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A review of flash-floods management: From hydrological modeling to crisis management

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Abstract

In a context of climate change, flash-floods are expected to increase in frequency. Considering their devastating impacts, it is primordial to safeguard the exposed population and infrastructure. This is the responsibility of crisis managers but they face difficulties due to the rapidity of these events. The focus of this study was to characterize the extent of the link between hydrologists and crisis managers. It also aimed to determine the limiting and the fostering factors to an effective integration of forecasting in crisis management during flash-floods. This was achieved through an extensive and methodological study of available literature in selected platforms. The models encountered were characterized on multiple levels including the physical, geographical and crisis

Abbreviations: ANFIS, Adaptive neuro-fuzzy inference system; ANN, Artificial neural network; CAO, Chief Administrative Officer; Cérema, *Centre d'études et d'expertise sur les risques, l'environnement, la mobilité et l'aménagement*—Center for studies and expertise on risks, the environment, mobility and development; Cinecar, A physically based and distributed hydrological model; COST 731, European Cooperation in Science and Technology's Action 731 titled "Propagation of Uncertainty in Advanced Metrology"; DEM, Digital Elevation Model; EM-DAT, The Emergency Events Database; ERICHA, indicator utilizing RaDAR-based rainfall monitoring and nowcasting for the upcoming 6 h; ESPADA, *Evaluation et Suivi des Précipitations en Agglomération pour Devancer l'Alerte*—Evaluation and Monitoring of Precipitation in Agglomerations for Early Warning; EU, European Union; Flood-PROOFS, Flood-PRObabilistic Operational Forecasting System; FRICS, Foundation of River & Basin Integrated Communications, Japan; HEC-HMS, Hydrologic Engineering Center—Hydrologic Modeling System; HEC-RAS, Hydrologic Engineering Center River Analysis System; Iber+, A hydraulic 2D model; IDW, Inverse distance weighting; IoT, Internet of Things; LiDAR, Light Detection and Ranging; LISFLOOD, LISFLOOD hydrological model; LSTM, Long Short-Term Memory; MAP-D-PHASE, Mesoscale Alpine Program Demonstration of Probabilistic Hydrological and Atmospheric Simulation of Flood Events; MDPI, Multidisciplinary Digital Publishing Institute; MLP, Multi-Layer Perceptron; OECD, Organization for Economic Cooperation and Development; QPE, Quantitative Precipitation Estimation; QPF, Quantitative Precipitation Forecast; RIWS, Road Inundation Warning System; SCHAPI, *Service Central d'Hydrométéorologie Et D'appui à la Prévion des Inondations*—Central Hydrometeorological and Flood Forecasting Support Service; SOBEK, System for Operational and Basic Hydraulic Engineering Calculations; SPC, *Service de Prévion de Crue*—Flood Forecasting Service; SWMM, Storm Water Management Model; TOPSIS, Technique for Order of Preference by Similarity to Ideal Solution; WMO, World Meteorological Organization; WRF-hydro, Weather Research and Forecasting Hydrological Modeling System.

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management level. The results revealed a limited link between the two involved parties with limiting factors such as the complexity of the modeling approach, the insufficient projection in the implications of operability of the models proposed and the financial aspect. On the other hand, acknowledging the threat of flash-floods and conducting cost-benefit-analysis were pinpointed as fostering factors. This study showed to reconsider the forecasting methods employed, particularly, the integration of machine learning, and the needs of end-user in these applications in a crisis management context.

KEYWORDS

crisis management, emergency decision-making, flash-flood, flash-flood forecasting, hydrological modeling, machine learning, operability

1 | INTRODUCTION

In a context of climate change and increasing population and urbanization, a larger population is exposed to more extreme or more frequent floods. Studies have shown that flash-flood occurrences are projected to increase, sometimes, significantly. For instance, modeling results have shown an expected increase of flash-flood occurrence by 72% in Nanshan Scenic Zone in China in the period of 2020–2049 (Zhang et al., 2021). A study conducted by Trambly et al. (2023) using flood data from 1958 to 2021 showed a shift in flood seasonality with an occurrence earlier by a month, on average. It also highlighted a change in flood properties with increased rain intensity and accumulation and a decreased initial soil moisture. These findings imply a need for closer tracking of their evolution. They also imply that the task of flash-flood forecasting is likely to become more intricate.

According to WMO (World Meteorological Organization) (2021b), a flash-flood is “a flood of short duration with a relatively high peak discharge”. It is often caused by heavy rain (more than 100 mm in a few hours). Also, this type of event usually affects small to medium-sized watersheds (no more than a few hundred sq. km.). Once the rainfall begins, the response time, inferior to 6 h, restricts anticipation. Flash-flood events are favored by many physical factors including initial moisture, soil permeability and slopes (ibid). They can happen anywhere in the world but they are most prevalent in the northern hemisphere in temperate and subtropical area (central Europe, Southeast Asia, India, China and the United States among others). They are also common in mountainous areas (Kuksina et al., 2017).

Flash-floods are responsible for 1000 to 5000 deaths, annually (EMDAT, 2023; WMO, 2021a). They are the deadliest types of floods in many areas in the world like South-America, USA (e.g., Texas), Greece, Portugal

(Petrucci, 2022; WMO, 2021b). They are also 3.1% deadlier than slow floods, in general (Ruin et al., 2020). Additionally, the accompanying economic losses are significant and increasing over time. They were estimated at 40 billion US dollars yearly for all floods between 2011 and 2015, based on the EM-DAT database (OECD, 2016). Population's migrations can be consecutive of these events. Some of the most recent events include the flash-flood of May, 2023 in the villages of Bushushu and Nyamukubi, Democratic Republic of the Congo, killing more than 400 people and affecting more than 20,000 people. In July 2022, Iran was also hit by a series of flash-floods combined with different types of landslides killing 92 people with damages estimated at 201 million US dollar (EMDAT, 2023).

The devastating impacts of flash-floods show how important it is to enhance damage minimization. Several assets can help diminish the human and material impacts: (1) Awareness of hazards and risks, (2) monitoring, forecasting and warning, (3) population sensitization, (4) factoring of risks in land-use planning, (5) reducing vulnerability, (6) crisis preparation and management, and (7) post-crisis management and feedback (Dedeyan et al., 2013). These elements are also included in the European Union Directive on floods (Directive, 2007/60/EC), which introduces and standardizes the flood risk assessment and management process for all member countries.

Flash-floods often cause a crisis situation where they strike. This situation could be characterized as extraordinary urgent, undesirable, unexpected, uncertain and threatening, physically, morally, or materially putting pressure on crisis managers and invoking their responsibility (Boin et al., 2016; Rosenthal et al., 2001). A necessary process to enforce in this case is crisis management (often called emergency management) which aims to diminish and avoid damages (Coombs, 2007). It is

conducted in three phases: (1) pre-crisis, (2) crisis response, and (3) post-crisis (Coombs & Laufer, 2018; Tokakis et al., 2019). Crisis management can also be further detailed as follows: (1) mitigation, (2) preparedness, (3) response, and (4) recovery (Fischer-Preßler et al., 2016; Seaberg et al., 2017). The pre-crisis phase is used for planning prevention and crisis management. The latter part of this phase involves forecasting, monitoring and warning (Yu et al., 2018). When the crisis is triggered (e.g., beginning of a flash-flood), the second phase starts. The last step is utilized for evaluation, feedback and improvement (Coombs, 2014). The responsibility of the management of the crisis depends on its scale. Flash-floods are often localized and therefore the responsibility of the government is engaged at a regional and/or city scale. In this article, crisis, disaster and emergency as well as crisis management and emergency management will be used interchangeably, respectively. In reality, there are nuances between these words, and differences in terminology and models regionally (Al-Dahash et al., 2016; Boin & Hart, 2010; van Wart & Kapucu, 2011). For instance, in France, the expression “crisis management” is used to refer to the process to mitigate hazards. In the case of flash-floods, which are very localized, communes are generally responsible for this process. They rely on “*plan communal de sauvegarde*” which translate to communal safeguard plans. On the other hand, in Taiwan, the process is called natural disaster management. The plans employed by local governments are referred to as Disaster Prevention and Protection Plan (DPPP) (Wang, Chen, et al., 2021; Wang, Kong, et al., 2021).

Hydrological modeling is another asset in flash-flood crisis management. Flash-flood forecasting methods and hydrological modeling techniques, in general, have evolved significantly in the last few years. The starting point was Mulvany's method (1850) for peak discharge computation through concentration time calculation (Singh, 2018). The nineteenth century knew further developments like the establishment of Darcy's law in 1856 and in the next century Sherman's unit hydrograph concept in 1932 (ibid). Models evolved even swifter, as a result of the computer revolution (1960s), expanding from empirical to complex numerical models, integrating multiple data sources, other sciences, and advanced algorithms (ibid). The hydrological models available today fall somewhere in the spectrum of conceptual to physical models (Devia et al., 2015). The most physical models seem to be preferred from a hydrological point of view (Clark et al., 2017). On the other hand, conceptual models are sometimes preferred for their simplicity. Nevertheless, both types of models present challenges in terms of their accurate representation of a hydrological

system as well as their capacity of forecasting discharge or water level. Hydrological models can serve many purposes. They can aid in understanding a hydrological system and in its representation. They could be also be useful for management of water resources as well as nature preservation (Devia et al., 2015). In addition, through forecasts and warnings, managers, whose field of expertise is often not physics nor hydrology, can make well guided and anticipated decisions. This is crucial considering the sudden and rapid nature of flash-flood minimizing planning and adaptation time.

One of the emerging methods increasingly employed in hydrological modeling are machine learning techniques. They were shown to have an adequate hydrological forecasting capacity. In addition, the use of these techniques permits to limit the complications associated with the multiple parameters and inputs in physically based models (Dtissibe et al., 2020). The first experiments in this field in the 90s revealed satisfying results (Kang et al., 1993; Thirumalaiah & Deo, 1998; Zealand et al., 1999). One of the oldest techniques is artificial neural networks (ANN) (Lange & Sippel, 2020). In the Mediterranean Region of the South of France, several ANN models were proposed to forecast flash-floods. Toukourou et al. (2011) suggested a feed-forward ANN model to predict water levels even without rainfall forecasts. For longer lead times or ungauged basins, recurrent models were preferred (Artigue et al., 2012; Johannet et al., 2008; Kong A Siou et al., 2012). The interest of machine learning techniques is the variety of tasks that they can perform (Lange & Sippel, 2020). On top of predicting discharge or water level, they can predict other variables. For instance, For the small Liane basin in northern France, ANNs were exploited to create a tool to assist crisis managers in determining vigilance levels in the context of rapid floods (Bertin et al., 2016). More recently, they were beneficial for predicting turbidity whose process is poorly known (Savary et al., 2021). They also have abilities such as classification and image comparison (Lange & Sippel, 2020). However, due to their novelty, machine learning applications in crisis management remain limited.

Regardless of the availability of these forecasting techniques, the emergences of new techniques based on machine learning, and the evolution of crisis management paradigms, impacts of flash-floods are still significant and expected to increase. Therefore, it is crucial to investigate possible areas of challenges. An interesting aspect to verify is how well forecasts made by hydrologists are translated into decisions made by crisis managers. Hydrologists use models to forecast water flows and heights. Crisis managers, for their part, adapt their strategic and operational response to the flood situation in hand. To do this, they need to understand the upcoming risk (temporality and

kinetics of the event, impacted area, etc.). Therefore, creating an effective link between crisis managers and hydrologists proves challenging.

It is, thus, worth investigating the extent of the link between hydrological modeling and crisis management. It is also important to determine the facilitating factors for a successful collaboration between hydrologist and crisis managers. Finally, it is capital to identify barriers to a functioning cooperation. To achieve these goals, an extensive literature investigation is conducted in the present study. Following the background provided in the introduction, the materials and methods are presented in Section 2. On the basis of a number of selected articles, the criteria and methods employed were identified in Section 3. Their integration into crisis management was analyzed, with a particular focus on flash-flood forecasting and machine learning in Section 4. Finally, the conclusion, presented in Section 5, suggests avenues for future study and operational actions to improve flash-flood crisis management.

2 | MATERIALS AND METHODS

The methodology employed is that of literature review. A literature review can be conducted for various reasons. In all scientific works, it is employed to provide context and highlight the contribution or relevance of one's work (Labaree, 2023; Snyder, 2019). When the contribution itself is a literature review, the aims are to improve understanding of a topic sometimes providing a fresh perspective (Rowley & Slack, 2004; Sanders, 2020; Snyder, 2019). The choice of the methodology to employ will depend on the broadness of scope and the specificity of a research questions. For mono-field and specific research questions, systematic reviews are preferred, as opposed to narrative that provide contextual and historical overview (Snyder, 2019; Vidal & Fukushima, 2021). Considering the variety of fields treated in this article and the relative specificity of research questions, the methodology to employ should lie somewhere in the middle of this continuum. In consideration of these factors and the quantitative-qualitative nature of the subject, it is best to develop new standards for this analysis (Snyder, 2019). Regardless of this customized standardization, the methodology adopted is based on some acknowledged principle steps: (1) plan or design, (2) conduct the search, (3) analyze the results and (4) write the review (Daldrup-Link, 2018; Sanders, 2020; Snyder, 2019). Following these steps, the methodology is declined as follows:

- Section 2.1: Selected literature databases
- Section 2.2: Search queries

- Section 2.3: Inclusion and exclusion criteria
- Section 2.4: Analysis criteria

2.1 | Selected literature databases

The targeted bibliographic database chosen to include in this study were ScienceDirect, MDPI (Multidisciplinary Digital Publishing Institute), Nature, Wiley and Web of Science. The choice of these database was based on their size, but also to benefit from the selection and indexing work they perform. They are limited in size compared to databases like Google Scholar restraining the number of articles to be selected. This offered the opportunity of a thorough analysis on these articles. These databases are also multidisciplinary which was important considering the scope of the study. Further details on these databases can be found in Table 1. The platform Web of Science was also included to retrieve additional articles. It offers the advantage of covering multiple databases. However, at the same time, the articles included remain limited because they are evaluated and indexed.

2.2 | Searched queries

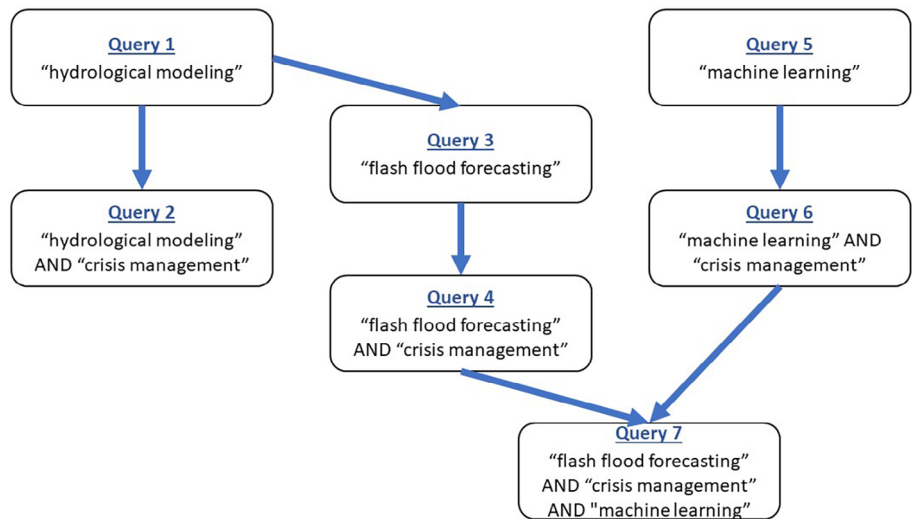
Several queries were conducted in the selected databases (Figure 1). At the beginning, the broad scope of hydrological modeling was considered. Then it was gradually narrowed using Boolean operators. “hydrological modeling” was also replaced by “flash-flood forecasting” as the hydrological application of interest. This gradual specification served to determine the proportions of research in crisis management, flash-flood forecasting and machine learning represent within the scheme of hydrological modeling.

Also, to diminish the chances of missing some journal articles, a large panel of equivalent or close search expression were determined (Table 2). They were defined through skimming the results of original expressions queries in Google Scholar and Science Direct. The list was completed with synonyms and similar words in the dictionary (Merriam-Webster, 2023). As for machine learning, a list of application in hydrological modeling defined by (Lange & Sippel, 2020) was utilized. Boolean operators and brackets were used to include the research expressions when possible. Otherwise, multiple searches were executed. For instance, query 2 was entered in Wiley's Online Library in the following format: (“hydrological modeling” OR “hydraulic modeling” OR “water-shed modeling” OR “rainfall runoff model” OR “precipitation runoff model” OR “runoff model” OR “discharge forecasting” OR “water level forecasting”) AND

TABLE 1 Description of publishing and review practices of databases considered in the study (information collected in June, 2023) (Author and Peer Reviewer Support, 2023; Author Services | Wiley, 2023; MDPI | Information for Authors, 2023; Overview, 2023; ScienceDirect.Com | Science, Health and Medical Journals, Full Text Articles and Books., 2023).

Platform	Publisher	Publication model	Fees of publishing	Editorial process
ScienceDirect	Elsevier (parent-company)	Traditional model Open access model (gold open access, hybrid open access, open archive, manuscript posting)	200–10,100 USD (depending on journal)	Peer review with at least 2 reviewers Median submission to accept time: 84–133 days (depending on journal)
MDPI	MDPI	Open access (APC based model)	1400–1860 USD	Peer review with at least 2 independent reviewers Median publication time: 40 days
Nature	Springer Nature	Traditional model and gold open access model	11,690 USD (OA)	Peer review, “several” reviewers Median submission to accept: 169 days
Wiley	John Wiley & Sons	Open access (APC based model) and gold open access	730–6540 USD (depending on journal)	At least 2 reviewers Average time for first decision: 2.3 weeks

FIGURE 1 Short version of queries entered in selected databases, their order and the link between them.



“crisis management” OR “emergency services” OR “emergency management” OR “emergency response management” OR “crisis resolution” OR “contingency planning” OR “emergency actions” OR “disaster response”).

2.3 | Inclusion and exclusion criteria

The research period of interest extended from 2011 to 2022. The choice of the period could be attributed to a few factors. First, it is a recent but not too extended period as the goal was not to conduct a historical overview. Second, it allowed to restrain the number of articles

to be examined allowing for thorough analysis. Finally, since review articles were considered, in addition to research articles, it was possible to encounter older research in these articles. Articles were not eliminated in the quantitative analysis using search queries. Only the results of query 4 are screened to determine the articles to be selected for further analysis. The titles and abstract were investigated to ensure that they corresponded to the search query. Research articles could be compared at various levels. This is because they are presented in the same format and employ, usually, a single methodology. To ensure the ability to compare these methods, only research articles with hydrodynamic forecasting models are considered.

TABLE 2 Expressions used in the keyword search.

Expression	Equivalent, close or related expressions
"Hydrological modeling"	"Hydraulic modeling", "watershed modeling", "runoff model", "discharge forecasting", "water level forecasting"
"Crisis management"	"Emergency decision making", "emergency response management", "crisis resolution", "contingency planning", "emergency actions", "disaster response"
"Flash-flood forecasting"	"Flash-flood prediction", "flash-flood warning system", "flash-flood detection method", "flash-flood early warning system", "real time assessment of flash-flood impact", "flash-flood impact forecasting", "rapid inundation forecasting", "rapid inundation prediction", "rapid inundation warning system", "rapid inundation detection method", "rapid inundation early warning system", "real time assessment of rapid inundation impact", "rapid inundation impact forecasting", "flash inundation forecasting", "flash inundation prediction", "flash inundation warning system", "flash inundation detection method", "flash inundation early warning system", "real time assessment of flash inundation impact", "flash inundation impact forecasting"
"Machine learning"	"Neural network", "supervised learning", "unsupervised learning", "reinforcement learning", "deep learning", "k nearest neighbors", "regularized linear model", "regularized regression", "lasso", "ridge", "elastic net regression", "support vector machines", "decision tree", "random forest", "gradient boosting", "stack generalization"

2.4 | Analysis criteria

The aim of the criteria investigation is to provide details on the flood forecasting methods exploited in the research articles. It also aims to define how these methods are utilized in crisis management. Specific criteria have been defined for research and review articles.

2.4.1 | Research articles

Research articles that were selected at query 4 described tools or proposal of tools for flash-flood forecasting that

TABLE 3 Criteria describing the general context.

Category	Criteria	Description
General context	First author's lab	Country
	Targeted region	Country of studied area
	Watershed class	According to author's description else undefined

TABLE 4 Criteria describing the modeling approach adopted and used and forecasted data in the selected research articles.

Category	Criteria	Description
Modeling approach	Model used	Name
	Model type	Spatial resolution Proximity to the basin's physics
	Machine learning	Yes/no/multi-approach
Data used and forecasted	Nature of acquisition of inputs	Observed, forecasted, simulated, other
	Nature of inputs	Rainfall, discharge, land use, soil moisture...
	Nature of outputs	Discharge, water-level, warning, alert...

could be beneficial to crisis managers. Studying these research articles permits to determine aspect of interest in the subject at hand. It also helps identify emerging technologies and their input.

General context

Determining the general context of the selected research articles was an important first step (Table 3). The countries of first author and the studied area could be compared to areas affected by flash-floods. This can reveal some factors that allow for research to thrive in some areas compared to others. On the other hand, watershed class can give insight on the methodology employed. Watershed class does not correspond to a hydrological concept per say. This criterion was filled in accordance with the author's description of the watershed, describing relatively unique characteristics (e.g., karst aquifer or highly urbanized watersheds). For instance, in the case of highly urbanized watersheds, hydraulic models could be privileged.

Model and data characteristics

The modeling approach is another aspect worth studying (Table 4). Some model types are easier to implement in

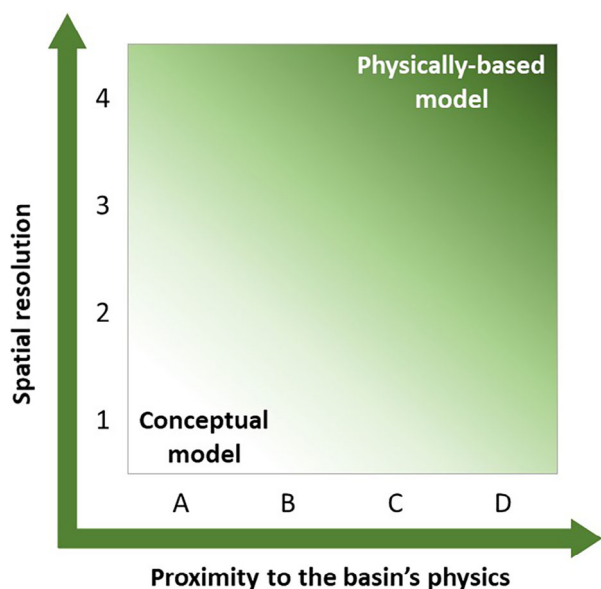


FIGURE 2 Schematic representation of the gradual transition from a physical model to a conceptual model.

an operational setting compared to others. Studying the incorporation of machine learning is also investigated. Additionally, data used and data forecasted are explored. This is because there isn't the same data accessibility everywhere. Data accessibility can also be affected by the impacted flash-floods. Finally, the outputs are also studied to define the information they can provide to crisis managers.

Amongst the criteria of interest, there is the typology of models. Classifying models accordingly is often a difficult task. This is due to two factors. Firstly, there are many ways to classify models. For instance, it is possible to differentiate models by their level of abstraction (physical vs. conceptual). Another way of classification is to consider the explicability of the outputs by the input variables (deterministic vs. stochastic) (Estupina Borrell, 2004). Nevertheless, it can be noted that the degree of abstraction and the spatial resolution cannot be decorrelated (Figure 2). A high distribution of the model indicates that either intermediate measurements (not at the output of the system) or spatially distributed physical features have been considered. The level of abstraction is then a function of the proximity of the basin physics but also of the resolution of the spatial distribution. Therefore, these two aspects will be considered in this article to determine the model type.

It is important to mention that the degree of detail varied from one article to the other. To homogenize the results and eventually be able to compare them, a choice was made to align all the entries to the lowest level of detail. For instance,

TABLE 5 Criteria describing the crisis management aspect in the selected research articles.

Category	Criteria	Description
Crisis management	Maturity levels	1 to 3 (1: only flood forecasting; 2: flood forecasting and forecasting of crisis management variables (e.g., alerts, warning, threshold exceedance, forecasted impacted population, building or infrastructure and decision recommendations); 3: flood forecasting and forecasting of crisis management variables, as well as conception of tools to disseminate this information to end-user (e.g., platform, website, application, messages, siren systems, operators for phone communications))
	Operationality level	1 to 3 (1: method described is not operational and author doesn't consider this perspective; 2: method described is not operational but the author considers this perspective; 3: tool is operational)
	End-users	Crisis managers, citizens, industrial or other (in this case, user is defined)

only the category of input data was specified and not the input itself. In this configuration, temperature and wind speed were referred to as meteorological data, for example. The categories considered were: rainfall data, hydrological data, other meteorological data (wind speed, temperature...), flood records, flood hazard and other data.

Crisis management

As for the crisis management aspect, three criteria were defined (Table 5). The first one is the maturity level which describes the nature of the outputs as well as the communication tools with the end-user. The other two

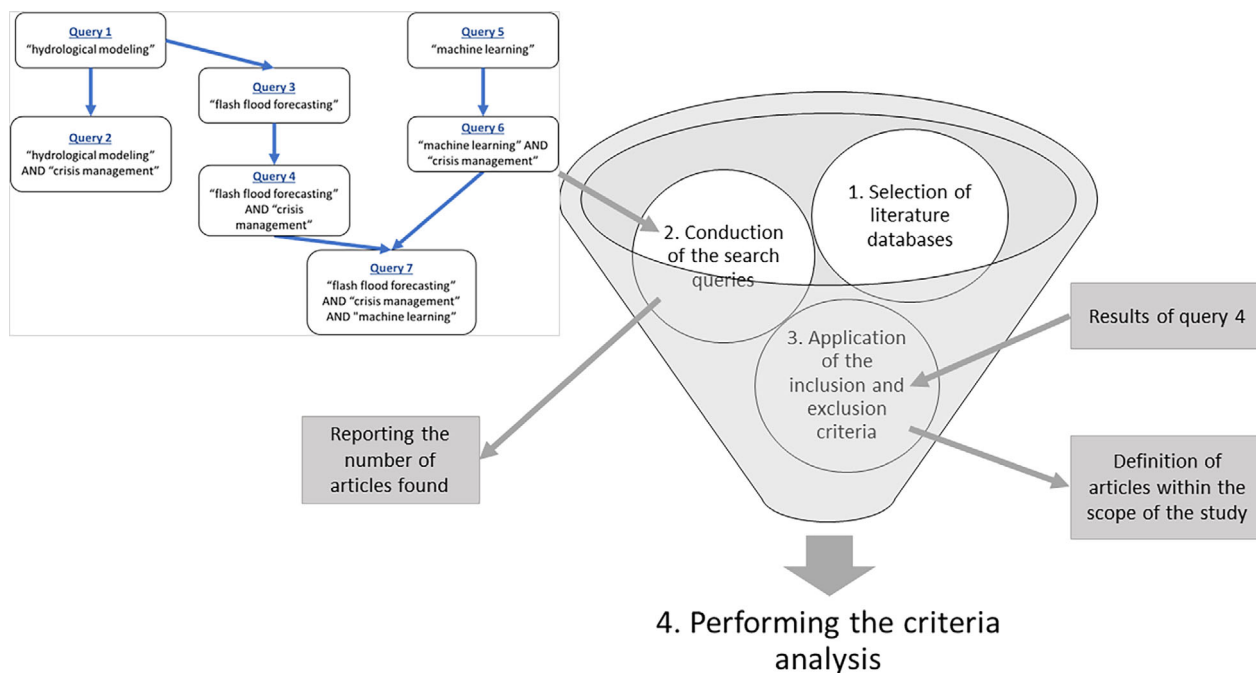


FIGURE 3 Flowchart of the methodology employed in the study.

criteria are the operability level and the targeted end-users.

2.4.2 | Review articles

Review articles were also considered in the criteria exploration. They reflected how well flash-flood forecasting and crisis management were treated simultaneously. For this objective, it was sufficient to define the main topic and the findings. Finally, other examples of flash-flood forecasting methods were extracted from the review articles. However, hundreds of examples could be mentioned in one article. Therefore, only medium and high maturity level examples were considered. This methodology answered the treatment difficulty. It still allowed to discover new techniques and enriched the list of facilitating factors and limitations in efficient linking of hydrological modeling and crisis management (Figure 3).

3 | RESULTS

3.1 | Submission of queries

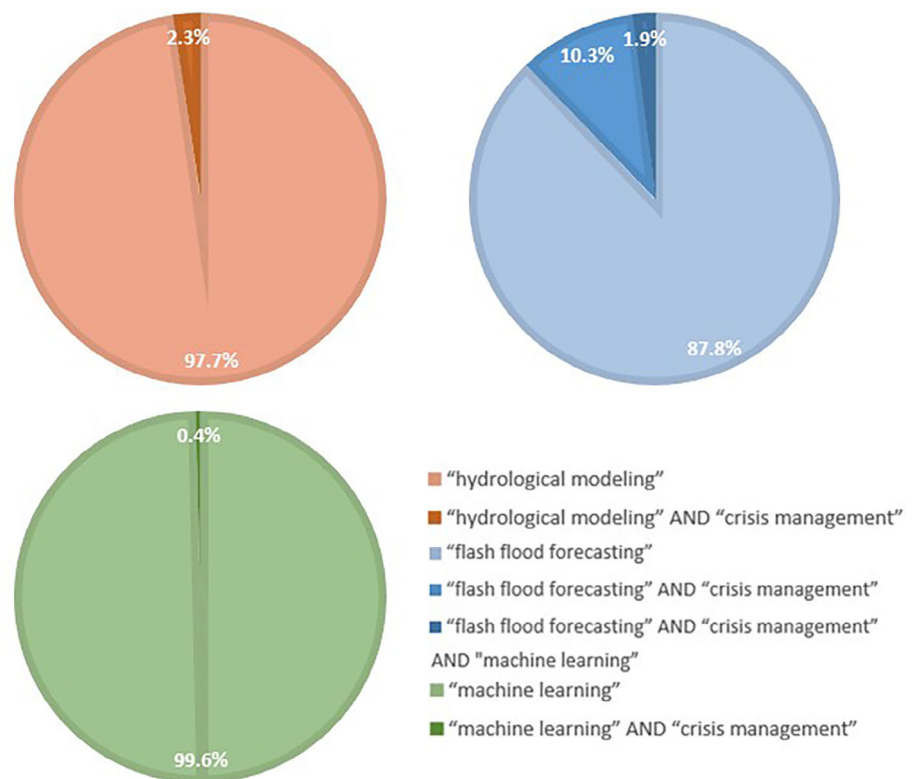
The numbers of articles found varied drastically from one platform to another (Table 6). ScienceDirect held the highest number of articles discussing hydrological modeling by far (20,269 articles). However, more articles were found in MDPI when queries concern flash-flood

forecasting (329 articles). The numbers of articles found with the expression “flash-flood forecasting” was very small (614) in comparison with the same number using the expression “hydrological modeling”. In general, the number of articles dropped significantly when “crisis management” was added to the search query. The reduction is considerable when the addition is applied to “flash-flood forecasting” (from 614 to 72). Nonetheless, it was less significant compared to when the original query is “hydrological modeling” (from 38,103 to 890 using “crisis management”). The number of articles found with the query “machine learning” was extremely high. However, upon including “crisis management”, a marked decrease in the number was observed (from 884,443 to 3265). Finally, out of the articles that mentioned “flash-flood forecasting” and “crisis management”, only a dozen of them also mentioned “machine learning”. They are all found in MDPI.

Among the papers discussing “hydrological modeling,” those focusing on crisis management were considerably underrepresented, accounting for only around 2% (as shown in Figure 4). However, among publications discussing “flash-flood forecasting,” the proportion of those citing “crisis management” was roughly 5 times greater (10.3%). When the search included “machine learning” along with the previous query, the percentage dropped back to around 2%. Interestingly, articles that covered both “machine learning” and “crisis management” were hardly noticeable on the chart, constituting just 0.4% of the total.

TABLE 6 Results of query search in the different platforms for the period of 2011 to 2022.

Query number	Short search expression/bibliographic database	Science direct	Wiley	Web of science	Nature	MDPI	Total
1	“Hydrological modeling”	20,269	4554	5519	118	7643	38,103
2	“Hydrological modeling” AND “crisis management”	435	51	24	1	379	890
3	“Flash-flood forecasting”	57	81	145	2	329	614
4	“Flash-flood forecasting” AND “crisis management”	15	5	1	0	51	72
5	“Machine learning”	268,329	150,747	588,347	33,953	111,396	884,443
6	“Machine learning” AND “crisis management”	1440	345	221	41	1218	3265
7	“Flash-flood forecasting” AND “crisis management” AND “machine learning”	0	0	0	0	13	13

FIGURE 4 Proportions of articles for each search expression.


Out of the 72 articles corresponding to query 4, more than half of the articles (39) were excluded from the criteria analysis (Section 3.2) (Alipour et al., 2020; Azam et al., 2017; Chen et al., 2019; Chu et al., 2022; Ciavola et al., 2018; Davies, 2015; Ding & Fang, 2019; Dresback et al., 2019; Habibi et al., 2021; Han & Sharif, 2021; Hofmann & Schüttrumpf, 2019; Ibarreche et al., 2020; Jha & Afreen, 2020; Jubach & Tokar, 2016; Kellens et al., 2013; Khan et al., 2018; Kim & Han, 2020; Kruczkiewicz et al., 2021; Li et al., 2022; Liu, Shi, & Fang, 2022; Liu, Zhou, et al., 2022; Lo et al., 2015; Munawar, Hammad, &

Waller, 2021; Munawar, Ullah, et al., 2021; Nakamura & Morioka, 2019; Ngo et al., 2018; Nguyen et al., 2021; Perera et al., 2020; Pielke et al., 2021; Prikryl et al., 2021; Rasquinho et al., 2013; Saravi et al., 2019; Smith & Rodriguez, 2017; Stamellou et al., 2021; Tammar et al., 2020; Tariq et al., 2022; Wang, Chen, et al., 2021; Wang, Kong, et al., 2021; Waqas et al., 2021; Watson & Ahn, 2022; Wernstedt et al., 2019; Zsoter et al., 2022). They were identified as out of topic or scope, not using a hydrological model or lacking the forecast component.

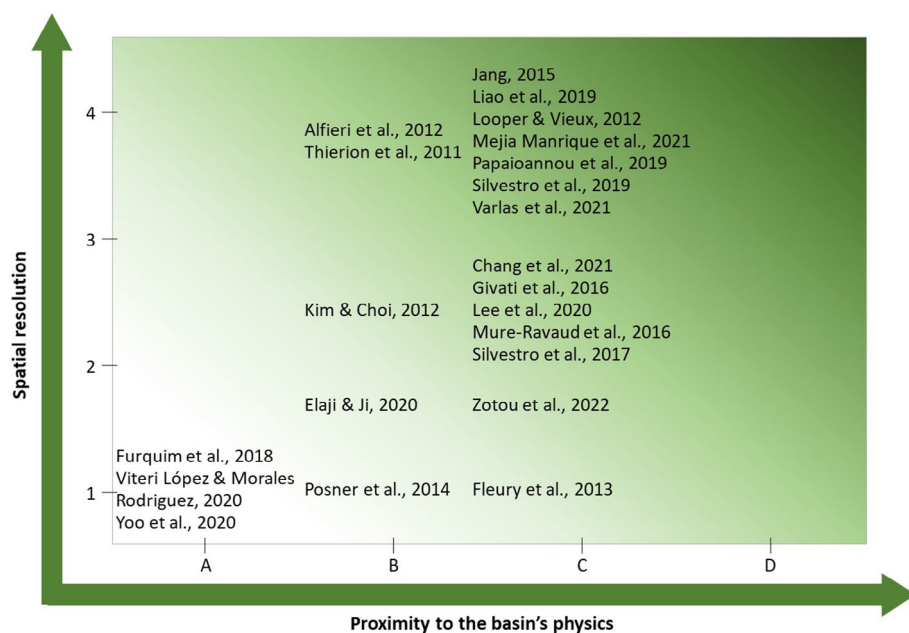


FIGURE 5 Illustration of citations and their corresponding modeling approach considering their spatial resolution (1: low to 4: very high) and proximity to the basin's physics (A: far to D: very close).

3.2 | Criteria analysis

3.2.1 | Research articles

General context

The first authors of the articles are working in eight different countries. Most of the countries were represented equally with three contributions in each of France, Greece, Italy, Korea and China. The highest number of articles was four in the USA. Continent-wise, the percentage of articles by the country of the first author are 38% for Europe, 33% for Asia, 19% for North America and 10% for South America. Target countries are generally similar to the countries of first authors except in one case. In this case, the first author is based in the U.S. and working on a watershed based between Thailand and Cambodia.

In terms of watershed class, almost one third of the articles found were interested in urban catchments. In another 27%, the watershed class of interest was not clearly defined. For the remaining nine articles, the classes varied and included karst aquifers, Mediterranean watersheds and ungauged catchments.

Modeling approaches

Some hydrological and hydraulic models were used more than others. For instance, HEC-RAS was used in at least four articles in combination with other models (Lee et al., 2020; Papaioannou et al., 2019; Varlas et al., 2021; Zotou et al., 2022). HEC-HMS, SWMM and WRF-Hydro are used in nine articles including four in combination with HEC-RAS (Chang et al., 2021; Elaji & Ji, 2020; Givati et al., 2016; Jang, 2015; Kim & Choi, 2012; Lee et al., 2020; Papaioannou et al., 2019; Varlas et al., 2021;

Zotou et al., 2022). The rest of the models exploited vary. They include models like Continuum, LISFLOOD and SOBEK as well as machine learning models like LSTM and MLP.

The models used are quite close to the basin's physics (Figure 5). Most are highly distributed, followed by small-catchment distribution and finally large catchment and global distributions. There are some models using simple reservoirs with varying levels and distribution. The three remaining models are global and empirical models (A1).

Machine learning has gained great interest as a means of hydrological modeling. Nevertheless, machine learning methods were used in only three articles including one case in combination with other methods (Furquim et al., 2018; Viteri López & Morales Rodríguez, 2020 & Yoo et al., 2020). The methods used are LSTM and MLP. In the original articles found, they were many examples of the use of machine learning. However, these works were not used for forecasting. Instead, machine learning approaches were mobilized to create crisis management documentation such as flash-flood susceptibility maps or risk zoning. Although this is important documentation for crisis management, it is not sufficient to make decisions. In addition, in the case of France for example, crisis managers already have access to hazard maps (“*carte des aléas*”) as a standard document.

Data used and data forecasted

The data utilized as input was mainly obtained through observation (Figure 6) (Fleury et al., 2013; Furquim et al., 2018; Kim & Choi, 2012; Liao et al., 2019; Looper &

FIGURE 6 Number of articles for each nature of input and means of acquisition.

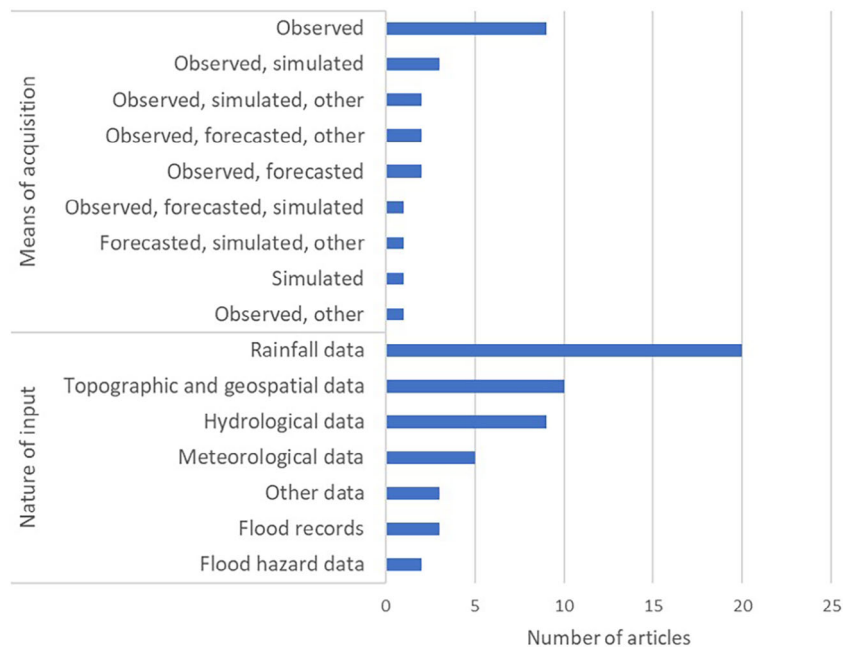
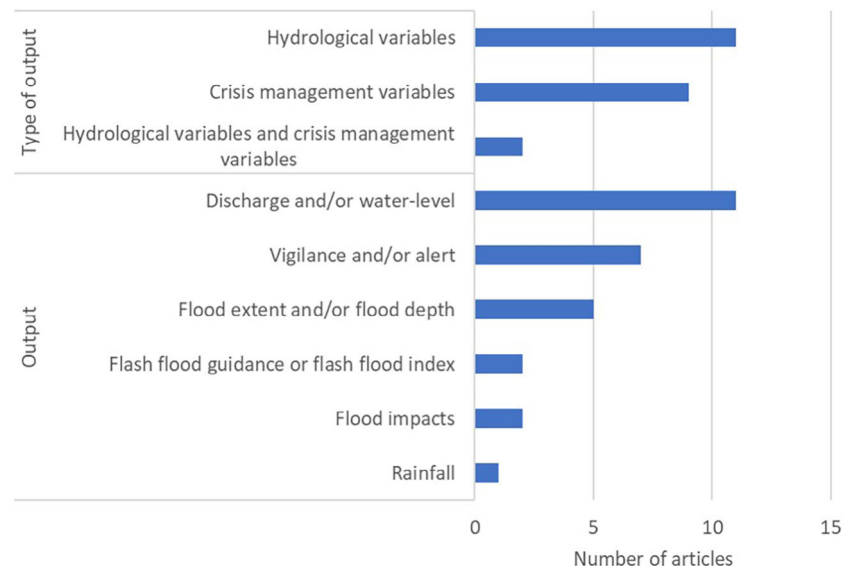


FIGURE 7 Number of articles for each output generated and its category.



Vieux, 2012; Thierion et al., 2011; Viteri López & Morales Rodriguez, 2020; Yoo et al., 2020; Zotou et al., 2022). In the remaining instances, observation was combined with forecasting, simulation or other relevant means. The implementation of simulation or forecasting alone was observed in one occurrence only (Varlas et al., 2021). As for the nature of inputs, rainfall was utilized in the majority of the articles examined. Topographic and geospatial data and hydrological data were implemented in a little less than half of the articles. Finally, the use flood hazard and flood record data were minimal (Jang, 2015; Liao et al., 2019; Posner et al., 2014; Viteri López & Morales Rodriguez, 2020).

The distribution of outputs was nearly equivalent between hydrological variables and crisis management variables (Figure 7). Discharge and water-level were the most predicted or simulated variables followed by alert and vigilance (approximately in a half and a third of the articles, respectively). In almost 25% of the cases, flood extent and flood depth were included in the outputs. The outputs of flood impacts, flash-flood guidance and flash-flood index were incorporated in a limited number of articles' output (Kim & Choi, 2012; Mejia Manrique et al., 2021; Mure-Ravaud et al., 2016; Posner et al., 2014).



FIGURE 8 Number of articles for each type of end-user, operationality level and maturity level.

Crisis management

In terms of **end-users**, out of the 22 research articles considered, more than half of the articles were directed at crisis managers (Figure 8). In the remaining instances, the targeted audience was largely undefined. Few articles present tools intended at the general public and one at sanitation system operators (Jang, 2015; Mure-Ravaud et al., 2016; Yoo et al., 2020). As for the *operationality*, it is regarded as a potential by most authors (level 2). However, only four of the tools presented are in fact operational (level 3) (Fleury et al., 2013; Givati et al., 2016; Looper & Vieux, 2012; Mure-Ravaud et al., 2016). Regarding the degree of maturity, a little more than half the tools are of an intermediate level. One-third of the tools presented exhibited a low level of maturity (level 1). Only three out of the 22 articles considered displayed a high maturity level (level 3) (Fleury et al., 2013; Furquim et al., 2018; Mure-Ravaud et al., 2016).

3.2.2 | Review articles

Main topic and findings

Technologies to employ in flood forecasting were the most discussed aspect in the review articles (Table 7). Authors were particularly interested by remote sensing techniques for data acquisition. Some technologies are well-established like LiDAR systems (Muhadi et al., 2020; Munawar et al., 2022; Zhao et al., 2022). Others are emerging like IoT approaches or paired with machine learning algorithms (Arshad et al., 2019; Binetti et al., 2022; Esposito et al., 2022). The link between flood forecasting and crisis management was, actually, considered in only three articles (Ding & Fang, 2019; Huang

et al., 2021; Rossa et al., 2011). This was not the main topic so the two aspects were not connected in depth. However, the articles refer to interesting research on that matter like elaborating tools to communicate uncertainty to end-users (Rossa et al., 2011).

Median and high maturity level examples in review articles

Only nine examples of median to high maturity level examples were spotted in the review articles (Table 8). This could be regarded as minimal considering the hundreds of references in each review articles. Physically based distributed models were utilized in more than half of the articles. In other instances, statistical, empirical as well as hybrid methods like QPE and QPF were mobilized. Various outputs were proposed: alerts and warning or their levels, warning reports, road inundation risk inundation and flood level. Their level or their emission can correspond to the exceedance of hydrological thresholds (rainfall and discharge) considering, for instance, return period, children as the most vulnerable population or previous flood impacts (Corral et al., 2019; González-Cao et al., 2019; Naulin et al., 2013; Rapant & Kolejka, 2021; Versini, 2012). In two other cases, multiple criteria were utilized to calculate flood warning and real-time on-the-road flood risk index (Goodarzi et al., 2019; Kim et al., 2014). Finally, the link with actual crisis management systems was identified solely in two articles. In Kim et al. (2014), the local Emergency Action Plan levels were conserved in the elaboration of the flood risk index. In Versini (2012), the road inundation risk level was proposed in response to previous damage of response vehicles as well as to facilitate emergency actions and their planning.

TABLE 7 Main topic and main findings of selected review articles.

Review	Main topic	Main findings
Huang et al. (2021)	Technology employed to forecast emergency events.	Challenges of prediction accuracy and data quality could be countered through data mining and swift damage evaluation techniques
Arshad et al. (2019)	Recent advances in computer vision and IoT sensor approaches used to monitor model and map coastal lagoons.	Although computer vision and IoT are commonly used for flood monitoring and mapping, the research on their use in coastal lagoon management is limited.
Binetti et al. (2022)	The utility of pairing weather RaDAR data with programming to detect atmospheric variations for disaster management and monitoring.	The use programming tools can help broaden the applications of weather data during extreme hydrological events to crisis management and fields like insurance claims.
Cea and Costabile (2022)	Review of the recent advances in flood risk modeling and management and future perspectives in an urban setting.	Efforts should be focused on fully benefiting from existing methods like 2D inundation model that require optimization of computation. Combining vulnerability and hazard should also be considered.
Ding and Fang (2019)	This article is an overview of flood risk in China on a multi-level aspect.	A decrease in flood fatalities was observed due to focusing more on mitigation and stakeholder involvement in management plans. Nevertheless, improvement in legislation and insurance aspects is needed.
Eposito et al. (2022)	Overview of the application of internet of things solutions in natural disasters early warning systems.	Fog/Edge architecture reduces latency, transmissions, and data processing. In the future, battery consumption, latency, communication efficiency, and reliability must be addressed.
Lecca et al. (2011)	The input of the grid computation in hydrological applications highlighted by six examples.	Grid technology was found to be faster, more precise and enables the evaluation robustness against uncertainty. Difficulties arise in real-time setting due to the large size of output file.
Muhadi et al. (2020)	Overview of LiDAR systems and the implementation of their Digital Evaluations Models (DEM) products in flood applications.	LiDAR was found to be beneficial in increasing accuracy of outputs and representing complex areas when combined with remotely sensed data. Use limitations could arise due to large data size.
Munawar et al. (2022)	Investigation of remote sensing technologies application in flood forecasting.	Remote sensing technologies could be classified into: multispectral, RaDAR, and light detection and ranging (LiDAR). A novel modeling and mapping approach were proposed to overcome limitations of actual technologies.
Rossa et al. (2011)	Description of the European project COST 731 Action which addresses uncertainties in hydro-meteorological forecasts, its outcomes, its new outlook on decision-making	Methodologies of quantitative precipitation estimation were diversified, and EPS QPF (Ensemble Prediction System Quantitative Precipitation Forecast) was more widely utilized. In addition, New tools and platforms for communicating uncertainty to end-users were proposed, including various visualization platforms like MAP-D-PHASE and the ensemble prediction system for Zurich railway station.
Zhao et al. (2022)	Summary of remote sensing methodologies and Earth Observation technology utilized in coastal and deltaic river zones and their response to climate variations. Process-related details are also provided for major technologies	Remote sensing methodologies were found to be essential in studying coastal and deltaic river zones and their response to climate variations and to anthropogenic activities, following their evolution and assessing hazards and risks.

TABLE 8 Methods employed and nature of outputs in identified median to high maturity level examples in review articles.

Author cited	Methods employed	Outputs
MAP D-PHASE (experimental demonstration platform) (Brueen et al., 2010)	Rainfall quantity assessment, atmospheric model, hydrological model and real-time nowcasting platforms	4 alert levels (generalized heavy rain alert, heavy rain alert by area, discharge alert by area, weather maps and hydrographs)
ERICHA (Corral et al., 2019)	QPE, QPF, comparing accumulated rainfall with its thresholds	Warning if accumulated rainfall computed exceeds threshold levels considered in return periods
Flood-PROOFS (Corral et al., 2019)	Continuum, regional statistical analysis	Warning if threshold exceeded, expressed in return periods
(González-Cao et al., 2019)	HEC-HMS and a hydraulic (Iber+) model	Warning report emitted to decision makers if the forecasted values exceeds the thresholds for children, the most vulnerable population, as defined by Cox et al., (2010)
Goodarzi et al. (2019)	WRF model, Bayesian Network, Fuzzy-TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)	Flood warning level and best alternative warning levels based on closeness coefficient
Kim et al. (2014)	Inverse distance weighting (IDW) method	Real-time on-the-road flood risk index
Naulin et al. (2013)	Road Inundation Warning System (RIWS) proposed by Versini et al., (2010), Cinecar (physically based and distributed model)	Road inundation risk level (1 to 3)
Rapant and Kolejka (2021)	Unit Hydrograph theory	Forecasted flash-flood hazard (no hazard, low hazard, high hazard)
Versini (2012)	QPE, QPF, RIWS and CINECAR model	Road inundation risk level (moderate, significant, high)

4 | DISCUSSION/ANALYSIS

4.1 | Current challenges

4.1.1 | Representation-oriented research v.s. operability-oriented research

An important gap in operability-oriented research (applications of flash-flood forecasting for crisis management) was highlighted. Research on flash-flood forecasting also seems to be limited. This could be interpreted in various ways. Flash-flood events are localized and poorly understood and documented at the space and time scales needed (few data). They also differ from one region to another. Finally, they can be triggered by various mechanisms (snowmelt, dam failure and heavy rainfall) (Gaume et al., 2009; Viglione et al., 2016).

Flash-floods are also very complex to model and forecast. This is due to various factors but mostly the small temporal and spatial scale in the physical and the crisis management processes. Hence, the forecast lead time has to be short. Additionally, data exploited has to be precise both in time and space. This can prevent delayed or shifted forecasts to surrounding watersheds. This is provided the data is available considering that most affected

basins are ungauged (Braud et al., 2018; Javelle et al., 2016; Perera et al., 2019).

Most importantly, operational tools are not necessarily published. In addition, they might not be elaborated in a research context. In France, for instance, there are multiple local systems or tools to forecast floods or emit flood alerts that can't be found in scientific literature. SAPHYRASS (Système d'Alerte et de Prévision HYdrométéorologique et RaDAR pour l'Agglomération Stéphanoise—HYdrometeorological and RaDAR Alert and Forecast System for the Stéphanoise Agglomération) in Saint-Étienne, SAL (Système d'Alerte Locale—Local Alert System) of SPC in Grand-Est region and Vigi'Orge are all such examples (Delorme, 2014; DREAL Grand-Est, 2021; Syndicat mixte de la vallée de l'Orge aval, 2024). The description of these tools in scientific literature could be useful for their development, feeding scientific reflection.

4.1.2 | General context

In this study, only half of the target countries or those of the first authors correspond to those most prone to flash-floods. In terms of frequency, the 10 nations most

affected by floods, in general, are: the USA, China, India, Indonesia, the Philippines, Australia, Vietnam, Russia, Brazil, and Bangladesh (Liu, Shi, & Fang, 2022; Liu, Zhou, et al., 2022). It should be noted that the size of the countries might have an impact on the frequency of flash-floods. Only three countries (USA, China and Brazil) were found in the list of the selected research. The rest being mainly euro Mediterranean and other Northern countries. On the other hand, the population most exposed is found in India, Bangladesh, Vietnam, Pakistan and Indonesia, respectively (Luo et al., 2015). None of these countries are represented in the research selected.

It could be noted that countries most affected by floods are least developed or developing countries. The lack of research in those countries could be attributed to financial factors. This issue was identified by a survey conducted by Perera et al. (2019). It is due to the high costs of training, recruitment, watershed instrumentation and sophisticated computers acquisition. Nonetheless, financial challenges, less accentuated, exist in developed countries. These challenges arise from many factors. One of them is inadequate estimation of costs due to the multi-disciplinary aspect and lack of follow-up. Another one is insufficient impacts/benefits analysis to justify the investment in building early warning systems. All of these factors could explain the lack of research in the field of flash-flood forecasting applications for crisis management.

4.1.3 | Choice of models: Between physical accuracy and operationality

Most models used in research were physically based. Additionally, a lot of watersheds explored were urban which might explain the choice of models like SWMM and HEC-RAS. Hydrologists prefer these models because they consider them to be more precise and representative. In fact, historically, the quest in hydrological modeling is that of physical realism (Clark et al., 2017). This could be in conflict with the goal of crisis management which requires swift and appropriate decision-making about the potential risk. Risk is a key notion here. It implies that not only hazard is addressed but an intersection of the latter with territorial vulnerability. From this perspective, understanding the phenomenon and thus taking measures, is particularly challenging. Applying physically based models also poses difficulties in a crisis management or an operational setting, overall. First, calculations could be long. For instance, in a flood management exercise, other sources of information were preferred since the model calculation pace was much slower than that of

decision-making (Leskens et al., 2014). Second, accessibility is decreased, and uncertainty is increased due large datasets requirements and complex calibration processes (Zanchetta & Coulibaly, 2020). Third, expert interpretation is required for the outputs of these models (Emerton et al., 2020; Golding, 2022; Perera et al., 2019). However, this is challenging to implement due to financial and time constraints.

Machine learning application in the examined research was limited. This can be explained by the novel characteristic and the limited experience in this technology. Most importantly, applying machine learning in this context requires multiple skills: hydrological modeling, crisis management, machine learning. Therefore, it is utilized mainly to propose hazard susceptibility maps (Jones et al., 2023). This was noticed in most of the research eliminated even though they are prevention and pre-crisis documents without a forecasting component. Regardless of this difficult launch, this technology can overcome some of the challenges encountered with physically based models. Its advantages include reliable results, relative rapidity and cheap costs. Another (maybe the most) interesting feature of machine learning is the possibility of forecasting non-hydrological variables because machine learning models do not necessitate any hypothesis regarding physics (Dtissibe et al., 2020). When addressing crisis managers, amongst the most popular tools used for flood prediction, are Artificial Neural Networks (ANN), in particular Multilayer Perceptron (MLP), and adaptive neuro-fuzzy inference system (ANFIS) (Dodangeh et al., 2020; Jones et al., 2023; Munawar, Hammad, & Waller, 2021; Munawar, Ullah, et al., 2021; Rasheed et al., 2022).

4.1.4 | Data used and data forecasted

Observed data, in particular observed rainfall, was generally preferred as input. In crisis management, during a flash-flood, the availability of rainfall data could be hindered. For instance, hydrometeorological stations could be displaced by the high river discharge. Alternatives should be considered for rapidly estimating and predicting precipitation that do not rely solely on rain gauge data. They include estimates from RaDAR and satellite data as well as predictions using machine learning (Parmar et al., 2017; Sun et al., 2018).

In terms of forecasted data, more than half of the forecasted variables proposed are hydrological variables. On the other hand, the crisis management variables proposed, in both research articles and identified median to high maturity level examples in review articles, are not in accordance with local crisis management plans.

Therefore, they require a certain level of expertise or important effort of interpretation by the crisis managers.

4.1.5 | Crisis management

Crisis managers are the targeted end-users. This is usually mentioned in the introduction or conclusion. There is also an aspiration to be operational. In this case as well, overall, the steps to attain this goal were not described. To make the proposed tools operational and used by crisis managers, significant analysis, preparation and investigation is needed. Moreover, it requires political will, particularly in terms of financial investment.

A significant part of the proposed models or methods were of median level of maturity. This criterion could have been detailed further. That is because only few of the articles concerned consider crisis management plans and needs in relation with their outputs. They required, therefore, additional investigation. Most importantly, they are more likely to be utilized by and be useful for crisis managers.

4.2 | Cost analysis, experience, and other facilitating factors for successful cooperation

In the operational examples presented, there is the example of FEWS (Flood Early Warning System) of the city of Austin, Texas (Looper & Vieux, 2012). This was identified as low maturity level system. Nonetheless, in reality, further investigation revealed that crisis managers are informed of recommendations of road closure, evacuation, as well as predictive mapping of flooded areas with forecast updated every 15 min (Janek, 2009). The initial costs of elaborating the system were 10,000 \$ (Pittman, 2012). The proposed budget (2017–2018) for hosting FEWS and another service for water resources was 96,802 \$ (City of Austin, 2017). The city estimated that, in the long term, running their own system was less costly than hiring externals (Pittman, 2012). In addition, on two occasions, in 1998 and 2001, the evacuations of hundreds of citizens had to be done while the flash-flood was ongoing (ibid).

A similar example in France is ESPADA dispositive for flash-flood prediction in Nîmes, France. It was created due to a shift in viewing flooding risk following the tragic flash-flood in 1988. Nine people died, 45,000 people were impacted and damages were estimated at one billion euros (Pla et al., 2019). In this case, as well, the city estimated that the benefits of implementing such a system significantly outweighed the costs. The implementation

of this system proved extremely beneficial in the crisis management, particularly regarding anticipation and alert (ibid).

In both cases, the choice of creating such a service was motivated by a cost analysis, the recurrence of floods and the population exposed. It is important to mention that these are not sufficient factors. In the case of developing and least developed countries, making such investments remains complicated (Perera et al., 2019). These services have created a direct link between forecasters and crisis managers.

Finding examples of successful operational flash-flood forecasting for crisis management is intricate as highlighted earlier. However, it is possible to gain insights on facilitating factors by examining the crisis management systems at an international level. A prime example is Japan, renowned for its risk management. For floods, for instance, based on its experience in volcanic eruption response, Japan fixed warning levels associated with specific actions (FRICS, 2023). Additionally, the growing research interest could provide new perspectives on the issues to address to enhance collaboration between crisis managers and forecasters. For example, Le Bihan et al. (2017) and Ritter et al. (2020) have attempted to forecast crisis management variables like impacts (e.g., casualties, economic loss, and damaged buildings). On the other hand, Giordano et al. (2017) investigated the interaction of actors during flash-floods, while Crétton-Cazanave and Lutoff (2013) studied how crisis managers interpreted hydrological information. As for Rapant and Kolejka (2021), they evaluated their hydrological model outputs by presenting them to crisis managers. Another example is the work of Kumar et al. (2023) and Yang et al. (2015) who were interested in the use of deep learning to increase accuracy and efficiency of their forecasts.

4.3 | Legal frameworks and their role in incentivizing stakeholder cooperation

In the European Union, there are many directives on floods or that discuss floods and their management like the Water Framework Directive (2000/60/EC), Natural Hazards and Catastrophes Insurance Directive (2009/138/EC) and Civil Protection Mechanism (Decision No 1313/2013/EU of the European Parliament and of the Council of 17 December 2013 on a Union Civil Protection Mechanism Text with EEA Relevance, 2013). The central directive, though, is the Floods Directive (2007/60/EC), and its updates in the cycles that followed. It establishes a framework for the evaluation and management of flooding risk. This directive promotes the inclusion of

different stakeholders and their cooperation, notably between crisis managers and hydrologists, in the different steps of flood management (ibid). Implementing this directive means producing a preliminary flood risk assessment, followed by risk mapping, to enable flood risk management plans. The latter includes information and warning measures and subsequently forecasting measures. Nonetheless, the usefulness of these documents depends on collective will (Albrecht, 2016). Indeed, the extent of cooperation between stakeholders is not detailed from an operational point of view.

Upstream of operationality, it has been noted that the European directive and its equivalents in various countries have initiated a shift in research from flood control to resilience (Wang et al., 2022). The latter is achieved when the right decisions are made throughout the crisis management process, underlining the need for dialogue between hydrologists and crisis managers.

The Water Directive has also led to changes in the information available to managers, with flood zone maps now made available to managers by the public authorities (e.g., in France, for certain stations on the Vigicrues website, produced by the SCHAPI—French flood forecasting service) (Vigicrues, 2023).

These directives have also motivated member states to create support organisms for local managers. For instance, the French Government created an independent public organism called Cérema (*Centre d'études et d'expertise sur les risques, l'environnement, la mobilité et l'aménagement*—Center for studies and expertise on risks, the environment, mobility and development). Its mission is to provide support to local managers in the elaboration, evaluation and application of local policies based on technical and scientific expertise (Cérema, 2023).

4.4 | The difficulty of conceiving flash-flood forecasting applications for crisis management

This study highlighted some factors to be considered in the conception of flood forecasting applications for crisis management. However, it is important to acknowledge that this represents a small portion of the aspects to be tackled. This stems from the multidisciplinary nature of the subject. For instance, the interpretation of forecasts by crisis managers is impacted by the way they are communicated, especially in expressing uncertainty, by the context and current situation, and by their trust in the forecasting model and the forecasters (Joslyn & Nichols, 2009; Maskrey et al., 2016; Morss et al., 2016 and Wernstedt et al., 2019). In addition, the focus was on

hydrologists and the tools they provide when multiple stakeholders are involved. It should be noted that profiles of crisis managers vary considerably and, subsequently, their forecasting needs. They can have different educational backgrounds. In France, for example, the mayors and the Chief Administrative Officer (CAO) (“*Directeur Général des Services*”) are in the heart of leadership and coordination in communal crisis management. The mayors are elected through universal suffrage. On the other hand, CAOs should, preferably but not necessarily, have a Master's degree political, legal or social sciences (Université Catholique de Lyon, 2023). Additionally, their decisions are influenced by their experience and personal biases (Merad et al., 2014). It should be noted, as well, that the decisions to be made will, inevitably, depend on the human, logistic, material, and financial resources available. Flood forecasters could also benefit from feedback reports of crisis management of previous events to adapt their tools. Unfortunately, reports are not often redacted or lack crucial details (Merian, 2022). Finally, there are ethical and legal difficulties when proposing tools (Lassagne & Dehouck, 2022). A Decision Support Instrument (DSI) or any type of decisional aid cannot replace the expertise of the crisis manager as they are held accountable for their decisions (Sauvagnargues et al., 2017).

5 | CONCLUSION

The interest in this study was to identify the extent of the cooperation between hydrologists and crisis managers. The results of the literature revealed limited studies that take into consideration both stakeholders. The research was even more constricted for the deadly phenomenon of flash-floods.

Various limiting factors were theorized. Some concern the phenomena of flash-floods themselves, like their local character, the poor comprehension of the process involved and the diversity of triggering mechanisms. This, in turn, renders their modeling and forecasting intricate. Financial factors also contribute to restrain the effective integration of flash-flood forecasting within crisis management. This is due to elevated costs in human resources and equipment acquisition and maintenance, even more difficult to bear considering the small size of the basins involved. In addition, the hydrological quest of physical realism is a major barrier. This is because the goals of such a quest are, not always, aligned with those of crisis management. Finally, an insufficient projection in the operationality of proposed tools was highlighted.

Some fostering factors were identified as well. A detrimental one is the recognition of the particularly elevated

risk, recurrence, vulnerability, and exposure by the authorities governing the area of concern. Another important factor is conducting a cost–benefit to display the relevance of investing in the integration of flash-flood forecasting in crisis management. Lastly, the governing body should be able to afford the costs associated.

This study was constrained to the analysis of scientific literature. The emphasis was also placed on the approaches and methodologies adopted by hydrologists. It is important to acknowledge that challenges arise from both sides along with the multidisciplinary aspect of the subject. In this regard, the disparity in the profiles of crisis managers in addition to insufficient feedback reports are major setbacks.

Finally, this study shows that further efforts should be made to investigate and consolidate the link between hydrological modeling and crisis management. In future research, it would be enlightening to consider additional perspectives in the investigation of the link between hydrological modeling and crisis management. Conducting surveys and interviews with both parties can further characterize their link. This can help to identify some methods missing from the literature. In addition, further research should be conducted on the ergonomics of forecast bulletins and their appropriation by the decision-makers.

Various solutions could be proposed to improve crisis management using flash-flood forecasting. Creating a forecasting service at a local level is a possible solution if the financial situation allows it. Another option is the construction of flash-flood forecast bulletins tailored for crisis managers. In that sense, one solution is the elaboration of bulletins that forecast crisis management variables using methods like machine learning that support non-physical variables and that are less costly. In addition, conducting feedback on crisis management process and experience sharing between stakeholders should be encouraged, financed and on a voluntary basis. This will allow better understanding of the interaction between crisis managers and the forecasters and its benefits but also mutual learning for stakeholders. All these tools should be accompanied with active communication between the involved stakeholders before, during and after a flash-flood event.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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