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Review

Review of Intelligence Required for Issuing Accurate Flood Early Warnings and Effective Disaster Response

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Abstract: Deaths and property damage from the flood have increased drastically in the past two decades due to various reasons such as increased population, unplanned development and climate change. Losses from floods can be reduced by having accurate intelligence of an emerging flood situation in order to make timely decisions for issuing early warnings and responding efficiently. This paper presents a thorough analysis of the types and sources of intelligence required for flood warning and response processes and technology solutions that can be used for capturing such intelligence. A structured review, covering a more comprehensive range of published literature on Flood Early Warning and Response Systems (FEWRS), was conducted to identify the necessary intelligence and the technology that can be used to capture intelligence required for various phases of a flood hazard as it develops. Twenty-seven different types of key intelligence required in the flood cycle were identified. A conceptual architecture was identified that illustrates how relevant technology solutions can be used to extract intelligence at various stages of a flood event for decision making for early warnings and response.

Keywords: flood warning; intelligence; information; response; FEWRS

1. Introduction

Flood is a frequently occurring hazard that imposes adverse effects on a significant number of human lives and causes substantial economic damage worldwide. It is the highest recorded hazard which is responsible for 43% of the total disasters during the period 1998 and 2017, according to the joint report by the Centre for Research on the Epidemiology of Disasters (CRED) and the United Nations Office for Disaster Risk Reduction (formerly UNISDR). The flood was accounted for 2 billion affected population and 142,000 deaths during the above period [1], and in recent years, flood frequency and its impact have been increasing drastically due to climate change and unplanned urban development [2, 3].

Panwar and Sen [4] suggest that the economic impact of natural disasters such as floods is more prominent in developing countries, and the CRED/UNISDR report [1, 5] discloses that deaths by natural disasters in low-income countries are seven times higher than that of high-income countries. The key contributing factors for such increased losses have been recognised as population growth and rapid urbanisation [6, 7]. Many researchers [5, 8] have asserted that such losses and causalities can significantly be reduced by implementing an effective Flood Early Warning and Response Systems (FEWRS). In this regard, Sendai Framework for Disaster Risk Reduction (SFDRR) emphasises the need for the availability of multi-hazard warning systems and disaster risk information to the community by the end of 2030. SFDRR promotes the necessity for having an integrated and coordinated approach to "generate, process and disseminate" disaster risk information using state-of-art technologies as a priority action in the member countries [9].

A study conducted by Rogers [10] reports that an effective forecast and warning system, based on accurate real-time intelligence on disasters, can reduce the average annual

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flood damage by up to 35%. Furthermore, in Seng [11], the author asserts that such a system can reduce vulnerability and mortality rates. The reasons for the existence of ineffective early warning systems that cause higher death rates are considered to be due to bureaucratic water management and digital divide related issues [12], resulting in the lack of timely information for issuing warnings [8]. Therefore, the availability of an information system (IS) that can offer accurate and timely data with high service quality and user satisfaction has been recognised as one of the key success factors for implementing efficient FEWRSs [8].

Intelligence is crucial for making sound decisions. Oxford dictionary defines intelligence as "the ability to acquire and apply knowledge and skills". According to Lowenthal [13], intelligence refers to information that meets the stated or understood needs of policymakers. Further, the author emphasises that "all intelligence is information, but all information is not intelligence". DIKIW hierarchy defines the relationship between data, information, knowledge, intelligence and wisdom[14]. In this hierarchy, raw data is processed to extract valuable information, whereas intelligence is obtained by transforming information and knowledge. Albus states that intelligence is needed to understand and identify risks to make future plans [15].

In the quest for intelligence for FEWRSs, a broad range of technologies such as Internet of Things (IoT) [16], big data [17] and near real-time satellite data [18] are used to capture critical information such as rainfall, rising river levels and floor rates to detect flood threats. Furthermore, integrated information systems [19, 20], geographic information systems (GIS) [21], and simulation techniques [22], are being used to process such information and to generate early warnings. Increasingly, crowdsource technologies based on social media [23], mobile apps [24], volunteer GIS [25] are being used for engaging communities in reporting incidents during the response phase. However, it is important to establish a clear understanding of the "intelligence" required and "technologies" that can be used in developing early warning systems. Therefore, this paper presents a full range of intelligence needed for flood warning and response phases, captured through a review of academic papers published between 2015 and 2020. The study also explores the technology that can be used to provide such intelligence for the decision-makers during various flood warnings and response stages.

2. Materials and Methods

The research question established in this review is "what are the types and sources of intelligence required for effective early warning and response for flood events ?". The methodology established by Webster and Watson (2002) was followed to identify and analyse the relevant literature for this review. A set of keywords was defined to search for the relevant research articles, and an inclusion/exclusion criterion was used to determine relevant and quality papers. A search criterion was established to filter relevant articles by conducting a "title" search by using a combination of keywords. The keywords "floods', "response" and "warning" were used in the search since the context of this study is "floods" within the scope of disaster management phases of "response" or "warning". The keywords "Information" and "Intelligence" were included to limit the articles that are written in the specific area of interest in this review. These keywords were combined to create the generic search string "Flood" AND ("Warning" OR "Response") AND ("Information" OR "Intelligence").

The keyword combination was used on Scopus, Web of Science, Wiley, Springer, Science Direct and Gale databases, which resulted in the retrieval of 156 records. These databases allowed literature search within a broad range of high-ranked journals and conference proceedings. Furthermore, a manual search in google scholar has added 16 more articles to the investigation. The overall search was limited to articles published from 2015 onwards and written in English.

Following the above step, the title and abstract of all the papers were thoroughly examined to remove duplicate records and false-positive. This exclusion step resulted in

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65 articles in the database for further in-depth analysis. During the in-depth analysis, the following inclusion criteria were used to select suitable papers after studying the full texts of: (i) the articles written on flood warning and response systems and processes (ii) the articles that describe the use of information and intelligence in the warning and response process. After the in-depth analysis phase, fifty-four papers (54) were selected for the structured review after studying the full text (see **Error! Reference source not found.**). Only the papers which focused on the intelligence for detecting, monitoring and evaluating the flood hazards during the warning to response stage were included in the above screening processes. Contributions that discussed flood hazard and risk assessments, flood preparedness, flood management, health and other emergencies were excluded. Each research article was analysed and synthesised to extract the state-of-art knowledge on intelligence used in flood warning and response stages, and the tools and techniques used to derive such intelligence.

Table 1. Overview of Search Results.

Source	Step 01 – Initial search	Step 02 – Removal of duplicates, title and abstract Assessment	Step 03 – In-depth search
Scopus	47	16	16
Web of Science	44	13	09
Willey Cross-Reference	18	09	06
Springer	06	0	0
Science Direct Elsevier	05	0	0
Gale	46	16	12
Google Scholar	16	16	11
Total	182	70	54

The scope of this review concurs with the flood risk management framework adopted by Adelekan [26]. According to Adelekan, planning for flood warning, evacuation, and relief are considered sub-activities in the preparedness phase, whereas emergency rescue, humanitarian assistance and reconstruction have been identified as sub-activities of the response phase. Following this framework, the intelligence related to "potential and historical flood inundation, damages and losses" is considered as it belongs to the preparedness phase, whereas the intelligence associated with the "actual flood levels, damages and losses" is considered as it belong to the response phase (see **Error! Reference source not found.**).

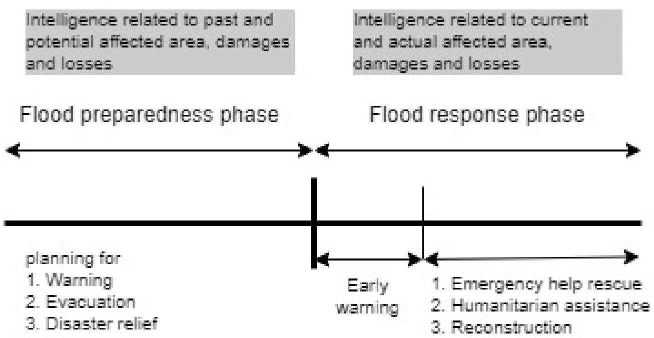

Figure 1. Scope of the intelligence used in the review (adapted from Adelekan [26]).

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Fundamental stages of early warning systems such as risk knowledge capture, monitoring and warning, dissemination and communication of warning, and preparedness to response defined by UNDRR [27]) are used to structure the review findings. As an outcome of the literature review, the authors aimed to establish a relationship among the flooding process, intelligence necessary at various stages of this process, and methods (technologies) that can be used to derive this intelligence (**Error! Reference source not found.**). As shown in **Error! Reference source not found.**, flooding is a physical process that undergoes several stages, such as the reception of rainfall in the river basin and the increment of river water level; downstream inundation; and flood impact on the people and infrastructure. Each stage of the flooding process can be sensed by various methods and technologies to derive intelligence in order to make decisions.

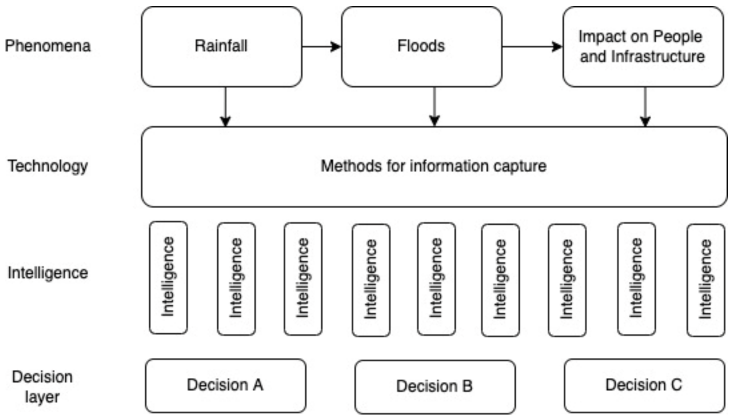

Figure 2. Conceptual framework for presenting relationships among the flooding process, methods for information capture, intelligence and decision making.

3. Results

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

3.1. Research landscape of the contributions

Figure 3 shows the spread of publications used in this review, between 2015 and 2020, Figure 4 shows where the study had taken place, distributed across 26 countries. The main contributors being China (3 articles), Philippines (3 articles), Pakistan (3 articles) and USA (5 articles). However, 10 contributions were either review papers, or were not classified under a particular country.

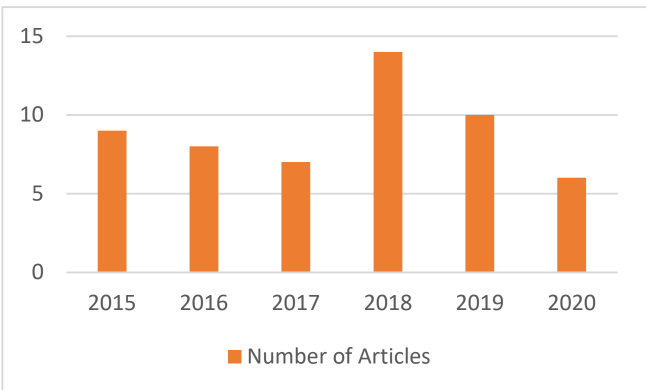

Figure 3. Distribution of articles based on the year of publication.

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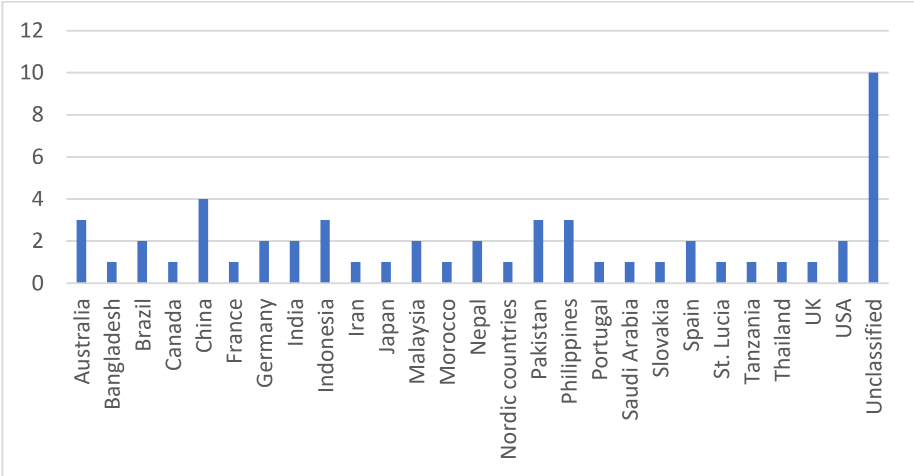

Figure 4. Distribution of articles based on the country of affiliation.

3.2. Intelligence used for flood warning and response phases

The types of intelligence that were identified as necessary for issuing flood warnings and responses from our review can be categorised as follows: intelligence on flood hazards; intelligence related to the population at risk; intelligence on impacted infrastructure; intelligence on resources and capacities required during the response phase. **Error! Reference source not found.** below summarises the type of intelligence under each category with their attributes, purpose/use, and citations.

Table 2. Intelligence required for flood warning and response.

Category	Intelligence	Attributes)	Purpose / Use	Reference
Intelligence on flood hazards	Rainfall values	Real-time rainfall	Flood forecasting in real-time	[23, 28-32] [31, 33, 34]
		Historical rainfall	Predict a possible flood scenario from past flood incidents for a given rainfall.	[35]
		Duration of rainfall	Quantify the rainfall and forecast the floods	[28, 36]
	River Flow/ water flow rate (total volume passed in a given location)		Forecast floods	[35], [37]
	River and flood water level	Measured from sensors or manual methods	Assess whether the river is about to be flooded or has flooded and issue warnings accordingly.	[16, 24, 25, 34, 37-41]
		Observed by the community		[23, 25, 42]
		forecasted by simulations		[19, 43-47]
Intelligence on flood hazards	Flood inundation	inundation extent	Establish a spatial representation of floods to understand the impacted area.	[17, 18, 21-23, 30, 36, 42, 48-61]
		inundation depth	Identify the hazard/risk level for the community and infrastructure	[23, 25, 29, 50, 60]
	Flood intensity	Flood frequency / flood magnitude /return period	Predict the hazard levels and use them to evaluate possible damage to the community, infrastructure and natural environment.	[25, 52, 62] [22, 36, 55, 56, 62-64]

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	Historical events	Historical flood event & level	Understand inundation levels and impact caused by past flood events and extrapolate this knowledge to an emerging flood situation.	[39, 42, 65]
	Flood propagation time	lead time, eg. upstream to downstream) or flood arrival time based on predicted or actual rainfall	Calculate lead time (travel time) of floods to plan early warnings, evacuation and response.	[30, 44, 45, 51, 55, 57, 58, 61, 62, 66]
	Soil moisture level		Determine the level of water infiltration and flood forecasting	[32, 34]
Intelligence related to the population at risk	Mobility of Crowd		Monitor movements of people during a disaster	[17, 48]
	Potentially Affected population		Plan for better response, evacuation, relief distribution and family reunification	[17, 24, 48, 56, 63, 67]
	population density / demography and distribution		Useful for response planning and relief operations	[19, 54, 59]
	Basic Needs (Food, water etc.)		Acquisition and managing basic needs during the response period	[56]
	Evacuation (estimated and actual)		Evacuation planning and relief management	[22, 49]
	Affected Population		Plan rescue operation and provide emergency treatments	[24, 48, 56, 68, 69]
Intelligence related to infrastructure at risk	Potential impact	Infrastructure	Develop response plan in preparedness phase to ensure efficient and effective response	[19, 50, 52, 70, 71]
		Roads	Make necessary re-routing of traffic as well as identify routes and transport methods to reach	[49, 63, 67, 70]
	Actual impact	Infrastructure	Conduct actual damage assessment during and after the disaster to support ongoing response as well as future risk management and response planning	[29, 57, 72, 73]
		Roads		[17, 49, 53, 56]
Intelligence on Resources and Capacities required during the response phase	Resources (helipads, evacuation centres, medical services etc)		Plan and co-coordinate response.	[59, 63]
	Active NGOs and other voluntary organisation		Advance response planning	[59, 63]
	Food and Supply Information		Understand help available for humanitarian support during response.	[59]

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	Service range (coverage) of responders (fire brigade, military, other emergency services)	Plan and coordinate response.	[67]

3.3. Intelligence on Flood Hazards

The inter-relationship between the stages of the flooding process, numerous intelligence captured to detect and monitor each stage, and tools and techniques that is being used to capture intelligence are discussed in this section.

Rainfall

Rainfall data at various point locations are typically captured through rain gauges [20, 23, 28-32], and its spatial variability is captured through doppler and satellite radar systems [31, 33]. Such live rainfall data, as well as historical rainfall data, are used as input to the hydrological models for flood forecasting [35]. However, in cases where rain gauge data is not available, satellite observation is used to monitor and predict floods [74]. In some cases, the analysis of past flood events and their magnitude has been used as the basis for preparing and responding to emerging flood events [31, 33]. The study reported in [32], shows how the analysis of 35 years of soil moisture, data derived from the satellite, integrated with gridded rainfall and elevation can be used for flood forecasting [32].

River Water Level

Measuring the water level could be classified into three categories based on the method employed to determine the water level: measured water level (by IoT) [16, 24, 25, 38-41], observed water level (by the public) [23, 25, 42], and forecasted water level [19, 43-46] through simulations. Many modern early warning systems have employed IoT devices such as automated river gauges to continuously measure real-time river water levels with greater accuracy [16, 24, 25, 38-41]. On the other hand, active and passive social media systems and crowdsourcing platforms are also being used to report water levels observed by the community as text and photographs with time and location data [23, 25, 42]. The crowdsourcing methods are beneficial for areas that do not have expensive sensor-based water level monitoring systems [25, 42]. The integration of these two approaches (IoT and crowdsourcing) can complement each other and enhance the confidence level of the water level measurements during disaster situations [25].

In order to gain further lead time for issuing an early warning for evacuation, predictive models such as hydrological models and rainfall-runoff inundation models [19, 43-46] are being used to forecast water levels at a given point. The accuracy of these models can be enhanced by providing continuous real-time data gathered through both IoT and crowdsourcing [16, 24, 25, 38-41].

River Water Flow

River water flow is a key parameter used in hydrology that measures the amount of water passing through a specific point over time. The flow rates are typically measured by gauge stations and are used in hydrology models [35] for predicting potential floods [37].

Flood Inundation

Flood inundation extent and inundation depth are two vital intelligence used in flood warning and response systems. At present, near real-time satellite data is being used to collect such intelligence during and post-event scenarios [17, 18, 21, 30, 42, 48, 50, 57]. Radar data analysis [18] tends to be the most popular method in flood inundation mapping during the rainy season as it has the capability to penetrate clouds. In addition to the satellite, airborne sensors attached to UAVs, that can supplement or even replace

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traditional satellite remote sensing systems can detect spatial coverage of flood disasters [21].

Passive crowdsourcing media such as Twitter, Facebook[23] and active crowdsourcing platforms such as Ushahidi[49] have become popular in collecting information on flood inundation and damages [56]. Citizen observation of the flood events in the form of photographs uploaded via social media and crowdsourcing applications has shown valuable for the decision making in response [42]. In Brouwer, Eilander [60], both probabilistic and deterministic approaches have been used to transform the Twitter response to flood extent. The review articles by Tomaszewski, B., et al. (2015) and Yu et al. (2018), elaborate on how the combination of satellite and crowed source information is being used to determine the flood extent in near real-time [17, 21]. Two case studies from the Philippines and Pakistan, reported in Jongman, Wagemaker [57], show how the combination of multiple sources such as near real-time satellite data and Twitter response, collected from the community, was useful for monitoring the flood extent. These case studies have demonstrated how the integration of traditional remote sensing data with real-time social media data could increase the situational awareness of the flood hazard context in the form of location, time, cause and impact hence improving the efficiency and speed of the response action.

Many are using numerical models and GIS-based inundation mapping to determine the possible inundation zones, which allows advanced planning for disaster response [20, 22, 33, 35, 64]. Such intelligence for response planning by disaster agencies offers sufficient time to mobilise their teams to respond efficiently and warn citizens well in advance.

Along with the inundation extent, flood depth can also be predicted before and after a flood [23, 25, 29, 50, 60] to estimate the impact on the people and properties in advance by relevant authorities [25, 75]. Flood depth is typically calculated using hydrological models [25], but recently social media systems such as Twitter have been used to collect the flood inundation depth [23].

Flood Arrival Time

Flood arrival time (lag time) is known as the time difference between rainfall time centroid and peak discharge [62, 76]. Early prediction of the arrival time of floods at a given point is used for issuing flood early warnings to the community [30, 45, 51, 55, 57, 58, 61, 66].

Traditionally this is measured by hydrological modelling techniques such as rainfall-runoff inundation modelling in combination with Geographic Information System (GIS) and Remote Sensing (RS) [30, 51]. Recently, researchers have used intelligence from multiple sources to improve the accuracy of predicting flood arrival time and eliminating false flood warnings. For example, Jongman, Wagemaker [57] present an approach that combines passive radar satellite response on soil moisture (AMSR) and social media to improve accuracy in flood prediction. Similarly, Tekeli and Fouli [66] present an approach that combines AMSR satellite data with Tropical Rainfall Measuring Mission (TRMM) satellite data to improve accuracy. In Zhou, Smith [62], the authors present the analysis of historical river gauge data and satellite data (radar) of various return periods to ascertain the lag time over a given river basin in Charlotte Metropolitan region in USA.

Flood arrival time is also being estimated by employing various Artificial Intelligence (AI) techniques since conventional methods are unable to capture nonlinearity and non-stationarity related to hydrological applications [45]. Fuzzy sets and artificial neural networks (ANN) are two other popular Computational Intelligence (CI) techniques that are commonly used in hydrology[45]. Recent research based on Wavelet Transform Neuro-Fuzzy (WT-NF) technique has shown promise in forecasting floods with an increased lead time [45]. Some researchers have explored how the accuracy of the CI techniques can be enhanced by using hybrid methods that combine different CI methods for improving the accuracy and lead time of the flood forecasting [45, 77]. For example,

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[78] combines ANN with Generic Algorithms, and [79] combines ANN with Wavelet to increase flood forecast accuracy.

Other developments in this area is the use of Service-Oriented Architectures (SoA) [55], linked with ontological frameworks [58], for capturing and processing data from a variety of sources (IoT sensors, social media, crowdsourcing, satellites) to support the prediction of flood arrival times using forementioned techniques.

Flood Frequency and Return Period

Flood frequencies and return period are two inter-related factors essential in understanding and preparing for possible situations since they indicate the magnitude of an emerging event [22, 25, 52, 55, 56, 62-64]. Flood frequency analysis is a statistical technique used by hydrologists to estimate the flood return period or exceedance probability by measuring peak discharge values over a period of time. Flood frequency analysis provides decision-makers to pursue a broader understanding of the hydrological behaviours of a given river from the perspective of flood response [62]. Higher peak discharge and runoff rates increase the flood frequency, hence increasing the severity of floods. Therefore, it is necessary to understand the flood hazard level at different flow conditions so that proper evacuation planning could be arranged in advance [22]. In addition to the frequency calculation, historical flood events are useful for validating various models, developing risk and damage functions and preparing for future events [39, 42, 65].

3.4. Intelligence Related to Exposed Population

Intelligence required to understand and estimate the exposed population and underpinning technology that can be used to acquire such intelligence during flood hazards is discussed in this section.

Population Densities, Distribution, and Demography

Spatial distribution and density of population is a primary data set that is required to identify and estimate an exposed population for a given hazard [19, 54, 59, 80]. Population data are usually obtained from the national census, available at spatially aggregated forms up to local administrative boundaries, which are too coarser for disaster impact analysis. Hence, land use maps [80] and satellite-derived settlement data [81] are being used to derive population density maps at finer scales. In addition to that, global data sources such as Landscan data also provide population grids at various grid sizes[82].

Potential Affected Population

The potentially affected population by the flood is the most important intelligence required by authorities to make decisions during the early warning and response stages [17, 24, 48, 56, 63, 67]. Furthermore, an estimation of the affected population is essential to plan for relief assistance and post-disaster impact assessments [56, 63]. Data from various sources such as government authorities and municipalities are typically combined with open-source spatial data to estimate the exposed population in the GIS domain [67]. Tzavella, Fekete [67] reports how VGI based methods have been successfully used in an extreme flood event in Cologne, Germany, to improve the efficiency of flood response with the decreased response time.

Numerous models and approaches have been used to evaluate the potential effect of floods on people. For example, the Disaster Diagnostic and Evaluation System (SEDD) offers a fuzzy rule-based classification system that can be used to assess the possible consequences on people just after a disaster [63]. It uses Emergency Events Database (EM-DAT) as the primary source of population data together with sources such as the Human Development Index (HDI), published by UNDP, to calculate the vulnerabilities. Deng, Liu [56] proposes a social media-based model to estimate the impact of a disaster on the

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community, which has been tested for typhoon Haiyan. In contrast, Ushahidi collects the actual affected population during the Haiti earthquake [48] using crowdsourcing.

Mobility of Crowd

The intelligence with respect to the locations and mobility of crowed is critically important in the emergency response phase, which provides response authorities to target the people who need immediate rescue and medical assistance. Call Detail Records (CDR), referred to as digital trails of modern mobile device users, can be used to monitor population movement and displacement and to disaster response planning [48], since it offers a detail record of mobile phone location and calls logs generated by mobile companies in real-time. The successful use of CDR techniques is reported in [17], during the Haiti earthquake. Even though CDR is a useful technology to understand population dynamics, it is still not widely used due to privacy issues and a lack of supportive legal frameworks [48].

Evacuation (estimated and actual)

People who need evacuation or have already been evacuated are another critical intelligence useful in the response phase. The number of people who needs evacuation is typically estimated and identified during the preparedness planning process for various flood simulation scenarios for multiple return periods [22]. However, a more accurate picture of the evacuated people can be captured through social media platforms, active and passive crowdsourcing and geo-referenced Volunteered Geographic Information (VGI) techniques during a disaster [48].

Affected Population

Intelligence on affected people such as those who are trapped, injured, and victims who need immediate rescue is critical during emergency response. Furthermore, they require a mechanism to connect with response teams and inform their situation to the families and friends who are concerned about their safety and well-being.

Crowdsource applications [48], social media microblogs [56, 69], and mobile CDR [48] are potential tools and technologies used to gather the status and needs of the affected people in real-time. As successfully demonstrated during the typhoon Haiyan, semantic analysis of the microblog, posted through social media, can help authorities to understand the concern of affected people at a different stage of the disaster and respond better [50]. Ushahidi is another popular crowdsource application that has been successfully used to collect, visualise and map data gathered from affected communities [48].

Eivazy and Malek [68] illustrate an example of how agent-based solutions, integrated with crowdsource services, have been used during the Aquala flood disaster in Iran in 2019 to help victims to obtain emergency support from the rescuers. In this example, individuals injured from a critical situation are reported through crowdsource systems, and an agent-based information system attempts to ensure the victims' safety by connecting them with the rescuers [68]. The increasing trend in providing safety checks through social media systems such as Facebook to inform friends and family during a disaster is now common and reported in [48]. Bachmann et al. [24] present a mobile app that can be used to reunify families affected by disasters.

Essential Needs

During the response phase, government authorities are also responsible for supplying essential needs such as food and water required by the displaced population. The intelligence regarding the essential needs is typically collected from microblogs such as Twitter [56, 69], social media and crowdsource systems [17]. Deng, Liu [56] reports how during the typhoon Haiyan, a community of Hainan city of China, used social media techniques ("Sina Weibo", a Chinese microblog similar to Twitter) and semantic analysis to inform the needs of the affected people to the relevant authorities.

3.4. Intelligence Related to Affected Infrastructure

Potential Impact on the Infrastructure

The potential impact of floods on infrastructures, buildings [50, 52, 70, 71] and roads [49, 63, 67, 70] are essential intelligence required for disaster preparedness and response. The geo-referenced data of buildings, critical infrastructure, and road networks obtained from administrative sources and VGI techniques, including OpenStreetMap, integrated with the flood inundations maps, can be used to obtain the infrastructure exposed to the floods [19, 70].

Potential damages to residential buildings and other infrastructures are typically carried out with the simulation techniques for multiple return periods with different exceedance probabilities of floods [50, 52, 71]. Vulnerability curves that represent damage functions of the building for different levels of floods are used to assess the possible damage to the buildings and to propose hard and soft mitigation solutions [52]. The monitory value of the damages is then aggregated at different scales, from an individual building to administrative boundaries to catchment areas [71]. In addition, early identification of road inundation possibilities allows authorities to explore different re-routing options during a disaster [67].

Affected Infrastructure

Intelligence regarding the actual impact on infrastructure, both during and after a disaster situation, is essential in managing disaster situations. The use of near-real-time satellite data and social media responses (Tweets) for calculating such intelligence is reported in Jongman, Wagemaker [57]. Similarly, the use of geo-tagged images of damaged buildings to conduct damage assessment is reported by Bica, Palen [72] and Nguyen, Ofli [73]. Based on a study conducted in Nepal, Bica, Palen [74] have observed a positive correlation between actual ground damage and the damage assessment results conducted using the geo-tagged Twitter response of the earthquakes that occurred in April and May 2015.

Analysis of historical damage data in multiple flood events provides a comprehensive view of past flood damages. In Rilo, Tavares [29], the authors presented a comprehensive database that captures actual damage for housing, infrastructure, and the economy for various historical flood events that can be used for future mitigation and response planning processes [29].

Intelligence regarding the inundated road network is necessary during the emergency response phase to plan and re-route rescue services as well as establish regular transportation. Road inundation during the flood is acquired mainly by social media, crowdsourcing, near real-time satellites and UAV [17, 49, 53, 56].

3.5. Intelligence on Resources and Capacities

Resources and Capacities

Intelligence on available resources and capacities are required in order to respond to disasters [59, 63], such as available response organisations and volunteers [59], health services [83] and food and supply information [59]. Saad, Latif [59] presents a successful implementation of an Integrated Flood Disaster Management system in the District of Kemaman in Malaysia, that is comprised of a database with critical resources and capacities required during the flood response. In their system, intelligence such as details of evacuation centres, data on non-Governmental Organisations (NGO) and other volunteer organisations and data on helipad locations have been identified as capacities necessary during the responses in order to manage logistics to transport foods and

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essential needs and efficient response management [59]. Locations of these facilities are typically organised and stored in GIS databases.

Locational data of health facilities and travel time to such facilities are considered useful intelligence in the emergency response phase to manage flood-affected victims [83]. OpenStreetMap (OSM) derived global health facility data with their locations, and other attributes are made available via www.healthsites.io. In Weiss, Nelson [84], access to healthcare facilities has been analysed and presented in global maps to visualise travel time by foot and motorised transport.

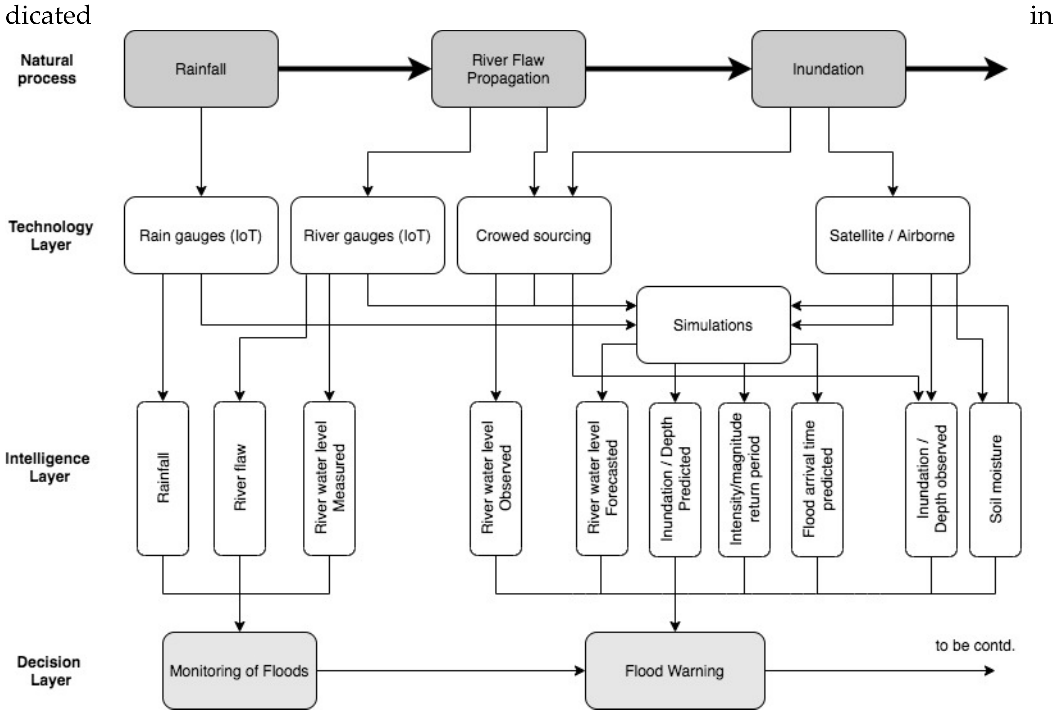
Tzavella, Fekete [67] calculate the service range of the first responders such as fire brigade, through network analysis, taking into account of the road network, points of resources and floods in Cologne, Germany.

4. Discussion

The critical analysis of the literature shows that the key intelligence required for flood warning and responses are associated with rainfall, river flow, inundation, impact on people, properties, and response capacities. It was observed that numerous tools and technologies are used to derive intelligence that transforms into decisions. The relationship between the flooding process, intelligence required, tools and technology to derive such intelligence can be presented as a conceptual system architecture of the overall decision making platform. This is simplified into four key segments for ease of understanding, as discussed below.

4.1. Conceptual model of flooding process and warning generation

According to the literature, it was observed that numerous technological approaches such as IoT [16, 24, 25, 38-41], crowdsourcing [23, 25, 60], satellites [18, 30, 50, 57, 66, 85] and numerical modelling [22, 44, 45, 71] are used to extract intelligence in relation to flooding at various stages, such as rainfall, river flow propagation, and inundation as indicated in



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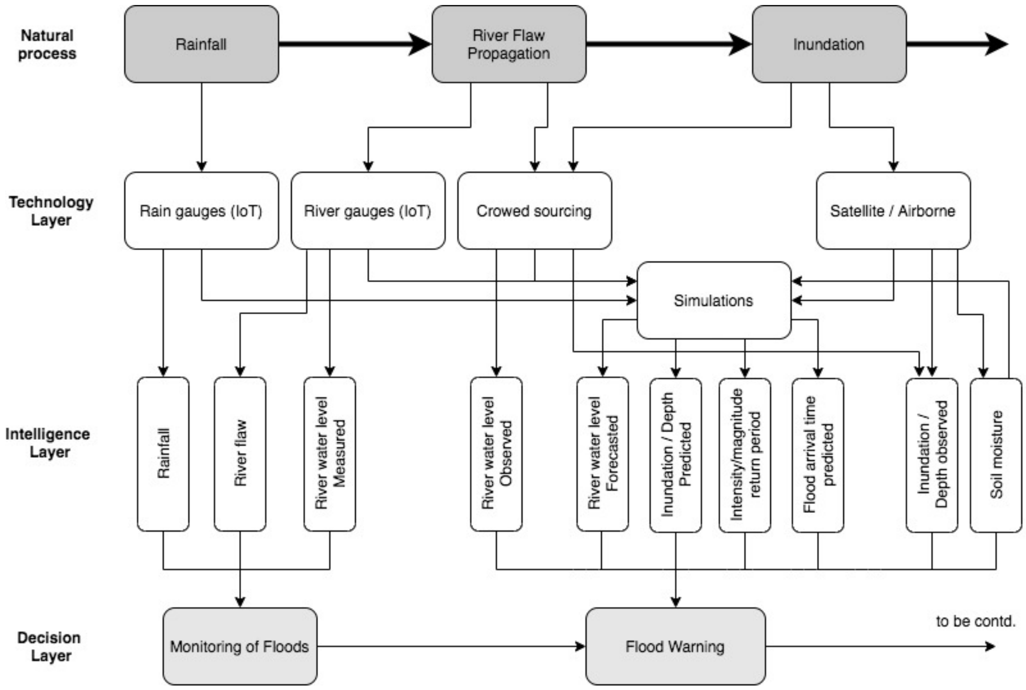
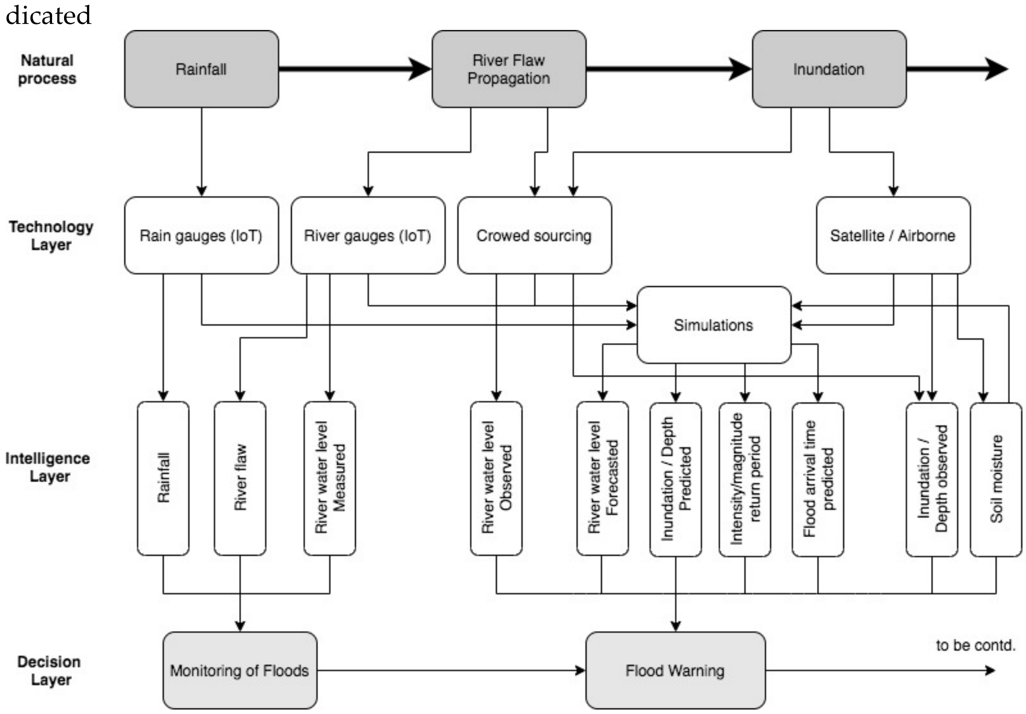


Figure 5. Intelligence Required for Monitoring Emerging Flood Situation.

According to the literature, it was observed that numerous technological approaches such as IoT [16, 24, 25, 38-41], crowdsourcing [23, 25, 60], satellites [18, 30, 50, 57, 66, 85] and numerical modelling [22, 44, 45, 71] are used to extract intelligence in relation to flooding at various stages, such as rainfall, river flow propagation, and inundation as indicated in



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The intelligence extracted from these technology includes rainfall, river level (measured, observed, and forecasted), both inundation depth and extent (measured, observed, and forecasted), flood frequency, return period, intensity, flood arrival time, and soil moisture.

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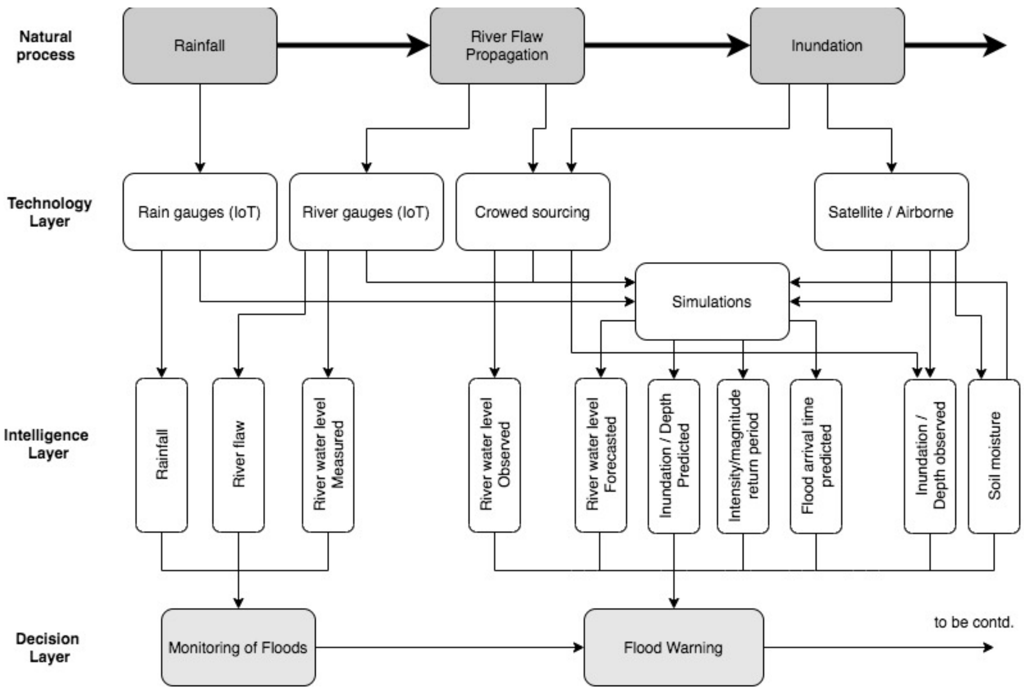
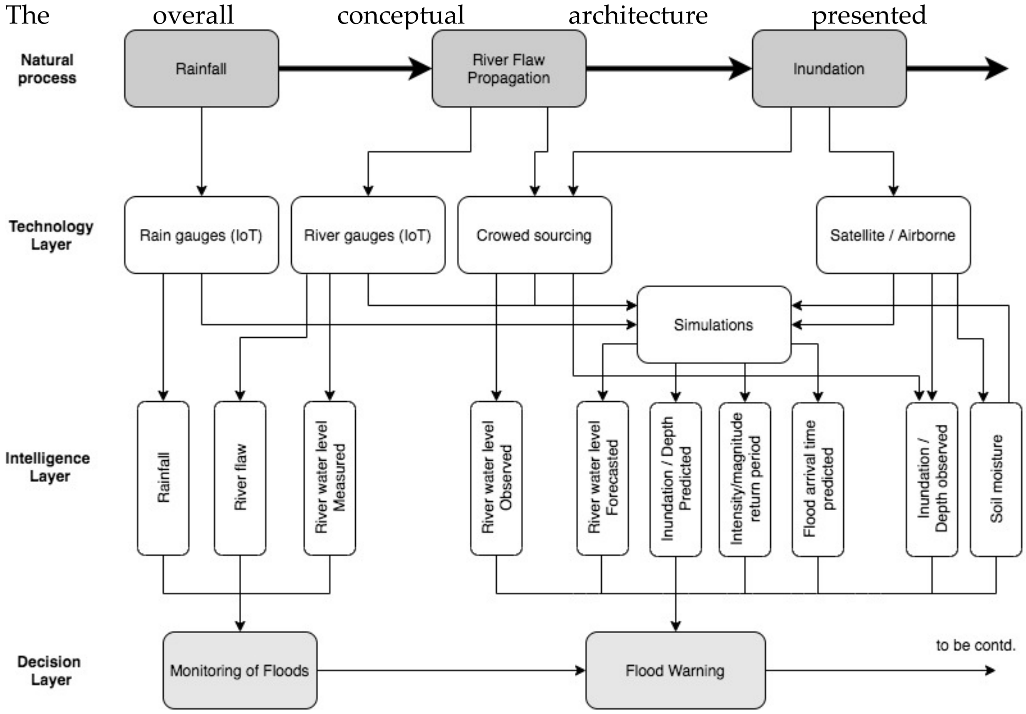


captures the use of technological approaches for extracting intelligence to respond to various activities by disaster management personnel during a flood disaster scenario. The overall conceptual architecture presented in



integrates four layers: process layer, technology layer, intelligence layer, and activity/decision layer. The process layer represents how the flooding process evolves, starting from the rainfall, river flow, and up to inundation. The technology layer then uses the technological solutions identified in this survey to monitor the evolving flooding situation and extract and pass the relevant information to the intelligence layer. The information captured in the intelligence layer can then be used by the disaster management authorities to monitor the evolving flood situation over time and generate flood early warnings in

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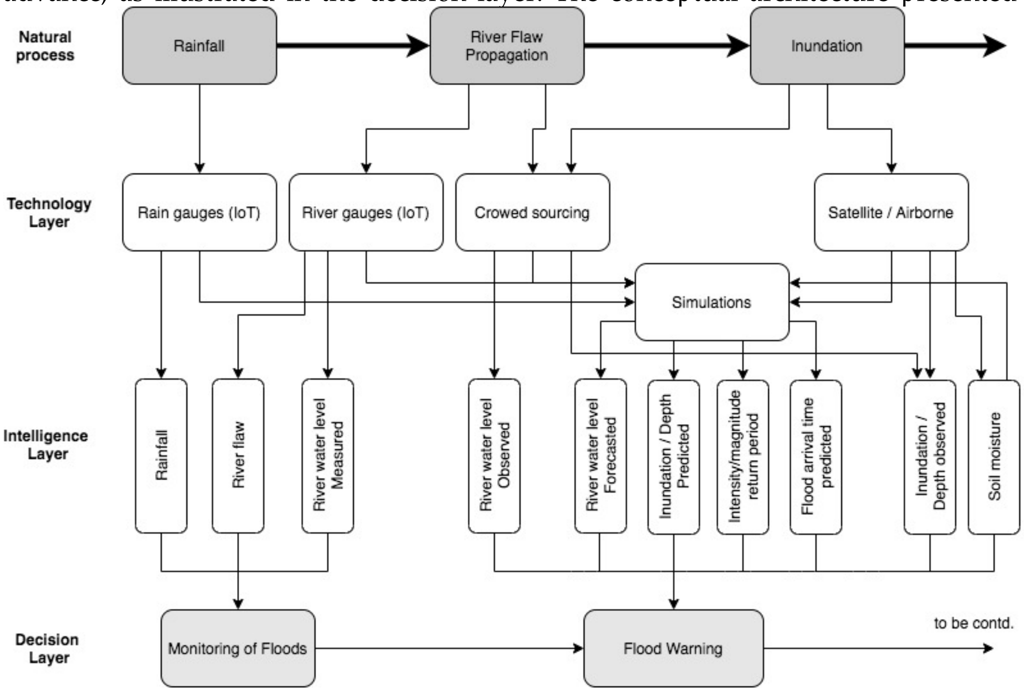
advance, as illustrated in the decision layer. The conceptual architecture presented in



can be implemented using the state-of-the-art technology presented in the previous sections to allow decision-makers to ensure public safety before, during and after the floods.

However, it should be noted that there are many barriers to implementing such systems [86], [87],[88]. Some barriers and challenges include (i) inadequate coverage of IoT sensors due to capital and maintenance cost and unavailability of internet connections [86] (ii) lack of accurate flood simulation models running on high-performance computers to provide near real-time response [87](iii) limitation of acquisition and limited coverage of near-real-time satellite images [88]. Although many developing countries have access to the International Charter for Space and Majors Disasters, Copernicus System, and Sentinel Asia System, the average time for satellite activation to first image reception is three to four days [89]. As a result, many disaster management agencies in developing countries resort to historical inundation information to estimate the possible inundation zones during flooding incidents. In this context, crowdsourcing techniques are more efficient than satellite observation, even with the limitation of its effectiveness and accuracy [90].

4.2. Conceptual model of flooding impact on people

When a population is exposed to floods, many intelligence such as movements of people, their vulnerabilities, numbers, and location of people trapped or injured, people evacuated and their basic needs are required by authorities and response teams. These are acquired during different phases of the disaster event (before, during and after) using simulations, crowdsource technique, voluntary GIS activities, social media, carrier detail records (CDR) and remote sensing.

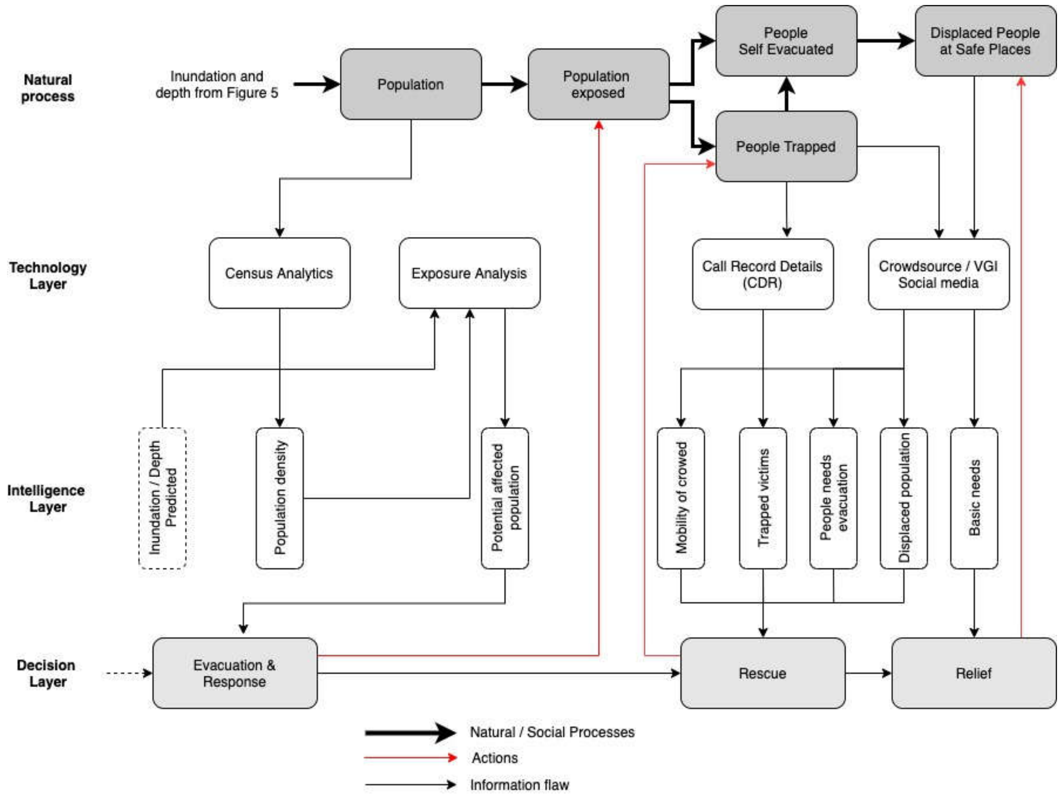
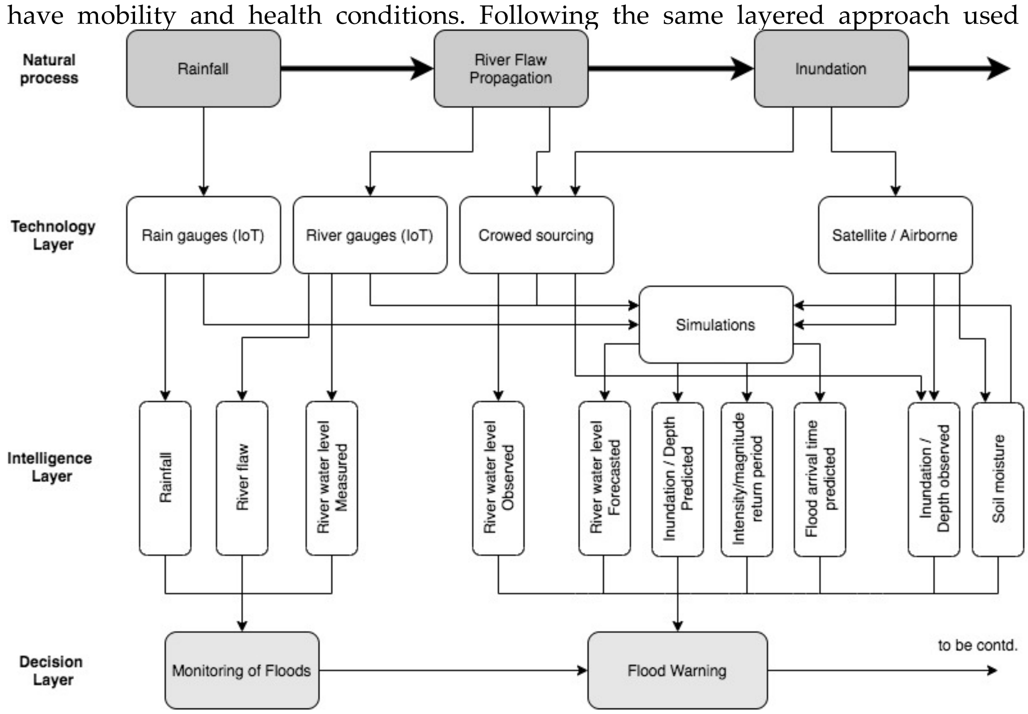


Figure 6. Intelligence Required for Issuing Early Warnings, Rescue and Relief Operations.

Error! Reference source not found. illustrate the relationship between the impact of flood inundation on the people and the technologies that can be used to derive intelligence for supporting evacuation and rescue operations. As shown in Figure 6, as the inundation is impacting on the population, people will begin to self-evacuate themselves, sometimes with support from government agencies and NGOs for evacuating vulnerable people who have mobility and health conditions. Following the same layered approach used in



, **Error! Reference source not found.** shows how various technology solutions, identified in this survey, can be used to extract intelligence required for issuing early warnings

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and conducting intelligence-driven rescue and relief operations as the inundation is impacting on the people as shown in the process layer.

The flood inundation results, derived by simulations and satellites, overlayed with census data have the potential for providing intelligence on potentially affected people and those who are at risk. Such information can be used to disseminate targeted warning messages to the people at risk before the floods, hence saving lives. As the flood begins to impact people, technologies such as CDR, crowdsource, and social media techniques can be utilised to gain intelligence on the affected people on the ground, in near-real-time, to coordinate evacuation and rescue operations.

However, the access to up-to-date population data is problematic since the population distribution and demography are obtained mainly from the national census, where most countries typically release such data sets in 10-year intervals. As a result, the population growth in-between years is not captured by these censuses. Furthermore, the national census registers do not usually capture the population dynamics at workplaces, schools, hospitals, hospices and other public localities. Hence, census data alone will not provide actual ground situations to estimate the potentially affected population during a flooding situation. Hence, there is a need for the local actors to maintain a more comprehensive database of their local population in order to better respond to disasters.

On the other hand, the accuracy of the predicted inundation scenario plays a vital role in determining the affected population. Therefore, simulation models used during disaster situations should be calibrated and validated well in advance to ensure the accuracy of their outputs.

Even though social media and crowdsourcing techniques exist, these systems are not standardised and well recognised in disaster response plans at a local level [91]. Furthermore, at present, community participation is not actively encouraged to get the maximum benefit of these techniques. On the other hand, CDR technology has the potential to offer active SIM locations and the movement of people at risk during a disaster [48]. The exploitation of these possibilities would require disaster management agencies to work closely with the mobile service providers and integrate them with their current disaster response processes while providing a legal framework for accessing such private data for emergency purposes.

4.3. Conceptual model of flood impact on infrastructure

Intelligence on physical properties such as housing, utilities, other infrastructure and road network that can be affected by the flood is another key intelligence required by authorities for optimum risk management planning and response. This intelligence needs can be classified into two categories: (i) pre-disaster intelligence on infrastructure that can potentially be affected, and (ii) intelligence on actually affected infrastructure during and post disaster phases.

Error! Reference source not found. presents a layered approach that represents the relationship between the impact of flood inundation on infrastructure and the potential technology that can be used to derive intelligence to support decisions. As in the previous sections, the layered architecture is represented through the activity layer, technology layer, intelligence layer and decision layer. The infrastructure that can potentially be impacted by floods is usually identified through exposure analysis using the infrastructure data collected from various government agencies and estimated inundation. This intelligence can be used for advanced evacuation planning, safeguarding household items and livestock, building mitigation plans and business continuation plans for infrastructure (utility, public services, government buildings and economic centres).

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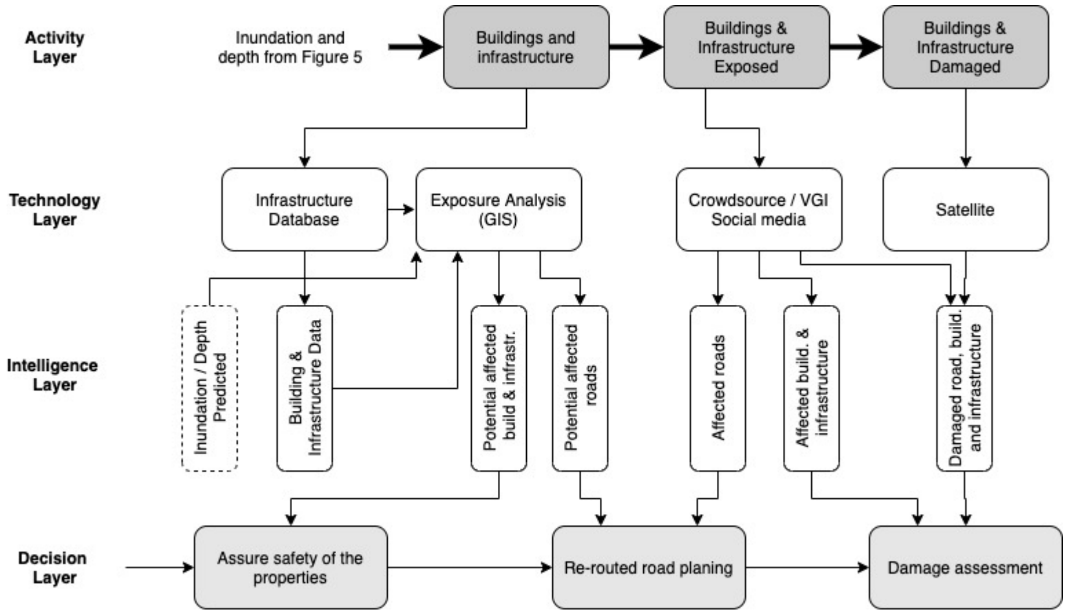

Figure 7. Intelligence Required for Identifying Affected Infrastructure.

Although the above flood preparedness plans allow authorities to identify potential risks to infrastructure and implement mitigation measures using existing data, sources such as social media, crowdsourcing technology and satellite imageries are important to establish the actual situation on the ground during a disaster. However, the use of satellite images for the response is still challenging as the acquisition, and the derivation of intelligence from such sources require considerable time [92].

4.4. Conceptual model on response capabilities

Intelligence on resources and capacities required for the successful response is necessary for the authorities to make timely coordination with relevant parties. For example, safe centre locations and their capacities during flood response are necessary for evacuation planning. Furthermore, authorities also require information on surge capacities for food, medical assistance, transportation and availability of volunteers in addition to the official resources.

Error! Reference source not found. illustrates the process where intelligence on capacities and resources can be obtained through numerous resource management databases and systems to assist in the decision-making process. More specifically, during a flood emergency, authorities need to locate the nearest evacuation centres and health facilities with appropriate capacities that match the requirement to re-locate displaced or treat injured persons. Typically, local flood preparedness plans identify such facilities and hosting capacities well in advance. In addition to that, volunteers, volunteer agencies, and other resources such as transport, heavy machines and tools are required to respond on demand.

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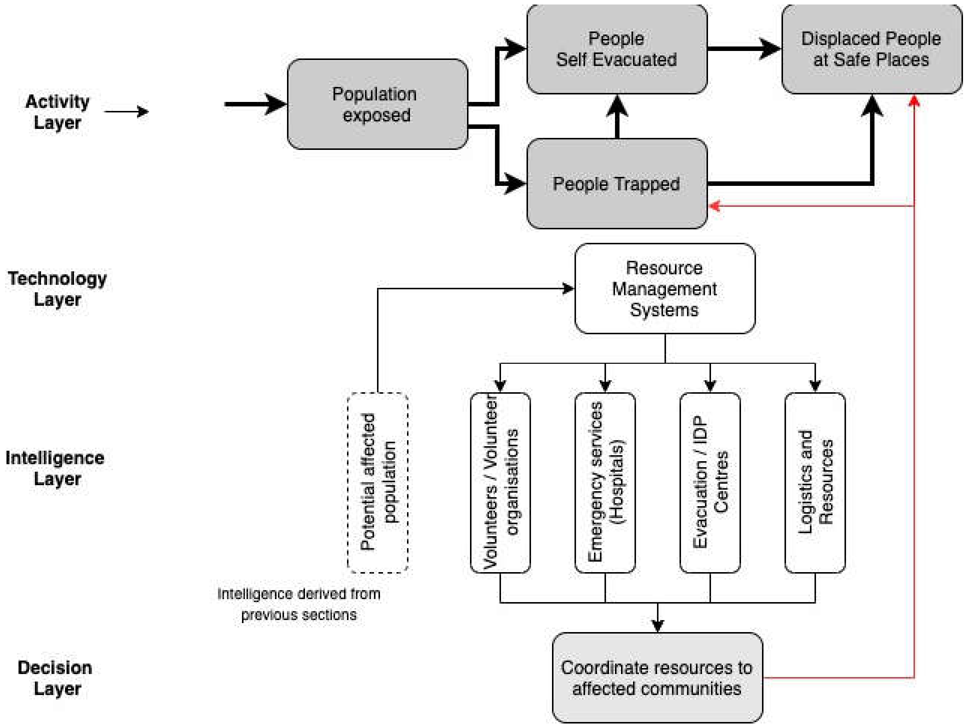

Figure 8. Intelligence Required for Capacities and Resources in Response.

5. Conclusion

The review of literature presented in this paper identified twenty-eight types of intelligence necessary during various stages of the FEWRS (pre-flood, during the flood and post-flood) to issue flood warnings in advance and to respond efficiently to safeguard people and properties. Over 54 published articles written on several bodies of knowledge, including information systems, disaster risk management, and hydrometeorology, have been examined and developed inter-relationship between the flooding phenomena, intelligence derived for decision making, and sources of technology that are used to extract this intelligence.

The pre-condition for extracting critical intelligence during a flood situation is the availability of exposure and vulnerability data of people and infrastructure of the flood-prone area under consideration. As the flood situation begins to develop, real-time information regarding the flood hazard can be captured using numerous techniques and tools: citizens as sensors, satellite remote sensing technology, IoT devices and mobiles. Information from citizens can be captured through social media and crowdsourcing techniques. These raw data can then be used by GIS, artificial intelligence (AI) or hydro-dynamic modelling to extract critical intelligence such as the dynamic characteristics of the hazard **(**rainfall, river water level/flaw, flood arrival time), population and infrastructure exposed or at risk, and capacities required during response as presented in **Error! Reference source not found.**.

The conceptual architecture presented in this paper provided guidance for deploying various advanced technology approaches for deriving the necessary intelligence required by disaster management agencies as the floods begin to spread and impact on the community and the environment. The architecture presented in Figures 5 to 8 illustrated how the required intelligence during the flood cycle need to be managed in order to inform, evacuate, rescue and offer relief to citizens and safeguard the properties in a timely manner.

Moving forward, the layered approach presented in this paper offers a foundation for developing a technology platform that disaster management agencies can use to issue early warnings with sufficient time for people to evacuate, better respond during floods and efficiently manage relief operations. Furthermore, the conceptual system architecture

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presents a range of technical solutions that can be adopted by the decision-makers, based on the availability of the technology, and offers a pathway to increase the accuracy and efficiency in receiving the necessary intelligence as the resources become available. It shows how information from sensors, databases, big data systems, GIS, hydrological simulations and satellite remote sensing can be combined to offer a rich set of information for decision making and interventions by various agencies. Integration of these technologies has the potential for increasing the effectiveness, efficiencies, and accuracy of the overall approach to flood monitoring and early warning and evacuation.

Such integration will overcome the limitations of the present early warning and response systems such as unavailability of information and intelligence [8]; insufficient information sharing [93-96]; lack of coordination among agencies [97, 98]; false early warnings [99]; lack of allocations of resources for response [97]; delayed response [100], which often result in crisis escalation and higher numbers of causalities.

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