detection	RescueNet	Real-World	+ + +	Not Addressed	+ + +
Shao et al. [127]	Response	Structural Damage Mapping	BDD-Net	Real-World	+ +	Not Addressed	+ +

(+) = Minimally Addressed, (++) = Moderately Addressed, (+++) = Comprehensively Addressed.

Table 9
Need-based analysis of literature for hybrid approaches in flood management.

Article	Phase	Assessment	Proposed Technology	Scope	Addressed Requirements		
					Accuracy	Responsiveness	Generalization
Zhang et al. [147]	Response	Flood Detection	conventional visual analysis	Real-World	Not Addressed	Not Addressed	Not Addressed
Balkaya et al. [59]	Response	Flood Detection	conventional visual analysis	Real-World	Not Addressed	Not Addressed	Not Addressed
Popescu et al. [148]	Response	Flood Detection	deep CNN models	Real-World	+ +	Not Addressed	+
Munawar et al. [149]	Response	Flood Detection	edge detection, transformations and SVM classifier	Real-World	+	Not Addressed	+ +
Bhola et al. [150]	Response	Flood Inundation Map	conventional visual analysis	Real-World	+ +	Not Addressed	+ +
Lin et al. [151]	Response	Water Level Detection	Canny edge detector and random forest classifier	Real-World	+ +	Not Addressed	+
Jimenez-Jimenez et al. [152]	Response	Structural Damage Assessment	image segmentation and detection analysis	Real-World	+ +	Not Addressed	+ +

(+) = Minimally Addressed, (++) = Moderately Addressed, (+++) = Comprehensively Addressed.

world challenges have been presented in detail. Debris management, citizen science, synthetic data generation, search and rescue, and reconstruction monitoring are some highlighted flood management assessments where computer vision technologies can efficiently be used in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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