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Survey of computational intelligence as basis to big flood management: challenges, research directions and future work

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ABSTRACT

Flooding produces debris and waste including liquids, dead animal bodies and hazardous materials such as hospital waste. Debris causes serious threats to people's health and can even block the roads used to give emergency aid, worsening the situation. To cope with these issues, flood management systems (FMSs) are adopted for the decision-making process of critical situations. Nowadays, conventional artificial intelligence and computational intelligence (CI) methods are applied to early flood event detection, having a low false alarm rate. City authorities can then provide quick and efficient response in post-disaster scenarios. This paper aims to present a comprehensive survey about the application of CI-based methods in FMSs. CI approaches are categorized as single and hybrid methods. The paper also identifies and introduces the most promising approaches nowadays with respect to the accuracy and error rate for flood debris forecasting and management. Ensemble CI approaches are shown to be highly efficient for flood prediction.

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Big data; flood management system; computational intelligence; natural hazard

1. Introduction

Flooding can create debris and waste that require a rapid response. Unlike in earthquakes, wherein waste will remain in place, floods will carry the solid waste along with water flow. Dead animals and people will increase the chances of spreading diseases, worsening water and sanitation issues across a wider area. Still more, it may cause blocking of drainage systems in urban areas. The flood might also carry floatable matter far away while sinkable heavy objects are dragged along the land on which the water flows (Jinxing, Lixian, Baoyuan, Shimin, & Xilin 2002). Improper drainage can also result in impoundment of water in low-lying areas, along with accumulated waste. It will increase breeding of mosquitoes and other vectors. As soon as a flood recedes, people will dispose of damaged items. These materials from demolished and dismantled houses will be added to the debris, worsening the above-mentioned issues. It is evident that inconvenient conditions, odors, diseases, water pollution, and scattered waste are serious issues worsened by unpunctual and incorrect flood disaster

management. Therefore, quick cleanup and proper flood debris management allow residents to continue with their life, while reducing public health risks and the potential environmental crisis originated by abandoning waste (Pielke & Downton, 2000).

This study aims to critically review the state of the art reports in flood forecasting and waste management techniques based on computational intelligence (CI) methods. The most successful approaches are identified, and the potential of those methods in further research on flood waste prediction is pointed out. The waste and debris generated from flood can be classified into several types such as liquid, solid, hazardous, and recyclable, among others. Since handling different categories of flood waste requires different management approaches, there is a need to estimate and separate flood generated waste according to its category. To do this, intelligent techniques such as machine learning are required to enable the construction of algorithms learning from data to classify and make predictions of the waste type generated by the flood. There are several researchers developing an

overall objects classification but only a few concentrate on classifying flood waste. The most promising approaches among those include methods such as decision trees (Ahmad & Simonovic, 2006; Wei, 2012) and regression (Belayneh, Adamowski, Khalil, & Ozga-Zielinski, 2014; Bolshakov, 2013; Dai, Li, & Huang, 2011; Lin, Wang, & Chen, 2016). However, most of this work suffers from low accuracy (Yaseen, El-Shafie, Jaafar, Afan, & Sayl, 2015). It is worth mentioning that while conventional linear models can compete with most techniques based on artificial intelligence (AI), they are unable to capture nonlinearity and non-stationarity related to hydrological applications. In the last two decades, researchers have investigated proposals to overcome disadvantages associated with traditional models. As a result, hydrologists adopted data-driven and CI techniques in the stream-flow forecasting discipline. CI is useful for efficient prediction and simulation of nonlinear systems, as well as capturing noise complexity in data sets of hydrological applications. For example, artificial neural networks (ANNs) and fuzzy logic are two popular CI-based approaches in flood prediction providing high accuracy, long lead-time and low computational cost. However, some of the CI methods do not perform in this way when they are used in isolation. This is the case of ANN suffering from over-fitting or fuzzy logic having issues in rule tuning (Lai et al., 2015). Hybrid approaches such as the combination of wavelets and ANNs have shown better performance compared to single models. We believe that many of these approaches could be optimized and adapted to flood debris flow detection and management. Bai, Chen, Xie, and Li (2016) considered multi-scale deep feature learning equipped with hybrid models for predicting the daily reservoir inflows using the historical daily data of the Three Gorges reservoir in China. State-of-the-art deep learning methodologies have been successfully applied on target recognition for remote sensing (RS) applications (Zhang, Zhang, & Du, 2016). Despite these highlighted works there is still a lack of critical review of CI methods applied to flood management systems (FMSs), and how to use them for flood forecasting.

The outline of the present work is as follow. Section 2 presents the methodology and the process for targeting the most interesting papers in the subject. Section 3 summarizes the previous selected methods and classifies them based on their characteristics and applications. This section also identifies and describes several data sets. Section 4 evaluates and compares the presented methods and provides highlights on the approaches based on accuracy, lead-time, error rate, and complexity. Section 5 presents the conclusions and suggests future work in flood waste prediction.

2. Research methodology

The current investigation uses more than 100 articles related to flood prediction and waste flow forecasting. All of them have the common point of using single and hybrid CI methods. The articles have been carefully chosen from valid, well-respected scholarly resources (e.g. IEEE, ScienceDirect), from high Impact Factor journals, as stated by Journal Citation Reports, and from prestigious international conferences. This literature review aims to foster future improvements in the early warning systems (EWSs) based on CI methods. We attempt, thereby, to draw scholars' attention towards potential EWS solutions by analyzing the significance of the used methodologies and their empirical performance.

In hydrology, the most widely employed CI approaches are based on ANNs, fuzzy sets, wavelet models (W-CI), support vector machines (SVMs), and evolutionary computing (EC), along with hybrid approaches which are a combination of those previously mentioned. Table 1 summarizes hydrological processes for which these methods have been applied (Nourani, Baghanam, Adamowski, & Kisi, 2014).

According to the observed results in the literature, EC and SVMs show lower error rates compared to the other approaches (Sivapragasam et al., 2008). Details are discussed below in more detail.

Table 2 provides various articles managing flood and waste flow prediction based on AI methods. These articles are classified on single and hybrid methods. The table also shows their features and existent challenges in intelligent flood and waste monitoring systems. Table 2 comprises eight horizontal sections: neural networks (NNs), soft computing (SC), machine learning (ML), evolutionary algorithms (EA), decision tree (DT), fuzzy logic (FL), regression (Reg) and hybrid methods (Hyb). There are four vertical divisions defining the article's classification, bibliographic reference, method used, and objectives.

Figure 1 provides an enhanced tree-visualization for Table 2. The proposed approaches are into three major categories under the following scheme:

- fuzzy logic (FL) and neural networks (NNs);
- computational intelligence (CI) approaches, consisting of:
 - soft computing,
 - evolutionary algorithm and
 - machine learning;
- hybrid methods, as combination of two or more of the approaches mentioned above.

Table 1. Example of the usage of CI methods in hydrological applications.

Hydrological applications	Sediment modeling	Water quality modeling	Groundwater modeling	Water level forecasting	Evapotranspiration	Evaporation	Flood	Drought
ANN	(Afan et al., 2015)	(Singh, Kandasamy, Shon, & Cho, 2011)	(Mohanty, Jha, Kumar, & Panda, 2013)	(Chang, Chen, Lu, Huang, & Chang, 2014)	(Kisi, 2008)	(Nourani, Komasi, & Alami, 2012)	(Chang, Chen, et al., 2014)	(Dehghani, Saghafeian, Nasiri Saleh, Farokhnia, & Noori, 2014)
SVM	(Lafdani, Nia, & Ahmadi, 2013)	(Liu & Lu, 2014)	(Liu & Lu, 2014)	(Liu & Lu, 2014)	(Tabari, Martinez, Ezani, & Talaei, 2013)	(Tezel & Buyukyildiz, 2016)	(Wu, Chau, & Li, 2009)	(Ganguli & Reddy, 2014)
Fuzzy set	(Wieprecht, Tolossa, & Yang, 2013)	(Patki, Shrihari, Manu, & Deka, 2015)	(He, Huang, & Lu, 2008)	(Alvisi & Franchini, 2011)	(Shiri et al., 2013)	(Shiri, Dierickx, Baba, Neamati, & Ghorbani, 2011)	(Lohani, Goel, & Bhatia, 2014)	(Bacanli, Firat, & Dikbas, 2009)
EC	(Altunkaynak, 2009)	(Eslamian & Lavaei, 2009)	(Katabchi & Ataie-Ashtiani, 2015)	(Kisi, Karimi, Shiri, Makarynsky, & Yoon, 2014)	(Abdullah, Malek, Abdullah, & Mustapha, 2015)	(Guyen & Kişi, 2011)	(Sivapragasam, Maheswaran, & Venkatesh, 2008)	(Song & Singh, 2010)
W-CI models	(Liu, Shi, Fang, Zhu, & Ai, 2013)	(Najah, El-Shafie, Karim, & Jaafar, 2012)	(Moosavi, Vafakhah, Shirmohammadi, & Behnia, 2013)	(Wei, 2012)	(Evrendilek, 2014)	(Abghari, Ahmadi, Besharat, & Rezaverdinejad, 2012)	(Sahay & Srivastava, 2014)	(Belayneh et al., 2014)
Hybrid	(Kisi, Dailr, Cimen, & Shiri, 2012)	(Chau, 2006)	(Rogers & Dowla, 1994)	(Kisi et al., 2015)	(Kumar, Raghuwanshi, Singh, Wallender, & Pruitt, 2002)	(Shiri et al., 2011)	(Solomatine & Price, 2004)	(Mishra, Desai, & Singh, 2007)

Table 2. Flood and waste management and prediction methods based on artificial computation approaches.

Type	Class and reference	Method	Objectives
Single	Neural network		
	(Tehrany, Pradhan, & Jebur, 2014)	SVM	Integrating SVM and weights-of-evidence
	(Tehrany, Pradhan, & Jebur, 2015)	SVM	Integrating FR ratio model and SVM to product a spatial model in flood susceptibility assessment
	(Huang, Zhou, Song, Lu, & Zhang, 2010)	SVM	Presenting improved SVM algorithm for flood prediction
	(Tehrany et al., 2015)	SVM together with GIS data	Presenting SVM approach based on GIS
	(Herbst, Casper, Grundmann, & Buchholz, 2009)	SOM	Comparative study of SOM techniques used for prediction
	(Tiwari & Chatterjee, 2010)	Boot-strap ANN	Developing hourly water level predicting patterns and changeable estimation
	(Yonaba, Anctil, & Fortin, 2010)	MLP	Examining Sigmoid transfer functions for predicting multistep ahead stream-flow using NNs
	(Fernando, Zhang, & Kinley, 2006)	MLP ANN	Forecasting the wastewater overflow in a combined sewerage reticulation system
	(Zhou & Cui, 2008)	NN	EWS for debris flow disaster based on neural network
	(Chang & Chao, 2006)	BPNN	Accurate analytical model for runout zones estimation of debris flows
	(Chang & Chao, 2006)	BPNN	Proposing a BPNN model based on seven critical factors to predict debris flow
	Evolutionary algorithm		
	(Chiang & Willems, 2014)	GA	Applying model predictive control and GA to propose efficient policies for flood control in the River Demer
	(Leon, Kanashiro, Valverde, & Sridhar, 2014)	GA	Proposing a dynamic framework for application of smart flood control in the Boise River
	(Rezoug, Meouche, Hamzaoui, & Feng, 2013)	Multi-objective GA	A multi-objective optimization approach relying on a GA is presented to improve urban flood modeling
	(Woodward, Gouldby, Kapelan, & Hames, 2014)	Non-dominated sorting GA	Development of a decision support system using several multi-objective optimization algorithms for application of flood risk analysis
	(He, Zhou, Kou, Lu, & Zou, 2011)	Chaotic DE (CDE)	Proposal of a new approach based on a disordered differential improvement algorithm to eliminate a fuzzy clustering iterative model for application of flood forecasting
	(Luo, Qi, Xie, & Zhang, 2015)	Multi-objective artificial immune algorithm with preference-based selection (MOIA-PS)	Presentation of a new multi-objective immune algorithm for flood control based on combining a new preference-based selection operator and a protected inspired optimization method.
	(He, Xu, Yang, & Liao, 2014)	Chaotic PSO (CPSO)	Proposal of a flood forecasting approach considering a disordered particle swarm optimization (CPSO) algorithm
	Decision tree		
	(Chen, Chen, Chou, & Yang, 2010)	DGBPNN Linear Transfer Function	Improvement of the BPN approach and developing the decision group BPN (DGBPN) for application of flood prediction
	(Jiang, Deng, Chen, Wu, & Li, 2009)	DT	Proposal of optimal operation release rules based on trees for flood forecasting
	(Tehrany, Pradhan, & Jebur, 2013)	Data method of rule-based DT (RBDT)	Comparison of two approaches for flood forecasting: DT and a combination of FR and LR
	Fuzzy logic		
	(Wang, Huang, & Baetz, 2015)	Fuzzy theory	Employing a fuzzy random coefficients model to expand false probabilistic-possibilistic programming
	(Zou et al., 2012)	The diffused-interior-outer-set model (DIOSM)	Integrating DIOSM in flood forecasting with a possibility-probability distribution to increase the accuracy of prediction
	(Wang, Huang, & Yang, 2012)	FP	Flood-diversion planning using a two-staged mixed-integer fuzzy programming equipped with interval-valued membership functions (TSMIFP-IVMF)
	(Esogbue, 1996)	FS	Review of the approach presented for disaster forecasting based on fuzzy sets
	(Shouyu & Yu, 2006)	VFS	Using a VFS to estimate the flood risk by selecting typical risk indexes for classification of risk degrees in flood control engineering
	(Pappenberger, Frodsham, Beven, Romanowicz, & Matgen, 2007)	FP	Presenting a method to estimate the uncertainty of inundation extent including the uncertainty in the observed distributed information
	(Nayak, Sudheer, & Ramasastri, 2005)	Fuzzy subtractive clustering	Analyzing the fuzzy computing based on the rainfall-runoff model in flood prediction
	(Badrzadeh, Sarukkalige, & Jayawardena, 2013)	VFS	Proposing a composite method using an improved information diffusion method (IIDM) and VFSs for flood risk management.
	(Kisi et al., 2012)	VFS and IDM	Establishing a fuzzy method for predicting the risk of flood using unfinished data sets using a compound method based on VFS and IDM
	(Ahmad & Simonovic, 2011)	3D FS	Proposing a method to manage the risk of flood which can take uncertainty done by spatial and temporal variability and ambiguity into account

(continued).

Table 2. Continued.

Type	Class and reference	Method	Objectives
	(Kalayathankal & Singh, 2010)	Fuzzy soft set theory	Proposing a flood model based on a fuzzy method including simulation of unfamiliar relations among hydrological and meteorological parameters
	(Jiang et al., 2009)	FCA, SFC and FSM	Using the fuzzy similarity method (FSM), fuzzy comprehensive assessment (FCA) and simple fuzzy classification (SFC) in assessment of flood risk in Malaysia
	(Mishra et al., 2007)	FP-IFTIP	Improving flood diversion planning using FP-IFTIP
	(Wang et al., 2012)	FP-IVFSP	Managing the municipal solid waste by employing an interval-valued fuzzy-stochastic programming (IVFSP) methodology
	(Berenguer, Sempere-Torres, & Hürlimann, 2015)	FL	Proposing a method to predict rainfall debris flow that can be used in the framework of debris flow early warning systems at partial measure
	(Lin, Chen, & Peng, 2012)	Fuzzy-rule-based (FRB)	To develop a FRB risk assessment model for debris flows
	Regression		
	(Bolshakov, 2013)	LR	Application of linear and symbolic regression to forecast and monitor river floods
	(Gartner, Cannon, & Santi, 2014)	LR	Using linear regression analyses for expanding two models to forecast the size of sinter deposited due to post-fire debris flow and sediment-laden flooding.
	(Seal et al., 2012)	PR	Introducing a model to be used in wireless sensor network (WSN) for forecasting floods in rivers to provide reliable and timely warnings
	(Yu, Chen, & Chang, 2006)	SVR	Real-time flood stage forecasting using SVR
	(Dai et al., 2011)	Two-stage SVR	Enhancing the analysis accuracy in optimizing the municipal solid waste management system through coupling the SVR with inexact mixed-integer linear programming
	(Bovis & Jakob, 1999)	Multiple regression	The study of the pattern of debris supply condition to forecast the activities of debris flow
	(Chevalier, 2013)	LogR	Determining debris-flow risk focusing on statistical morpho-fluvial susceptibility models and magnitude-frequency relationships
Hybrid	Soft computing		
	(See & Openshaw, 1999)	ANFIS	Developing a new method for assessing the water level of a river and early flood warning system based on soft computing method
	(Kant et al., 2013)	ANFIS	Water level forecasting using multi-objective evolutionary neural network (MOENN)
	(Bazartseren, Hildebrandt, & Holz, 2003)	ANFIS	To compare three approaches of water level forecasting
	(Turan & Yurdusev, 2014)	GF	Reliable river flow forecasting
	(Wu & Chau, 2006)	GF, GA, ANN	Comparison between three models in flood forecasting
	Machine learning		
	(Merz, Kreibich, & Lall, 2013)	Data Mining	Applying a three data-mining approach in flood damage analysis
	(Dhanya & Nagesh Kumar, 2009)	Data Mining	Taking advantage of data mining based on the concept of minimal occurrence to forecast flood and drought in India
	(Ball, 2014)	Data Mining	Improving flood detection using data mining techniques
	(Damle & Yalcin, 2007)	Time series data mining (TSDM)	Using TSDM and chaos theory in river flood prediction
	(Lobbrecht & Solomatine, 2002)	ANN	Using machine learning approaches (ANN and fuzzy adaptive system) in flood forecasting
		ANN	Developing an ANN-based model with a simple structure and ample accuracy to predict the waste generation amount
	(Duncan et al., 2013)	A time-lagged ANN	Using ANN to predict flooding in a real-time manner relying on weather radar and rain gauge rainfall information
	(Yazdi & Neyshabouri, 2014)	MOGA and ANN	Presenting an adaptive meta model for flood forecasting using a combination of hydrodynamic model, MOGA and ANN
	(Kia et al., 2012)	ANN together with GIS	Developing a model for flooding using several flood causative factors employing an ANN method and GIS
	(Osanai, Shimizu, Kuramoto, Kojima, & Noro, 2010)	ANN-RBF	Developing a system to pre-identify the debris flows and slope failures based on rainfall indices using a RBF network
	(Baum & Godt, 2010)	ANN-RBF	Presenting a pre-identification system to identify the debris flows and rainfall-induced shallow landslides
	(Holz, Hildebrandt, & Weber, 2006)	ANN based on DM	Study of using information potential and communication technology (ICT) in a flood management system
	(Schnebele, 2013)	ML classification	Proposing a new method for flood assessment based on remote sensing and ML
	(Di et al., 2015)	ML	Proposing a ML approach for long lead flood forecasting by applying extreme precipitation and non-extreme precipitation definition
	(Napolitano, See, Calvo, Savi, & Heppenstall, 2010)	ANN	Presenting NN model for hourly water level forecasting using an adaptive, conceptual <i>Tevere</i> Flood Forecasting model and a data-driven approach using the applied TNN model
	(Rahim & Akif, 2015)	ANN	Proposing an optimized ANN model to predict the runoff and sedimentation yield
	(Nagy, Watanabe, & Hirano, 2002)	ANN	Prediction of sediment load concentration in rivers using an ANN model
	(Pyayt, Mokhov, Lang, Krzhizhanovskaya, & Meijer, 2011)	AI component with neural clouds	Presenting a flood monitoring system based on artificial intelligent methods

(continued).

Table 2. Continued.

Type	Class and reference	Method	Objectives
	(Fazel, Mirfenderesk, Blumenstein, & Tomlinson, 2014)	BPNN	BPNN model for predicting flood and its application to a short response catchment
	(See & Openshaw, 1999)	Naïve	Exploring the benefits of applying soft computing approaches in flood prediction
	(Aqil, Kita, Yano, & Soichi, 2006)	ANN MLP	Developing an EWS up to 5 hours in advance
	(Hall, Manning, & Hankin, 2011)	Bayesian	Employing a Bayesian method to calibrate spatial observations of flood extent data
	(Vogel, Riggelsen, Merz, Kreibich, & Scherbaum, 2012)	Bayesian	Studying the flood damage and its influencing factors using a BN model
	(Lee & Lee, 2006)	Bayesian	Analyzing the traditional probabilistic risk using a BN
	(Sättele, Bründl, & Straub, 2015)	Bayesian	Evaluating the EWSs for pre-identifying the debris flow using a BN
	(Sabzi, Humberson, Abudu, & King, 2016)	ANFIS, GA, PSO, ANN	Applying an adaptive fuzzy logic controller combined with evolutionary algorithms in flood control
	(Chau, Wu, & Li, 2005)	ANN, FIS and GA	ANN-GA and ANFIS hybrid methods are proposed and evaluated
	(Badrzadeh, Sarukkalige, & Jayawardena, 2015)	ANN, WNN and ANFIS	Real-time runoff forecasting using hybrid methods
	(Minglei, Bende, Liang, & Guangtao, 2010)	BPNN and FC	Employing a hybrid ANN-fuzzy clustering model
	(Lai et al., 2015)	FCE and GT	Using FCE in flood forecasting
	(Karbowski, Malinowski, & Niewiadomska-Szynkiewicz, 2005)	-	Mixing analytic and rule-based approaches
	(Liu & Pender, 2015)	SVR and LR	Presenting a flood prediction method based on a v-SVM regression model
	(Lin et al., 2016)	SVM and SOM	Predictive model for reservoir inflow to improve the short lead-time flood predicting performance
	(Luo et al., 2015)	PSO and EDA	Using PSO and EDA in flood control and solving multi-objective problems
	(Jinxiang et al., 2002)		A study on the pre-identify method concerning debris flow
	(Kasiviswanathan, He, Sudheer, & Tay, 2016)	WNN ensemble	Predicting the stream-flow for managing the flood using a WNN method

Note: v-SVM, variant of SVM.

3. State-of-the-art on AI techniques for flood and waste management

AI is the field of computer science that aims to make intelligent machines, especially computer systems, by mimicking human behavior. This intelligence involves the ability to interact with the environment by learning from and modeling it to make decisions, even in the case of unexpected scenarios. AI techniques are adopted for resolving a vast domain of science and engineering difficulties. This is also the case of flood management as detailed in the current survey. In the current section, we provide an overview of each previously introduced AI category in flood-control management and highlight the advantages and disadvantages of each approach while studying their related references.

It is essential to introduce a data mining framework within the explanation of AI methodologies as they are mainly based on machine learning and data mining algorithms. Machine learning approaches are classified into symbolic approaches (rules, trees, and logical data representations) and statistical approaches. Statistical approaches include methods such as *k*-nearest neighbors, instance-based learning, Bayesian methods, NNs, and SVMs, among others. The concept of data mining covers the use of machine learning methods to extract some new, nontrivial, information from (large) databases. Data mining's techniques come into two

categories: descriptive and predictive data mining. In the descriptive paradigm, the database is described according to its general properties. From the predictive point of view, the analyses are made by inferring from the data available (Han, Pei, & Kamber, 2011). According to this classification, pattern recognition, association rules, clustering, and deviation detection are categorized as descriptive data mining. Regression and classification are encompassed in predictive data mining.

Machine learning and data mining techniques are extensively applied in administrative, business, scientific, and engineering projects. Predictive data mining methods have been widely used in flood forecasting studies. However, these studies are inadequate to accurately predict (infrequent) extreme episodes. These techniques mine databases for hidden patterns and finding predictive information which is beyond the expectation of experts. The application of data driven models to real-time forecast urban flooding has been described in a study by Duncan et al. (2013). This work is based on radar data and recorded rain gauge rainfall history. The following literature mentions other successful examples of using machine learning and data mining in hydrology. Merz et al. (2013) proposed a tree-structured model using regression and bagging decision trees to estimate the damage caused by a flooding event. The main parameters that influence that damage were: water depth, building's floor space, return period,

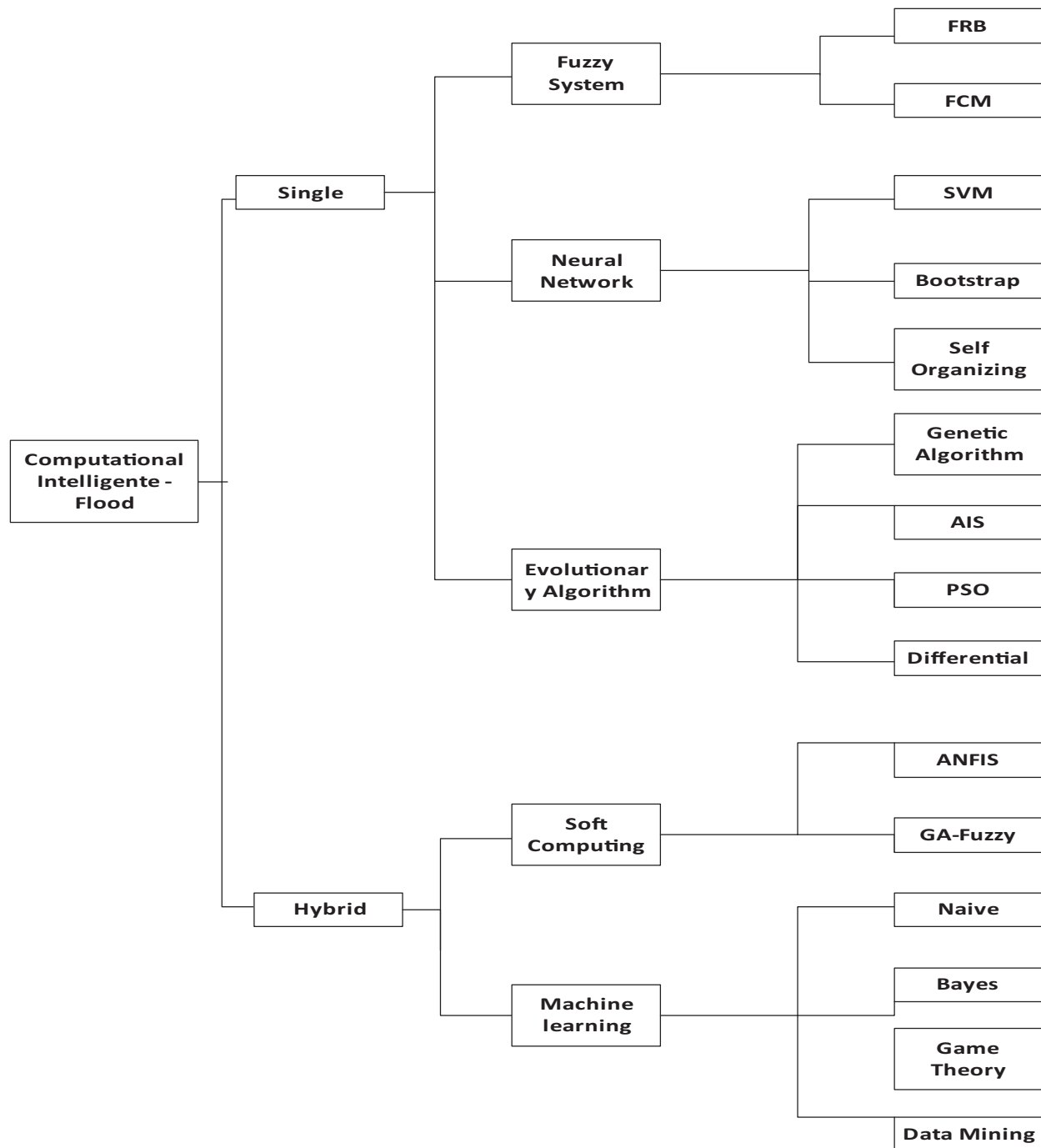


Figure 1. Tree plan classification of flood and waste management approaches depending on computational techniques.

contamination, inundation duration, and the indicator used for taking precautionary measures. Spatio-temporal relations should also be considered to have a better understanding of the features involved in urban flood management. Spatio-temporal data analysis takes into account spatial dependence among the geographic information under study, but also considers every point as a data stream forming as many time series as monitored points are available (Wang, Liu, & Liu, 2013; Yeh, Wang, Yeh, & Lee, 2015)

3.1. Single methods

3.1.1. Fuzzy system (FS)

Only employing pure probabilistic approaches for analyzing natural hazards' uncertainty would lead to unreliable results. This is the working hypothesis by Chongfu (1996) to propose a fuzzy framework to approach the risk of earthquakes, site intensity, entity response, and losses originated in a city. Fuzzy systems analyze input values corresponding to truth-values or membership values

(fuzzy sets) in terms of logical variables ranging between zero and one. That is to say, zero represents an absolute falseness while one is an absolute truth. A fuzzy system deals with all the intermediate grades of truth or membership (Faizollahzadeh_Ardabili, Mahmoudi, Gundoshmian, & Roshanianfard, 2016).

Regarding the uncertainty nature of natural disasters, the fuzzy theory (Zadeh, 1999) can be successfully applied as it is a mathematical method suitable to approaching risk assessments. Risk management and probabilistic safety assessment studies have been conducted by Misra and Weber (1990) using fuzzy set theory. Warmerdam and Jacobs (1994) proposed an approach for ideal placing and routing hazardous waste operations. Fisher (2006) used fuzzy-based decision-making frameworks for improving the quality of risk environments. Fu (2008) presented a fuzzy-based optimization technique for solving multi-factor decision-making problems. In an important risk management study, a fuzzy-set risk analysis method to merge and rank fuzzy risk estimates was proposed by Bardossy, Bogardi, and Duckstein (1991). Lee and Chen (2008) presented a novel fuzzy approach. This work introduced various issues approached by fuzzy risk analysis. In the all the mentioned studies, researchers used either fuzzy set theory alone or in combination with another CI methods to obtain a better result. A risk estimation model was proposed as alternative approach to solve the fuzzy treatment risk (Reyna & Brainerd, 2008). However, it has not been widely used yet in literature.

3.1.1.1. Fuzzy rule base. The primary benefit of a fuzzy system is accounting for the uncertainty of modeling parameters in two ways. One of them is to approach the preference dependent input parameters for addressing uncertainty modeling. The other one is to take the input parameters as interval data for addressing fuzziness modeling (Adriaenssens, De Baets, Goethals, & De Pauw, 2004). Where a lack of certain and precise system inputs leads to an inability to generate a systematic model of the system, fuzzy systems are widely accepted as universal approximators and are one of the best choices to estimate complex system behavior (Kreinovich, Nguyen, & Yam, 1999). Fuzzy-based approaches to flood prediction have been introduced relying on information diffusion theory for flood risk assessment (Zou et al., 2012).

In a significant study, done by Wang et al. (2012), two-staged mixed integer fuzzy programming equipped with interval-valued membership functions (TMFP-IMF) is introduced. According to this, the interval-valued fuzzy membership function can be used in solving uncertain, complex systems. TMFP-IMF cannot exclusively handle the uncertainties related to fuzzy sets and probability

distributions. However, it can combine the pre-regulated water-diversion policies with its optimization process.

A survey of different approaches based on a fuzzy set to control and predict natural disasters has been published by Esogbue (1996). Kalayathankal and Singh (2010) presented a fuzzy analysis which is able to simulate meteorological and hydrological characteristics with unfamiliar relationships. Developing a flexible, real-time method by considering fuzzy logic's concept, Mendel (1995) classified debris flow warnings into several levels in the framework of an EWS. This has been reported by Berenguer et al. (2015). A fuzzy rule-based risk assessment model that considers the risk assessment accuracy has obtained results to confirm that risk assessment model systems are highly suitable for debris flow risk assessment, with a normalized relative error of 4.63% and a resultant ratio of success of 96% (Lin et al., 2012).

3.1.1.2. Fuzzy C-means. Regarding mining complex and multidimensional data sets with partial or fuzzy relations' members, fuzzy clustering is used with the help of Fuzzy C-means (FCM) which was introduced by Dunn (1973) and revised by Bezdek (2013). FCM can define and repetitively update the data point's membership values to more than one cluster. Cluster centers and membership values of the data points are updated at each iterate of an iterative process (Chattopadhyay, Pratihari, & Sarkar, 2012).

As far as the authors know there has been no work done in hydrological disaster prediction solely using FCM but few works have been done implementing FCM along with other methods. This is the case of Kisi (2015) who investigated the ability of least-squares SVMs (see Subsection 3.2.2.2) and adaptive neuro-fuzzy (see Subsection 3.2.1.1) embedding FCM (ANFIS-FCM) for monthly stream-flow modeling.

3.1.1.3. Effective fuzzy. Several effective fuzzy-based models have been proposed and employed in flood prediction (Jiang et al., 2009) ranging from formal concept analysis (FCA) to simple fuzzy classifier (SFC) problems. According to the results of a comparative study published by Jiang et al., (2009), see Table 3, among three approaches FCA is the most accurate model.

Table 3. Comparing FCA, SFC, and FSM in flood prediction applications (Jiang et al., 2009).

Method	Risk
Formal concept analysis (FCA)	75.43
Simple fuzzy classification (SFC)	72.15
Fuzzy similarity method (FSM)	70.89

The results of the three assessments show that risk levels of flooded areas are less than or equal to 4.54%.

3.1.1.4. Variable fuzzy sets. Variable fuzzy sets (VFSs) reliably define membership degree and linked membership functions. They get objectives' weights to perform risk appraisal comprehensively. Ultimately, VFSs convert experience and knowledge into a qualitative and quantitative information index system. Shouyu & Yu (2006) proposed the VFS method for evaluating a flood control engineering system model.

The generalized likelihood uncertainty estimation technique is employed for assessing uncertainty in flooding events and for providing flood inundation maps (Pappenberger et al., 2007). Fuzzified synthetic aperture radar can generate more realistic inundation risk maps. In addition, several approaches have been presented according to information diffusion theory in VFSs to analyze the flood risk (Li, 2013; Zou et al., 2012) similar to what is proposed by adaptive neuro fuzzy inference system (ANFIS) (see Subsection 3.2.1.1). Ahmad and Simonovic (2011) used 3D fuzzy for figuring out the flood risk dynamic features and its spatial variability.

An additional VFS application is to eradicate data scarcity gaps. VFSs are, then, adapted to transport information gathered in the data sets to the gaps and to extract the maximum useful data from that sample. This process is known as the information diffusion method (IDM) and it is designed to improve the system recognition accuracy (Li, Zhou, Liu, & Jiang, 2012). According to the literature, ANFIS and VFSs show high accuracy in their application to flood and debris flow forecasting. In the case of VFSs, studies show that they can improve the accuracy by up to 15%, in comparison with ANN approaches, by using the IDM.

3.1.2. ANN

An ANN is a flexible and adjustable architecture, which can make fuzzy rules by performing weight adjustments connecting the layers that commonly form an ANN. It is an algorithmic function that is used in association with learning rules (e.g. back-propagation) to formally modify the weights in the network construction. The ANN model has several mathematical structures, which are able to model highly complicated physical systems. Furthermore, ANN models are more flexible and also a less presumption-dependent method for hydrologic systems (Sudheer & Jain, 2004). Therefore, ANNs have been used in different water resources problems. Some of the instance of these applications are: rainfall-runoff modeling (French, Krajewski, & Cuykendall, 1992; Hsu, Gupta, & Sorooshian, 1995; Chidthong, Tanaka, & Supharatid, 2009); stopped sinter estimation (Cigizoglu & Kisi,

2006; Partal & Cigizoglu, 2008); stream-flow prediction (Cigizoglu, 2003, 2005; Tayfur, Moramarco, & Singh, 2007; Zealand, Burn, & Simonovic, 1999); stored inflow forecast and operation (Chang, Chang, & Chang, 2005; Jain, Das, & Srivastava, 1999); sea level height estimation (Sertel, Cigizoglu, & Sanli, 2008); analyzing and predicting regional droughts (Shin & Salas, 2000), among others (Chen et al., 2010).

Chang and Chao (2006) proposed a back-propagation algorithm for development of an ANN model with seven primary agents which lead to ~94% success rate on predicting remaining flows, aiding this way to mitigate their consequences and to keep systems safely. These factors include effective watershed area, length of creek, shape coefficient, average slope, median size of soil grain, effective rainfall intensity, and effective cumulative rainfall. Osanai et al. (2010) proposed a system which uses a radial basis function network-ANN technique to enhance timing and location to set a criterion for flooding prediction based on rainfall data recorded (Baum & Godt, 2010). Kia et al. (2012) proposed a flood model engaging ANN technique with the use of seven factors and geographic information system (GIS) which generates these seven factors to model and simulate flood-prone areas.

Long-lead flood predicting is crucial to reduce the cascading uncertainty with prediction errors associated with any flooding model. Simulating physical-based numerical models of these phenomena are incredibly complex and inaccurate, as it is of primary importance to predict natural disasters 6-15 days ahead of time. Di et al. (2015) used an ANN combined with a nearest sample to handle imbalanced data sets. The maximum accuracy obtained reached 60.5% for predictions made at a suitable time in advance. A similar approach has been applied using back-propagation feed-forward networks (BP-FFNs) and Bayesian regularization (Napolitano et al., 2010).

3.1.2.1. Back-propagation neural network. Chen et al. (2010) used back-propagation neural networks (BPNN) as the common training approach of NN for predicting flood discharge. A BPNN receives its name as result of how it is trained by the ANN. For BPNN, training lies on a gradient descent method regarding all the weights in the network. This process sets the ANN connections weights for optimizing its further performance (Rumelhart, Hinton, & Williams, 1986). In an investigation done by Schmidhuber (2015), suitable historical load data for the ANN training data set is approached by using a similarity degree parameter. In the aforementioned paper, a BPNN was introduced to decrease training time and raise convergence speed. Another work trained an ANN using

an artificial immune system (AIS) learning algorithm (Curteanu, Dragoi, & Dafinescu, 2015), which has more improvement in mean average percentage error than the back-propagation algorithm.

Many researchers study flood forecasting by a deterministic BPN model. They emphasize the structural network alteration, the resolution of the type and number of input variables and hidden layers, and the training data. To minimize the estimated outputs' error, BPN modifies the parameters based on the 'generalized delta rule' of a supervised learning process (Zurada, 1992; Hsiao, Lin, & Chiang, 2003; Zealand et al., 1999). When the training criteria are satisfied, the parameter adjustment ceases and some parameters are selected to design a deterministic BPN model.

3.1.2.2. SVM. SVM is a reliable and efficient algorithm for classification and regression of noisy data sets. The key concept for using a SVM method is the classification problem. The understandable mechanism and the prediction accuracy of this method make it preferable among other methods. SVM reuses a kernel trick to minimize complexity and prediction error (Tehrany et al., 2014).

The evaluation of flooding using a GIS-based SVM model with various kernel types was introduced by Tehrany et al. (2015). Linear (LN), polynomial (PL), radial basis function (RBF), and sigmoid (SIG) as four popular SVM kernel types were employed to examine SVM model's robustness. According to the validation results of these four SVM kernel types, the forecasting rates for flood susceptibility maps were 84.63%, 83.92%, 84.97%, and 81.88% for the SVM-LN, SVM-PL, SVM-RBF, and SVM-SIG, respectively. To develop spatial modeling in flood susceptibility assessment, a new ensemble method for integrating SVM and frequency ratio (FR) was introduced by Tehrany, Pradhan, and Jebur (2015). The validation results of the ensemble method show the success on the FR prediction rate. A general optimized SVM model for estimating flood disaster loss is introduced by Huang et al. (2010) and the results confirm high generalization and better evaluation of its outcomes, which makes it a candidate to use in multi-index comprehensively evaluation for more applications.

3.1.2.3. Bootstrap neural networks. Bootstrap (Efron & Tibshirani, 1994) employs severe resampling with replacement for uncertainty decrement. Furthermore, this uncomplicated method does not need the huge computations used in linear methods or the Monte-Carlo solutions employed in some other approaches such as a Bayesian network (BN) (Tiwari & Chatterjee, 2010; Kant et al., 2013). Research has been conducted to analyze the uncertainty nature of hourly flood forecasting using

bootstrapped artificial neural networks (BANNs). In this research, BANNs are used to compute ensemble prediction. The obtained results represent that the models of ANN-hydrologic forecasting with confidence bounds are able to increase the reliability of applying ANN for flood forecasts (Tiwari & Chatterjee, 2010).

3.1.2.4. Self-organizing map. The self-organizing map (SOM) approach is based on the ANN to make a non-linear mapping from high-dimensional data structures into a lower-dimensional grid. Kohonen (1982) introduced the SOMs encompassing input and clustering layers. A SOM is an efficient method for classifying a high-dimensional input vector (e.g. grid-inundated depths) to construct a meaningful topological map. The information extraction and visualization are two significant advantages of SOM. The method has been extensively applied to water resources issues. It is worth mentioning that SOMs have remarkable properties such as their visual interpretation and efficient clustering ability (Chang, Shen, & Chang, 2014).

In an investigation conducted by Wu and Lin (2015) to build stream-flow forecasting models, four different ANN-based methods were employed: BPN, RBF, SOM, and SVM. This work approached a cross-validation test showing NN-based models as those with better performance for stream-flow prediction. In another study by Mwale, Adeboye, & Rustum (2014), a SOM is used as a feature extraction from raw data. The results showed that gap-riddled data leads to improved predictive capabilities through a SOM. Specifically, a SOM feature extraction process was used by the multi-layer perceptron ANN (MLP-ANN) to propose a forecasting model. Useful predictive outcomes were then achieved for up to 2 days lead-time. When combining a SOM with ANN-based methods, it has been observed that the SVM is the most successful method. Nourani et al. (2014) proposed a wavelet neural network (WNN) as a successful approach compared to bootstrap NN and to a standard ANN.

3.1.3. Bayesian methods

Bayesian inference uses probability theory to represent all forms of uncertainty. This way, an initial formulation of a subjective knowledge of any problem might be defined by a model expressing qualitative aspects of interest. A prior probability distribution of the unknown parameters is associated to this model. A posterior probability distribution is then proposed combining the likelihood for the parameters (given the data) and the previous knowledge. This is the case of adding as much information available as possible into the models. The objective is to reduce the

uncertainty associated with the different sources of information (Merz & Blöschl, 2008a, 2008b). Flood frequency analysis is one of the most common challenges in which a Bayesian framework has shown its suitability (Viglione, Merz, Salinas, & Blöschl, 2013).

3.1.3.1. Naïve Bayes. Naïve is one of the most cost-effective forecasting models within the machine learning approaches, and provides a benchmark to compare the efficiency and accuracy of more sophisticated models. A naïve BN classifier (Drawid & Gerstein, 2000), the so-called naïve Bayes classifier (NBC), is an easy to use and accurate classification method. An important assumption in this classifier is that all the attributes are mutually independent given the class label.

Regarding time series data, applying a naïve method would generate predictions that are the same as the last observed value. According to a study by See and Openshaw (1999), if the time series is supposed to have seasonality, the seasonal naïve method may be more suitable where the forecasts are equal to the value from last season.

3.1.3.2. Bayesian network. A BN encodes statistical relationships into a graph probabilistic tool based on Bayes' theorem. BNs provide a distribution probability to be employed in further quantitative reasoning analysis. This model has been widely used in flood prediction. According to the inspiring study of Patcha and Park (2007), the drawback in BNs is their requirement for massive computational effort. BNs have been applied in assessment of economic flood and debris damage (Merz, Kreibich, Schwarze, & Thielen, 2010). Although the prediction of the relative flood loss is comparable to state-of-the-art methods, the work by Vogel et al. (2012) shows how BNs benefit from capturing the joint distribution of all factors influencing flood loss. Hall et al. (2011) proposed a Bayesian method and improved the sensitivity compared to previous approaches.

3.1.4. Evolutionary algorithms

Evolutionary computing (EC) techniques are classified into four major classes. These classes are evolutionary programming (EP) (Fogel, Owens, & Walsh, 1966), genetic algorithms (GAs) (Holland, 1992), evolution strategies (Schwefel, 1981), and genetic programming (Koza, 1992). All of these classes have a common basis: using evolutionary processes. EC techniques use a crossover operator to guarantee a heredity criterion. In addition, EC uses a mutation operator to keep variability criteria. A selection procedure 'favors' the more relevant entities that will be more frequently generated than others (Londhe & Dixit, 2012). In stream-flow modeling and prediction, EC showed a better performance

than other CI methods such as ANNs (Yaseen et al., 2015). EC approaches have also been employed for modeling stream-flow problems using time series. Some of the keys to the big success of EC methods are their capability to be adapted to parallel computing processes, to capture dynamic changes, and to approach complex problems by the exploration and exploitation of mathematical properties.

EC techniques encompass other bio-inspired methods in addition to GAs. Highlights include methods based on swarms of birds looking for food (see Subsection 3.1.4.3 about particle swarm optimization, PSO). Another family of bio-inspired methods is ant colony optimization (ACO). This mimics the behavior of ants routing from their nest to a source of food. ACO has been shown to be useful to manage flood control and water reservoir operations (Kumar & Reddy, 2006). Another ACO application aids finding an optimal evacuation route when facing a tsunami event (Forcael et al., 2014). The behavior of how bees communicate between themselves has also been adapted to a mathematical model. Hmadi and Akaichi (2014) proposed this approach to aid the decision-making process in the management of post-disaster areas after a flooding event. In the same work, the authors developed a flood tracking system for the affected areas also inspired by the behavior of bees.

Regarding evaluating flood disasters, a chaotic differential evolution algorithm to solve a fuzzy clustering iterative model is proposed by He et al. (2011). This research employed an upgraded logistic chaotic map and a penalty function to correctly determine the objective function. The results of simulation and comparison to other methods demonstrate that the performance of a chaotic differential evolution algorithm is competitive regarding the other optimization approaches investigated in the literature.

In various impressive studies (Reddy & Kumar, 2006; Reddy & Nagesh Kumar, 2007), a multi-objective genetic algorithm (MOGA) and a multi-objective differential evolution were applied to the Bhadra Reservoir system. Qin, Zhou, Lu, Li, and Zhang (2010) introduced multi-objective cultured differential evolution to deal with the reservoir flood control operation problem.

3.1.4.1. Genetic algorithm. A GA allows a population of several individuals to infer maximum fitness and minimum cost functions through a set of selection rules. Based on previous research studies, GA showed a closer global optimal solution than other optimization or gradient search methods. The special feature in using GA that does not exist in ANN, SVM, and ANFIS models is that GA provides a mathematical input-output variable expression to the 'rainfall-runoff' relationship.

Among the GA applications to flooding management, we highlight the work of Yazdi and Neyshabouri (2014). This research proposed a combination of a multi-objective GA and ANN model to solve a high-dimensional design issue. A 74% time saving was reported compared to conventional models. Nonlinear problems in river system forecasting have been addressed using GAs and enhancements have been shown compared to current regulation strategy that are based on fixed regulation rules (Chiang & Willems, 2014). A dynamic framework for the intelligent control of flooding has been proposed in Leon et al. (2014). This work coupled a robust and numerically efficient hydraulic routing approach with the popular multi-objective non-dominated sorting GA (Rezoug et al., 2013).

3.1.4.2. Artificial immune system. Artificial immune system (AIS) models are used in a vast range of disciplines. The two main features of an AIS are the clonal selection and the negative selection. In addition, when an AIS is transferred to produce a vast detector set number, its time and space complexity are significant. Therefore, the main drawback is its tremendous resource consumption (Luo et al., 2015) for dispatching schemes presented a multi-objective immune algorithm with preference-based selection (MOIA-PS) that reach the final water level constraint in decision making.

3.1.4.3. Particle swarm optimization. The particle swarm optimization (PSO) technique has been developed inspired by bird flocking or fish schooling. PSO is based on social interaction and intelligence makes it an attractive optimization approach (Elbeltagi, Hegazy, & Grierson, 2005). The promising performance and low computational requirements of PSO are the keys to its success. PSO showed better performance than other heuristic methods according to several optimization case studies. Nowadays, massive attention is grasped by multi-objective PSO which investigates PSO techniques for considering multiobjective problems (Luo et al., 2015).

Montalvo, Izquierdo, Pérez, and Tung (2008) proposed a PSO approach for handling hydraulic and hydrology issues. Reddy and Kumar (2007) presented an elitist-mutated PSO (EMPSO) to determine reservoir operation policies for multi-purpose reservoir systems. Baltar and Fontane (2008) introduced and applied an implementation of multi-objective PSO (MOPSO) to a multi-purpose reservoir operation issue. An improved non-dominated sorting PSO algorithm (I-NSPSO) was introduced by Guo, Hu, Wu, Zhang, and Lv (2013) to employ the multi-reservoir operation issue.

3.1.4.4. Differential evolution. Another social behavior inspired algorithm is differential evolution (DE). The initial concept of DE for minimizing nonlinear and non-differentiable continuous space functions is developed by Storn and Price (1997). The first generation of a population is initialized randomly, and extra generations develop through the application of certain evolutionary operators until a stopping criterion is fulfilled. DE is used for many kinds of optimization issues that mostly include constraint conditions in engineering.

3.2. Hybrid methods

3.2.1. Soft computing

Soft computing (SC) classifiers are used to observe patterns, adjust mathematical forms, and make predictions. The primary usage of SC classifiers was modifying the classification performance of AI methods (Zadeh, 1994). Neuro-fuzzy and genetic fuzzy models are used to set the structure and parameters of a fuzzy system in SC classifiers. The aim of SC is to offer an optimal, continuous membership function that recognizes abnormal behavior with supervised monitoring techniques, high detection rate, and low false alarm rate.

3.2.1.1. Adaptive neuro-fuzzy inference system. An adaptive neuro-fuzzy inference system (ANFIS) is a hybrid technique. An ANFIS is an appropriate approach to dealing with fuzzy sets that are unclear, imprecise, and have incomplete information (Faizollahzadeh_Ardabili, Najafi, Ghaebi, Shamshirband, & Mostafaeipour, 2017). ANFISs are, then, specifically suitable to approach numerical computations by using linguistic labels. Linguistic terms and 'if-then' rules make fuzzy approaches a comprehensive framework. However, the capacity to deal with changing external environments is still required. One widely used option for fuzzy rules is to learn from their environment by a MLP. ANN and neuro-fuzzy approaches have been used for handling the scenarios of data scarcity (Bazartseren et al., 2003). According to previous papers, both ANN and neuro-fuzzy systems have good performance in upstream hydrological conditions. These hybrid approach showed better computational efficiency and accuracy than linear statistical models.

According to a study by Wu and Chau (2006), an ANFIS is one of the most effective methods for approaching predictive tasks in a complex system framework. Table 4 shows that this method has lower error and training time compared to linear regression (LR) and a ANN-GA which is also a hybrid method based on an ANN and a GA. The associated number of parameters required for implementation of an ANFIS is higher than for the other

Table 4. Training time, number of required parameters and error rate of different prediction methods.

Model	RMSE	Training time	Number of required parameters
LR	0.238	0	4
ANN-GA	0.213	135 s	16
ANFIS	0.204	49 s	135

approaches (see Table 4, 4th column). This is the main disadvantage of an ANFIS.

In an ANFIS, the grid partition method that uses several fuzzy rules for optimizing parameters is generally used for the training phase. This makes it inappropriate because of its large number of input variables. In some papers, FCM is used instead of GA. The ability of least-square support vector regression (LS-SVR) and ANFIS with fuzzy c-means clustering (ANFIS-FCM) models in forecasting monthly stream flows is also investigated in several research works. For instance, in the study by Kisi (2015), LS-SVR and ANFIS-FCM forecasts are compared with those coming from applying autoregressive moving average (ARMA) models. Both LS-SVR and ANFIS-FCM improved ARMA outcomes for 1-month-ahead stream-flow forecasting. In addition, the LS-SVR model significantly reduced the average root mean square error (RMSE) value with respect to the ARMA model. Another part of the work by Kisi (2015) focused on the precision of the LS-SVR and ANFIS-FCM models in stream-flow prediction. The results indicate that the LS-SVR model's performance is better than that of the ANFIS-FCM model.

3.2.1.2. Genetic fuzzy systems. Genetic-fuzzy (GF) systems are a family that recently appeared in AI techniques and have already been used in hydrology and water resources management. Operationally speaking, GF systems are fuzzy systems that have the capability of learning from genetic algorithms (Cordón, Herrera, Hoffmann, & Magdalena, 2001). These fuzzy systems are constructed through the input/output data used with no expert knowledge insertion. There are reports showing that GF systems have higher accuracy compared to ANFIS, ANN and WNN methods indicating the exceptional capability of GF systems in prediction problems. The results show that this methodology can be integrated into operational flood forecasting and warning systems which are able to work more accurately and cost-efficiently.

3.2.1.3. Multi-agent systems and game theory. A multi-agent system involves a group of autonomous entities (agents) residing in a shared structured entity (environment) (Weyns, Parunak, Michel, Holvoet, &

Ferber, 2004). The agents have environmental communication, working autonomously while they are coordinating themselves with other agents. Therefore, in a cooperative community, agents have a combination of the specific abilities that can solve whole issues. Game theory (GT) is a mathematical model, which cooperates between irrational and rational agents to address conflicts among two or more participants (Myerson, 2013). In GT the objective of each participant maximizes the anticipated value of its payoff, and the decision-making by all participants is rational for each participant. Consequently, all participants make an independent but cooperative decision that maximizes all of the expected utility payoffs of participants, suggesting that the decision includes the consensus or a compromise. There are few works using GT in flood applications. An example is estimating flood risk in the Dongjiang River Basin. In Lai et al. (2015) a model based on fuzzy comprehension evaluation (FCE) has been proposed by GT methods.

Montalvo, Izquierdo, Pérez-García, and Herrera (2014) proposed a combination of various swarm-based algorithms organized in a hierarchical structure. Each layer of the optimization system can be composed of a different kind of swarm, which can be named as agents to generalize their definition. Therefore, this agent swarm optimization (ASO) can be considered a hybrid method as it is an ensemble of several single methods. ASO has shown a greater robustness in its results when compared to other methods. ASO applications range from hydraulic to hydrology issues.

3.2.2. Machine learning

3.2.2.1. SVM and SOM. The excellent data-driven tools that incorporate regression features are the SVMs. However, if the data are noisy or the correlation is weak, the ability of generalization decreases. Furthermore, the SVMs can only account for limited noisy information for long-time forecasting. The model cannot forecast inflow challenges well (Baliyan, Gaurav, & Mishra, 2015). Therefore, the SOM is adopted to group the inputs of SVMs in order to sort this issue. This means that, for each group, the inputs concerned in various inflow processes have a similar characteristics. The forecasts obtained by SVMs developed using inputs in the same cluster have greater accuracy (Lin et al., 2016).

3.2.2.2. Combinations with support vector regression. The support vector regression (SVR) predictor is presented with the points lying outside the region that are formed by the size band $\pm\epsilon$ around the regression. The concept of a SVR-fine grid model (FGM) or a linear regression (LR)-FGM as computational frameworks, as introduced by Liu and Pender (2015), reduces

computational running time without reducing the accuracy of the FGM. The presented technique's simulation results show great predictive results and lead to savings in computer time.

Least-squares versions of SVMs (LS-SVMs) can solve a set of linear equations and estimate failure rates in water distribution networks. Aydogdu and Firat (2015) approach this application by comparing the results coming from LS-SVM, feed-forward neural network (FFNN), and generalized regression neural network (GRNN) techniques. The presented results for the LS-SVM model show better performance than the FFNN and GRNN models. In conclusion, using fuzzy clustering and LS-SVM techniques can make higher sensitivity estimation techniques.

3.2.2.3. ANN and fuzzy logic. Regarding load demand prediction, an ANN-based fuzzy logic imports a predictive model ANN to classify a large input data set has been developed. Yang and Zhao (2009) presented a technique that focuses on reducing the complexity of the system structure and improving predictive performance. Based on the results, load forecasting might be increased to a certain extent. Jain and Satish (2009), by using interval type 2 fuzzy logic systems (IT2 FLSs), increased the prediction accuracy.

In Corani and Guariso (2005), a novel real-time forecasting framework is introduced by combining a fuzzy clustering model and neural network within a conceptual hydrological model. This is based on classifying historical floods by their flood peaks and runoff depths. The method employs a fuzzy clustering model, while the conceptual hydrological model is calibrated for each class of floods. A BPNN is then trained using real-time rainfall data and fuzzy clustering model's outputs. The BPNN presents an accelerated online classification for real-time flood disasters.

3.2.2.4. ANNs and GAs. A GA is an exploration search method, which can be applied to finding an optimal solution in various applications. By combining a GA with an ANN, the number of input and hidden layer neurons in the ANN architecture can be globally optimized. GAs can be applied to optimization problems by using the evolution method and survival of the fittest. They can also be used in optimization of the weights between an ANN's neurons or with the combination of other algorithms (e.g. PSO, fuzzy logic) to decrease the error in the prediction of load demand (Tahmasebi & Hezarkhani, 2012).

3.2.2.5. ANN and PSO. PSO is successfully exerted in various optimization problems in several emerging disciplines. A novel training technique for a RBF

neural network, based on a quantum-behaved PSO has been proposed by Nourani and Andalib (2015). Also, Dong, Wang, Chen, and Yu (2008) present a novel PSO algorithm with an adaptive inertia weight factor and incorporated chaos with PSO. They explained that PSO improves the searching efficiency and significantly increases the searching quality for efficient load forecasting.

3.2.2.6. Estimation of distribution algorithm and PSO.

A hybrid PSO-estimation of distribution algorithm (EDA) method has been developed to solve a multi-objective RFCO problem. Because the PSO algorithm falls into a local optimum, it is simply not appropriate for solving complicated optimization issues. To defeat the deficiencies of PSO, an EDA-based reproduction method is also applied to develop the proposed PSO-EDA approach. EDA is an evolutionary optimization model based on probabilistic modeling of solutions. The primary purpose of the EDA is extracting the population distribution model. The aim is to determine the variable of connectivity information to profit offspring generation. If the variable interaction structure within the probability model used in EDA is correctly chosen, the EDA could converge to globally optimal solutions. By taking advantage of the EDA, it is expected that the multi-objective PSO-EDA can be reliable for solving multi-objective RFCO problems (Luo et al., 2015).

3.2.2.7. Fuzzy neural network with genetic algorithm.

The classified real-time flood forecasting framework consists of four basic components: a fuzzy clustering model, a real-time classification model based on a BP neural network, a parameter calibration program, and a conceptual hydrological model. Using the available flood records, the fuzzy clustering model is used in the literature to classify historical floods. The conceptual hydrological model is then calibrated for each class of floods and an optimal set of parameters is derived using a GA optimization method. The neural network real-time classification model is first trained using the results from flood classification (different flood classes) and historical flood data. Then, it is used to predict the classification of a real-time flood event using the real-time rainfall data (Minglei et al., 2010).

3.2.2.8. Wavelet neural network. Wavelet neural networks (WNNs) combine the theory of wavelets and neural networks. A WNN generally consists of a FFNN, with one hidden layer, whose activation functions are drawn from an orthonormal wavelet family.

After Fourier transform, wavelet analysis is usually employed for approaching multi-resolution analysis of

complex non-stationary signals. The Fourier transform is a principal tool for stationary signal processing. On the other hand, wavelet analysis can measure the signal in both domains of frequency and time, simultaneously. Flood and waste flow data series contain a broad range of frequency components, so therefore using the multi-resolution analysis of a wavelet transform decomposes non-stationary signals of time series into their major sub-components (Cannas, Fanni, See, & Sias, 2006; Zhou, Coatrieux, Bousse, Shu, & Luo, 2007). This makes it possible to apply AI models to estimate the decomposed signals at distinct resolution levels, while using the decomposed signals to reconstruct the original time series. Compared to WNNs, standard ANFIS and ANN methods have certain limitations. For example, in extreme conditions their performance rapidly decreases without any control (Badrzadeh et al., 2013). ANN, ANFIS, WNN, and hybrid ANFIS with multi resolution analysis using wavelet analysis and neuro-fuzzy (WNF) have been successfully applied by Badrzadeh et al. (2015) to overcome the difficulties in the time series of river flow. It was confirmed that the hybrid wavelet-based models significantly outperformed the ANN and ANFIS models in longer lead-time estimating.

Kim and Valdés (2003) employed neural networks and dyadic-wavelet transforms in order to predict the droughts in the Conchos River Basin in Mexico City. Based on their results, using the proposed method significantly improved the prediction ability of single neural networks. Partal and Kişi (2007) developed a hybrid wavelet-neuro-fuzzy model in order to estimate the daily rainfall of three stations in Turkey. Kişi (2009) implemented neural networks to discrete wavelet transform (DWT) as a hybrid model (wavelet transform-neural network [WT-NN]) for estimating the periodic river flow. Based on results DWT significantly increased the river flow estimating performance of the ANN model. Adamowski and Sun (2010) employed a hybrid WT-NN method for flow prediction in terms of single and ternary days. Based on their results, WT-NN provided the more accurate prediction compared with that of the common ANN model.

WT-NN and hybrid wavelet transform-neuro-fuzzy (WT-NF) techniques have been employed by Badrzadeh et al. (2015) in flood prediction. Based on their results, the proposed methods had a high ability of 1, 6 and 12 h ahead forecasting. However, increasing the lead-time from 12 to 48 h decreased the prediction reliability. Cross-comparison of the models indicated that the hybrid models had a significantly high performance compared with the ANN and ANFIS models, especially when the lead-time was longer than 24 h.

4. Model performance comparison

4.1. Data sets

Based on the results provided in the literature, this section compares the above introduced methods in terms of the configuration parameters (such as the input data set and the evaluation criteria) and the performance parameters (accuracy, average error, and computational time).

Table 5 shows different data sets used in various approaches. In summary, it is seen that three types of data are used in these applications including statistical data, maps, and images. These data sets can be either real-time data collected from applied radar or level meter sensors or historical data recorded before. Historical data based on the application could be hourly, daily, and monthly. The statistical data normally contain historical data including level, flow and speed of water in the river or reservoir, or simply the rainfall data. In case of waste, real-time or historical images are normally used together with the rainfall data, vibration extent, and river flow in order to predict debris flow.

Figure 2 provides the chronology of CI approaches that focus on single and hybrid methods. This figure specifies that some approaches are originated from other approaches to strengthen their design efficiency and productiveness. For example, in a single method division the SVM approach might be originated from the root of the Kernel method. It is seen that wavelet, PSO, and evolutionary algorithms have been used recently and achieved promising results.

4.2. Performance criteria

In terms of checking the usability of measures to assert the predictive accuracy of any of the previously introduced candidate models (Adamowski & Chan, 2011), the popularity of error rate measures is computed in evaluation of the prediction methods for flood and waste modeling. These computations are summarized in Figure 3, which contains information from up to 70 published articles. It was found that most of the studied articles have been evaluated based on the correlation coefficient (R) and the RMSE, while other evaluating factors such as relative error (RE), mean absolute error (MAE), mean square error (MSE), Nash–Sutcliffe (NS) coefficient, and sum of squares error (SSE), have the least use. Figure 3 presents the portion of each factor in evaluating the results.

Wavelets, PSO and evolutionary algorithms have been used recently and achieved promising results. Combining ANN with these methods is clearly seen in 2015, while ANN has been used as a single method mostly from

Table 5. Different data sets used in flood and waste flow prediction.

Data set	Type	Application	Reference
Rainfall data	Statistical	Water level prediction	(Duncan et al., 2013)
Meteorological data	Statistical		(Nkoana, 2011)
Sediment load, the used data consists of 42 years (1968 to 2009) flood discharge.	Statistical	Flood discharge	(Adib & Mahmoodi, 2017)
Estimation in flood inundation mapping (water levels and flow rates)	Statistical	River research and applications	(Faghih, Mirzaei, Adamowski, Lee, & El-Shafie, 2017)
Object specific flood damage data collected by computer-aided telephone interviews with households and companies	Statistical	Rainfall–runoff analysis	(Astel, Walna, Simeonov, & Kurzyca, 2008)
354 daily water level data	Statistical	Water level forecasting	(Sehgal, Sahay, & Chatterjee, 2014)
Hourly water stage data	Statistical	Real-time flood stage forecasting	(Yu et al., 2006)
hourly water level data	Statistical	Flood forecasting	(Kant et al., 2013)
Real data extracted from sensors	Statistical	Flood monitoring	(Pyayt et al., 2011)
Simulated historical rainfall data	Statistical	Water level prediction	(Chiang & Willems, 2014)
Debris flow disaster historical accident	Statistical	Debris flow disaster EWS	(Zhou & Cui, 2008)
Recorded statistical data from debris flow in floods	Statistical	Debris flow prediction	(Chang & Chao, 2006)
Rainfall computer sensor and RS instrument collect real-time rainfall data	Statistical	Flash flood and debris flow disaster	(Jinxing et al., 2002)
GIS-based data from floods	Statistical	Flood debris flow assessment	(Lin et al., 2012)
Radar automated meteorological data acquisition system	Statistical	Early warning system for flood debris flow	(Osanai et al., 2010)
Daily data of sediment load and discharge	Statistical	Modeling of sedimentation yield and runoff	(Rahim & Akif, 2015)
River flow forecasting	Statistical	River flow estimation using nearby river flow data.	(Tayyab, Zhou, Zeng, & Adnan, 2016)
Flow forecasting in basins with limited data	Statistical	(i) There is no prior data, and (ii) only limited data is available (1 year for the Swedish catchment and 1 season for the Mekong River).	(Ashrafi, Chua, Quek, & Qin, 2017)
Water demand forecasting	Statistical	This method was tested using 3 years of daily water demand and meteorological data for the city of Calgary, Alberta, Canada.	(Tiwari & Chatterjee, 2010)
Ground vibration data using geophone sensors and flow information using radar devices	Statistical	Debris flow warning system	(Sättele et al., 2015)
River hourly historical data	Statistical	River level forecasting	(See & Openshaw, 1999)
LiDAR	Images	Flood inundation modeling using SVM	(Liu & Pender, 2015)
GIS-based images	Images	Flood susceptibility assessment	(Tehrany, Pradhan, & Jebur, 2015)
Radar quantitative precipitation estimate (QPE) maps	Maps	Debris-flow forecasting	(Berenguer et al., 2015)

2010 to 2013. In addition, fuzzy-based approaches and GAs have been applied many times in hybrid and single methods.

4.3. Results

In this section different approaches are compared together under similar simulation conditions based on availability. All the approaches are summarized together, indifferently of homogeneous conditions, to give a complete guideline. Figure 4 shows the average error rate for linear discriminant analysis (LDA), SVM, k-Nearest Neighbour (kNN) and random forest (RF) at flood forecasting applications (Khondoker, Dobson, Skirrow, Simmons, & Stahl, 2016). It shows that KNN and RF have almost double the error rate compared to SVM and LDA.

Similarly, several models have been compared and the results are reported in Table 6 for application of flood

EWS (Caruana & Niculescu-Mizil, 2006). Bagged tree, SVM and ANN are the most accurate approaches in this application.

Kruppa et al. (2014) compared various approaches in terms of MSE. Figure 5 illustrates the results. SVM and bagged Nearest Neighbours (BNN) are considered as the most accurate approaches. RF and regression present lower accuracy levels.

Based on the published data in image classification applications, a comparison of genetic machine learning algorithms for image classification-learning time and error rate are expressed in Table 7. It is seen that DTs require the least learning time. However, their error rates are unacceptable. On the other hand, SVMs and RF need moderate learning time and their accuracies are much more than that of DTs.

In Table 8, single and hybrid methods are compared in terms of RMSE and R. It is worth mentioning that these

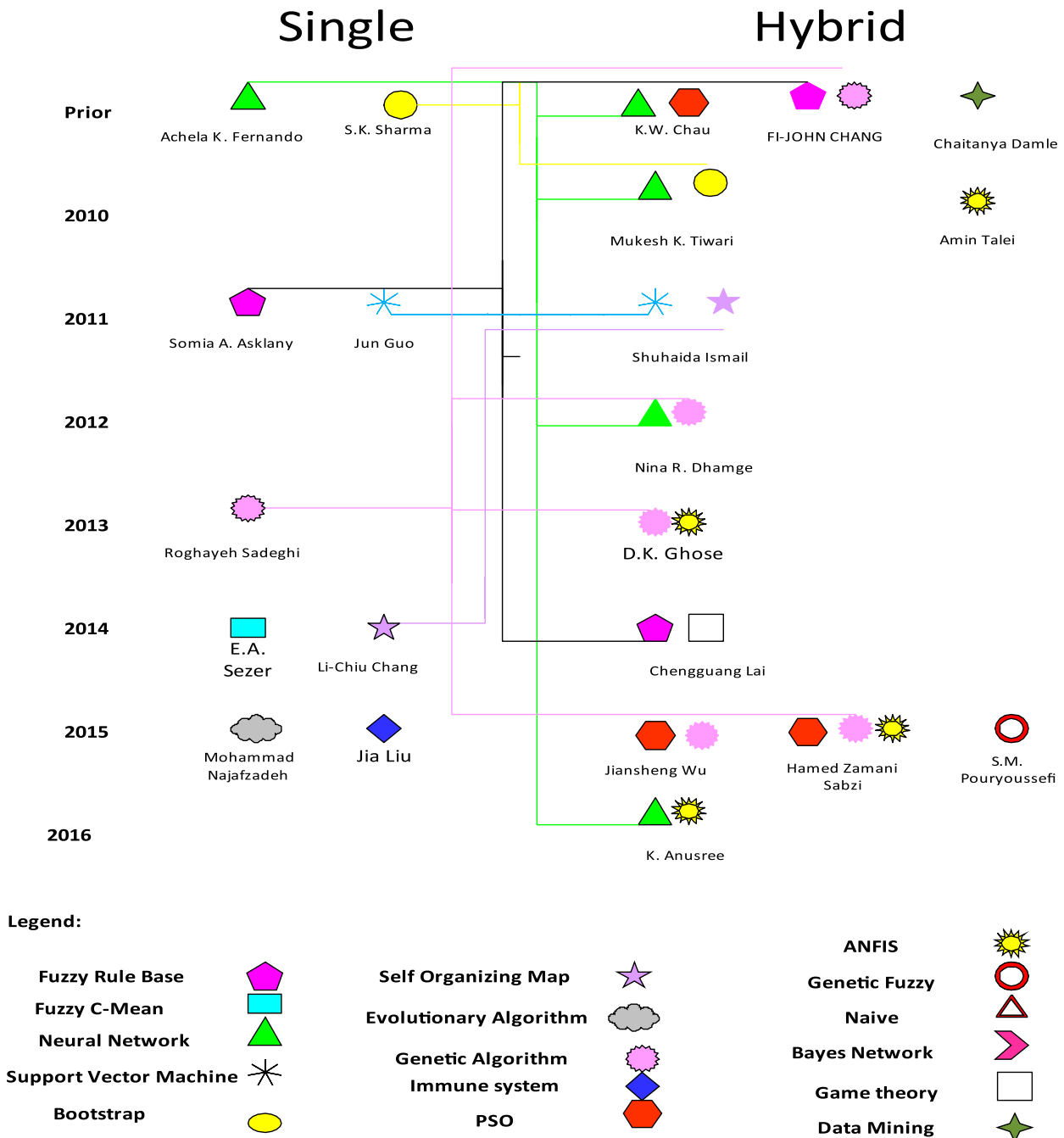


Figure 2. Chronological order of the flood and waste prediction methods.

methods are not compared under homogeneous conditions. However, it has been attempted to compare these approaches under the most similar situations in terms of lead-time, data set, and applications. Data which are from the same reference have been evaluated under the same conditions.

To increase readability, according to Table 8, RMSE is plotted for single and hybrid approaches in Figures 6 and 7.

As can be seen in single methods, the SVM, BPNN and EC have almost the same RMSE, which are the lowest

compared to other methods such as the fuzzy set and ANN. According to the literature, the following advantages are listed for the SVM. It is able to cope well in noisy conditions, has the potential to trace back historical events, improves future prediction, has a high accuracy, provides guarantees regarding over-fitting, is fast, and is scalable. On the other hand, the SVM does not show high accuracy in short-term forecasting and is a computationally expensive approach.

In hybrid methods, it is seen that a combination of an ANN and a GA has the lowest error (Figure 7).

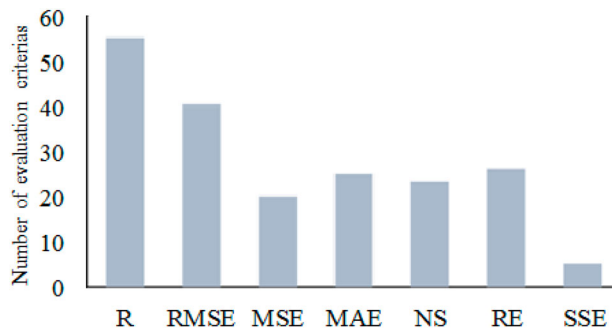


Figure 3. The portion of performance factors used to evaluate the modeling results.

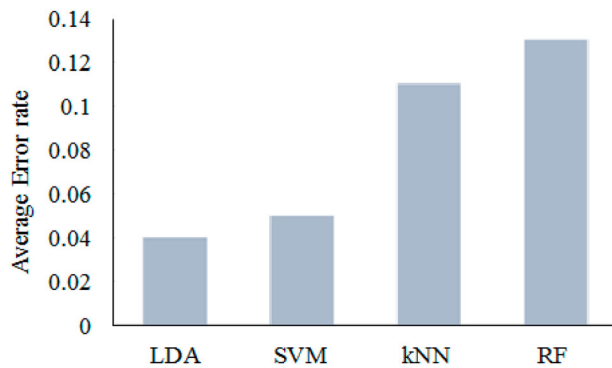


Figure 4. Average error rate for different prediction methods.

Table 6. Comparison between state-of-the-art prediction techniques, accuracy, and average error rate.

Model	Accuracy	Average precision rate	RMS	MSE	Mean	opt-sel
Bagged trees	.846	0.93	.845	.872	.887	.899
SVM	.824	0.89	.831	.836	.862	.880
ANN	.815	0.89	.811	.821	.854	.885
KNN	.757	0.87	.742	.764	.815	.837
DT	.648	0.75	.590	.589	.709	.774
LR	.636	0.73	.593	.604	.685	.695
Naive	.579	0.72	.572	.555	.654	.661

Note: opt-sel, selection based on optimization.

Integrating wavelet and NNs also improves the accuracy to a great extent. Other methods, such as the WNF, tunable nearest neighbor (TNN), WL-ANN, GA, and FL have almost the same error. Interestingly, the ANFIS shows a high error compared to other approaches with improved accuracy. For purposes of completeness, ANN's RSME at the same situation has been included in these methods. According to the results, hybrid methods have the potential to reduce RSME up to three times.

Another important parameter for modeling for prediction is computational time. Table 9 shows the computational time of different approaches for two test benches containing 1000 and 5000 samples. The test has been done using an Intel Core 2.60 GHz CPU with 2 GB main

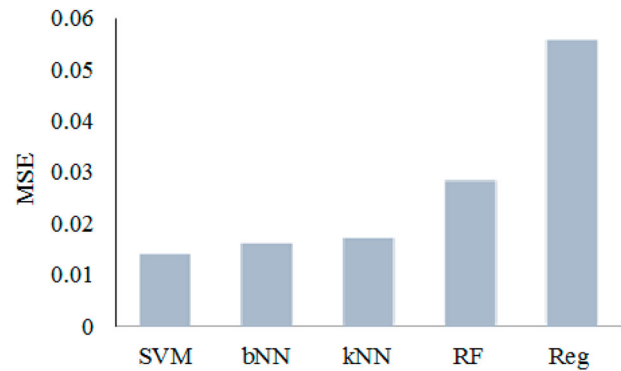


Figure 5. MSE for different approaches in water level forecasting.

Table 7. A comparison of genetic machine learning algorithms for image classification – learning time.

Method (Marée, Geurts, Visimberga, Piater, & Wehenkel, 2004)	DT	Bagging	RF	Boosting	SVM
Learning time	7 min	5.0 h	20 min	6.2 h	28 min
Error rate	11.5	4.42	3.0	2.29	1.95

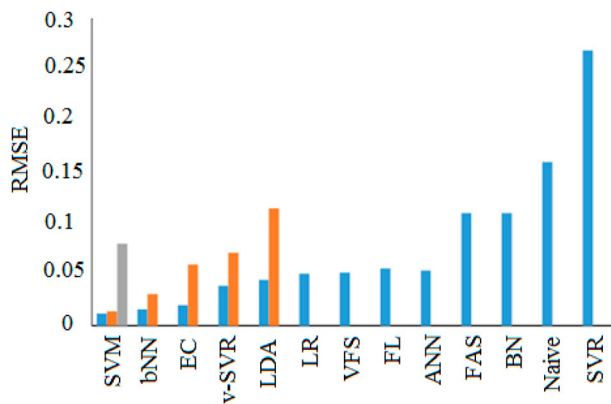
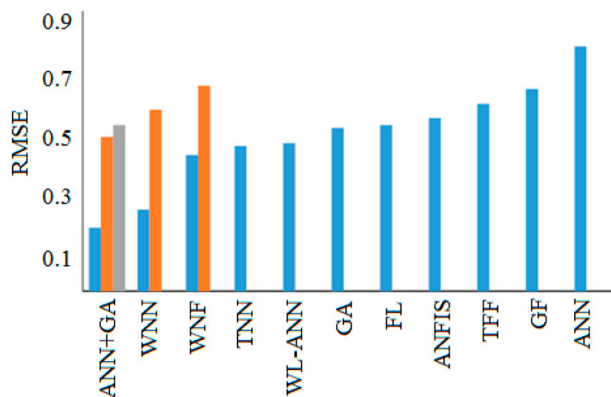
memory (Kruppa et al., 2014). As the results show, kNN has very high speed; later we check that the accuracy is not sufficient for a good prediction. The SVM is not as quick as the kNN but its computational time is acceptable, considering its high accuracy.

A summary of different debris based on the type of disaster has been provided in Yaseen et al. (2015). Table 10 shows several kinds of waste such as household waste and hazardous waste from hospitals and factories that can be carried by disasters. In addition, it is seen that floods can carry all these waste types and therefore can be considered as the most dangerous disasters in terms of waste.

One of the challenges to classify the type of flood waste is due to the possibilities of the object belonging to the same field but varying in many aspects. The object also may have various colors and have pictures or patterns on their surface that would made the recognition process harder to achieve. Other challenges involve distortion, background clutter, illumination and viewpoint changes, partial occlusion, and geometrical transformations (scale change, rotation, skew, etc.). Moreover, the image of two distinct objects may be placed so as to be overlapping which may create confusion. Hence, it is important to identify the meaningful spatial hints in the images. The matching process establishes a similarity between visual entities, which is crucial for recognition. For region-based recognition, it is not only important to detect good regions, but it is also crucial to match them in a reliable and efficient way. A region-based approach

Table 8. Comparison between single and hybrid artificial methods used in debris flow and flood forecasting for lead-time of between 4 to 6 hours.

Method	Reference	R	RMSE	Lead-time	Others
ANFIS	(Bazartseren et al., 2003)	0.995	2.66	5 h	
TFF	(Napolitano et al., 2010)	$R^2 = 0.87$	0.62 m	12 h	
TNN		0.95	0.48 m	12 h	
Hybrid	(See & Openshaw, 1999)		0.056		Late percentage 20
Autoregressive integrated moving averages (ARIMA)			0.098		90
SVM	(Tehrany, Pradhan, & Jebur, 2015)				
Bootstrap	(Tiwari & Chatterjee, 2010)		0.140 m	10	
GF	(Turan & Yurdusev, 2014)	$R^2 = 0.74$	6.7		$E = 0.74$
ANFIS		0.72	6.89		0.72
ANFIS	(Badrzadeh et al., 2015)		0.204		
ANN-GA			0.213		
WNN		0.961	0.27	5 h	
WNF		$R^2 = 0.822$	0.478	5 h	
ANFIS		0.634	0.553	5 h	Training time = 135 s
ANN		0.651	0.805	5 h	49 s
SVM	(Lin et al., 2016)			3 h	MRMSE = 252 m ³ /s
SOM-SVM	(Lin et al., 2016)			3 h	MRMSE = 204

**Figure 6.** RMSE for single methods in flood and debris flow forecasting.**Figure 7.** RMSE for hybrid methods in flood and debris flow forecasting.**Table 9.** Computation time (in seconds) for different methods. The analyses were run with 100 repeats on one Intel Core 2.60 GHz CPU. Number of training samples has been shown in the left (n).

Model	kNN	SVM	BPNN
$n = 1000$	2.5	21	306
$n = 5000$	3.4	135	10103

is absorbing because it captures the whole shapes of the objects and parts. Region detection is a long-standing research topic in computer vision, and scales are critically valuable for multi-view matching problems such as a wide-baseline stereo or instance recognition. Due to its strengths of blockage and deformation, conforming local appearances has long served as a key part of many computer vision difficulties especially in object recognition and image detection tasks which use local points for image description.

The classification and estimation of the waste types starts by acquiring a set of waste images. These images will be preprocessed to reduce the level of noise that could intervene with the accuracy of the end results. An efficient region segmentation algorithm is then applied to separate the region of interest from the background images. The process of image segmentation continues with the process of extracting salient features via feature extraction techniques. The feature extraction process is important so as to reduce the computational cost to process a large set of input data that is normally suspected to be redundant. Here, it is necessary to have a knowledge of

Table 10. Different types of waste flow in various disasters.

Typical debris streams							
Disaster	Vegetative	Construction material	Household items	Hazardous waste	Soil and sand	Vehicles	Putrescent
Hurricanes	*	*	*	*	*	*	*
Typhoons	*	*	*	*	*	*	*
Tornados	*	*	*	*	*	*	*
Floods	*	*	*	*	*	*	*
Earthquake		*	*		*		
Fire	*		*		*		
Ice storm	*			*			

what features make good predictors of class membership for the waste. By selecting the appropriate set of features, good classification of the flood waste categories could be accurately estimated.

The flood phenomenon and its characteristic pattern together with its associated waste are not easily foreseeable because they are determined by having non-stationary, high complexity, non-linearity, and dynamism. This prediction is divided in two main fields: short-term (real-time) prediction and long-term prediction.

5. Conclusions and future work

The increasing frequency and intensity of severe weather events such as drought periods, heavy rainfall, or heat waves is an expected result of climate change. This work copes with this matter by presenting the state-of-the-art CI methods applied to flood management along with a comprehensive taxonomy for them. We briefly discuss the literature related to each of the presented methods aiming to be introduced both by theoretical and applied approaches. The proposed literature review also assesses and classifies the procedures into two main categories: single and hybrid CI methods. The single CI category has been divided into three subcategories: fuzzy systems, neural networks, and evolutionary algorithms. Soft computing and machine learning are the subcategories for the hybrid CI methods.

This review includes pros and cons for each of the presented methods to evaluate their accuracy regarding error rates. This makes possible further comparisons from which we can conclude that hybrid methods are the best choice for dealing with flood management through CI. The review shows hybrid methods to be the ones with greater potential to improve the accuracy and lead-time of flood and debris forecasting. Among the single methods, the SVM has the lowest error and is simple in terms of implementation. In hybrid methods, the wavelet method shows an extraordinary capability for integration. It was found that decomposing the inputs with the wavelet, excluding some of their components (the detail

coefficient), and using just the approximation component, leads to significant improvements in the model efficiency. In future, prediction projects integrating the SVM and wavelets should therefore be further investigated. To foster improvements of any methodology related to CI on flood management, it is planned to implement a systematic mapping so as to gain a more detailed classification of the related works, including their potential inter-relationships, and to present a useful guide to aid in the future choice of any CI method.

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No potential conflict of interest was reported by the authors.

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