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REVIEW PAPER

Quantitative and semi-quantitative methods in flood hazard/susceptibility mapping: a review

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Abstract

Flood mitigation and risk management is a very challenging task that requires accurate identification of flood hazard/susceptible regions for adequate planning and management. Accurate determination of locations that are prone to flood hazards needs the application and adaptation of techniques that will provide flood hazard/susceptibility maps with minimal uncertainty. Previous literature reviews on flood hazard analysis have focused on the flood hazard mapping methods such as hydrodynamic, conceptual, and multi-criteria decision-making (MCDM). Thus, this current study thoroughly reviews studies that applied MCDM, statistical, and machine learning (ML) methods in the identification of flood hazard/susceptible regions. The paper presents information about these methods, their integration in flood studies, strengths, limitations, uncertainty, and recent developments. Conclusively, the paper provided observations and recommendations to enhance the existing information for relevant knowledge in future studies. This will assist stakeholders and key policymakers in making good decisions for flood analysis for a sustainable climate disaster risk reduction management.

Keywords Flood hazard mapping · Flood susceptibility mapping · Multi-criteria decision-making · Statistical method · Machine learning · Climate disaster risk reduction

Nomenclature

AdaBoost	adaptive boosting
ADT	alternating decision trees
AHP	analytic hierarchy process
AI	artificial intelligence
ANFIS	adaptive neuro-fuzzy inference systems
ANFIS-PSO	adaptive neuro-fuzzy inference systems-particle swarm optimization
ANN	artificial neural networks
ANP	analytic network process
Bagging-REPTree	bagging- reduced error pruning trees
BP-ANN	back propagation artificial neural network
BRT	boosted regression tree
CART	classification and regression trees
CTree	classification tree
DEMATEL	decision-making trial and evaluation laboratory
DT	decision trees
FA-ANN	firefly algorithm-artificial neural network
FA-LM-ANN	firefly algorithm- Levenberg–Marquardt -artificial neural network
FT	functional tree
FURIA-GA	fuzzy unordered rules induction algorithm and Genetic algorithm
GA	genetic algorithm
GAM	generalized additive model
IR	interval-rough
IR-N	interval rough number
KLR	kernel logistic regression
LM-ANN	Levenberg–Marquardt -artificial neural network
LMT	logistic model trees
LR	logistic regression
MARS	multivariate adaptive regression splines

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MaxEnt	maximum entropy
MCDM	multi-criteria decision making method
ML	machine learning
MLP	multilayer perceptron
MLP-ANN	multilayer perceptron artificial neural network
NB	Naïve Bayes
NBT	Naïve Bayes trees
PSO	particle swarm optimization
PSO-ELM	particle swarm optimization-extreme learning machine
QDA	quadratic discriminant analysis
REPTree	reduced error pruning trees
RF	random forest
RS-BRT	random subsampling- boosted regression tree
RS-GAM	random subsampling- generalized additive model
RS-MARS	random subsampling- multivariate adaptive regression splines
RS-REPTree	random subspace- reduced error pruning trees
RTF	rotation forest
SIA	swarm intelligence algorithm
SVM	support vector machine
TOPSIS	technique for order of preference by similarity to ideal solution
VIKOR	VlsseKriterijumska Optimizcija I Kaompromisno Resenje
WOE	weight of evidence

Introduction

Floods can cause deaths, relocation of people, and environmental harm, seriously jeopardize urban improvements, and disrupt the community's economic activities (EU-Directive 2007). There is a developing unease at the extent and the rate at which people are affected by natural disasters annually with flooding explainable for more than 75% of these figures. Additionally, in Asia, floods accounted for 47.6% of natural disaster occurrences in 2019 (ADRC 2019; USA-NOAA 2001). Floods result from the natural processes that make up the hydrologic cycle. It has also contributed so much to natural disasters and according to the report by CRED (2018), it accounted for close to 50% of the global natural disasters recorded for the year 2018. Even though there is no absolute solution in flood control measures, there is a pressing need to think and seek an integrated technique in handling the complexity of flood occurrence (Chen et al. 2019). Due to the major and global devasting impact of flooding, it is very crucial to create mitigation, prevention, reduction, and adaptable measures to address it. In this regard, the reduction of damage caused by floods and the implementation of universal flood control measures are very crucial with a major target in flood prevention, risk, and management (EU-Directive 2007).

The progression in the systems applied in the identification of flood hazard areas has been dynamic and has amassed a lot of consideration. Flood hazard/susceptibility are very important tools for flood damage, risk, and exposure management. Flood hazard/susceptibility mapping also significantly plays a critical role in the early warning system (EWS) which provides key policymakers with decisions and prior information about zones that are susceptible to flood risk. Flood hazard mapping (FHM) is a key tool in identifying the spatial extent, magnitude, intensity, duration, and damage of a flood event. A flood hazard analysis estimates the probability that a specific intensity of a flood event to re-occur (Wright 2016) for varying conditions which can be created through quantitative or qualitative approaches (Gebre 2015). On the other hand, flood susceptibility mapping (FSM) is the probability of occurrence of flood events in a specified locality which is related to the area's landscape features and geographical region. FSM is a fundamental component when planning and designing for flood mitigation and management (Vojtek and Vojteková 2019). The major difference between FSM & FHM is the fact that FSM does not incorporate the estimation frequency of flood events and its recurrence interval (Santangelo et al. 2011).

Assessing flood hazard/susceptible regions requires a practical representation that can enable easy comprehension in the form of a varying index that describes the level of risk or susceptibility (Tsay and Lin 2013). FHM/FSM identifies flood-prone zones by synthesizing hydrological, geomorphologic, climatic data, and most importantly a large field of knowledge by applying various techniques. Various approaches have been applied in the identification of flood hazard/susceptibility regions over the years to effectively measure, predict, comprehend, and explain flood events and their associated damage and risk. The events in the past and the physical processes that trigger flood generation serve as parameters for flood analysis.

In recent years, researchers have put in serious effort in understanding, predicting, estimating, and explaining flood hazards to aid in quantifying the associated risk, damage, vulnerability, and spatial extent of this natural disaster. The various methods accessible to model flood hazards are the popular hydrodynamic, physically based, and empirical models. The traditional hydrodynamic modeling approach requires hydrologic and hydraulic parameters as model input (Wu et al. 2015), the more recent quantitative methods require terrains' physical processes parameters sourced through remote sensing as the model input, and the semi-quantitative requires the same model input as the quantitative, but also requires qualitative reasoning by an expert in the field (Hategekimana et al. 2018; Wang et al. 2011). The semi-quantitative and quantitative methods can also be categorized as index-based or probabilistic methods. These index-based methods can be evaluated by applying several semi-quantitative and

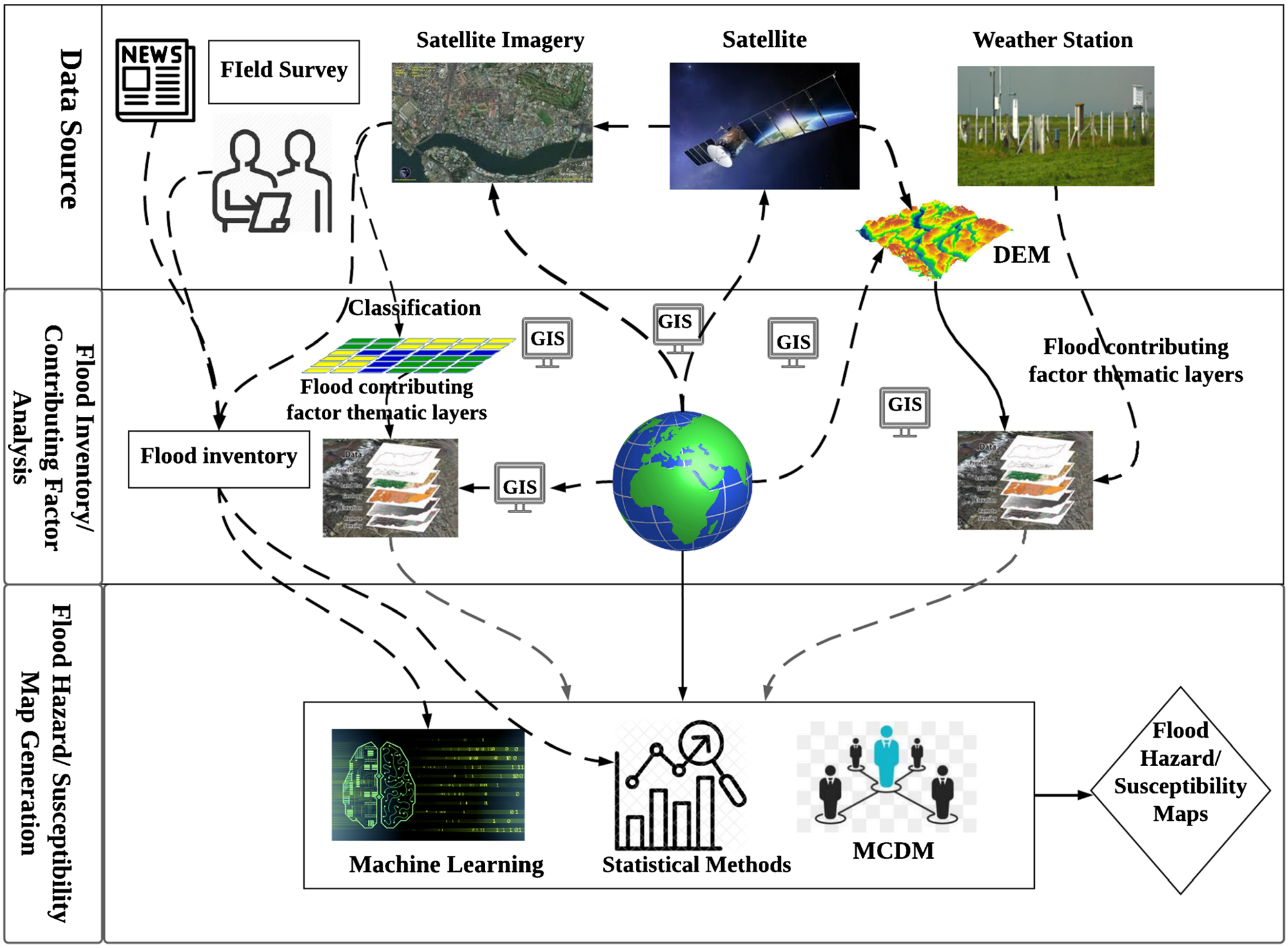


Fig. 1 An overview of quantitative and semi-quantitative methods in FHM/FSM

quantitative methods through consideration of several flood contributing factors (FCFs) generated via remote sensing data and processed with geographic information systems (GIS). The resulting maps describe the analyzed area in terms of varying probability indexes of flood hazard/susceptibility such as very high-very low. The hydrodynamic models are mathematical-based (deterministic methods (Candela and Aronica 2017)) that try to simulate fluid motion and incorporate flood plain characteristics for the model. Asides from requiring large hydrologic input data and taking a longer duration to compute flood parameters, some hydrodynamic models' basic assumption gives room for uncertainty and sometimes difficult to model complex flow and terrain. Furthermore, the physical models also need a huge dataset, and oftentimes need experimental validation.

All these methods have been applied in FHM/FSM to describe and predict different aspects of processes and development of flood but more recently, there is a shift in the trend of applying the common hydrodynamic model and the physical-based methods because of the scarcity of data or insufficient data and the limitations of methods. Researchers are now seeking solutions to these problems in the quantitative and semi-quantitative methods of FHM/FSM.

Previous review studies have focused on the application of MCDM methods in flood risk management (De Brito and Evers 2016) which is semi-quantitative but did not cover the index-based flood mapping studies which encompass both the quantitative and semi-quantitative methods. Rehman et al. (2019) focused on methods in flood vulnerability assessment, whereas Ali et al. (2016); Ologunorisa and Abawua (2005); Tsakiris (2014); and Wright (2016) focused on flood risk and hazard assessment methods. This current study proposes a review of the quantitative and semi-quantitative approaches in FHM/FSM to help understand their objectives, techniques, contributions, limitations; and most importantly the advantages of this method over the others. Moreover, the study proposes to give a clearer insight into the approach used, associated uncertainty, and the manner it is addressed to provide robust information for future studies and stakeholders in charge of flood mitigation and management.

Methodology

The methods in this section are discussed to explain (i) the general background of the semi-quantitative and quantitative methods; (ii) the data requirement and source of data input; and (iii) the parameters that enable identification of flood-prone areas which are relevant in pre-study for flood damage and risk assessment. These methods can be categorized into three mainly based on their data-driven approach which are the MCDM, statistical, and ML methods. The methods explained in this study are mainly the index-based flood hazard/susceptibility mapping methods which allow the identification of flood hazard/inundated or susceptible zones based on varying indices which explains the level of flood hazard/susceptibility through FHM/FSM. An illustration of these methods in FHM/FSM is shown in Fig. 1.

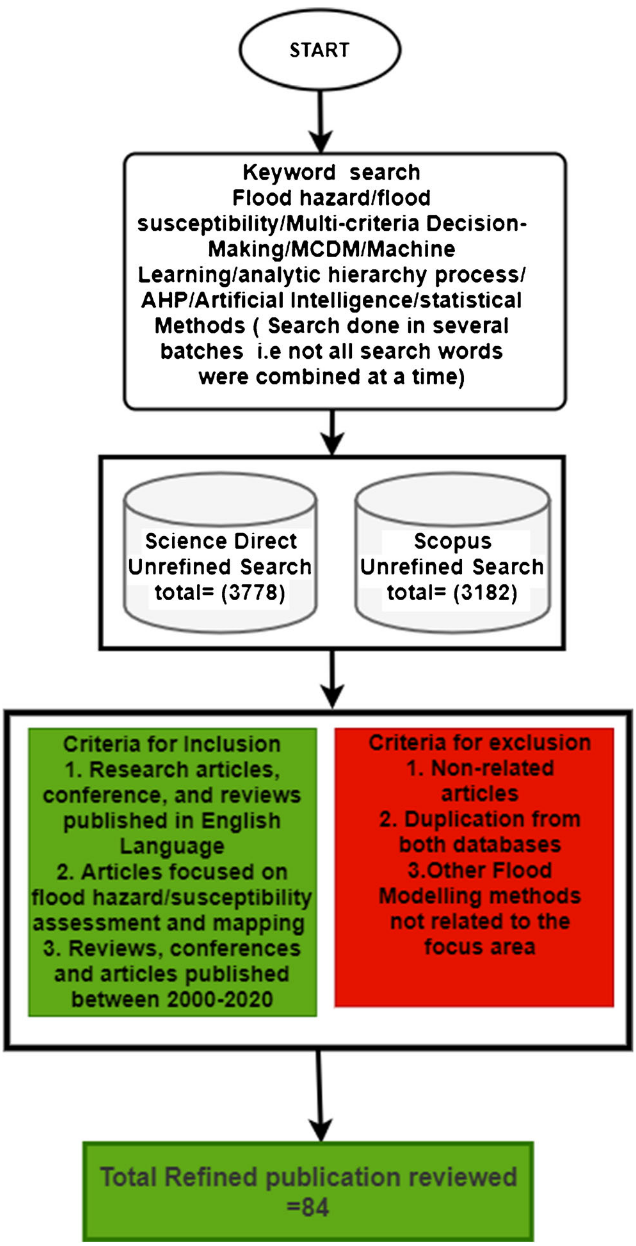


Fig. 2 Flow chart showing the search procedure

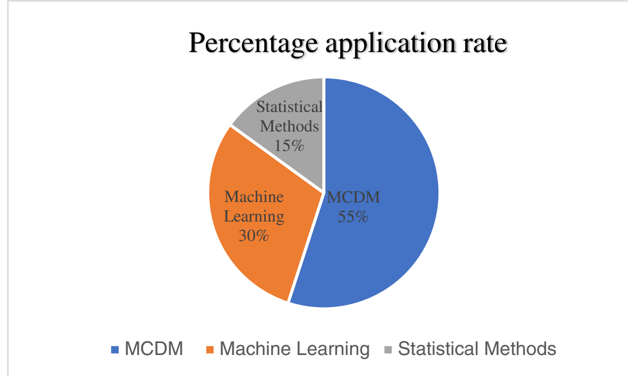


Fig. 3 Application of methods in FHM/FSM in reviewed papers

Search strategy

To present a summary of various past studies on FHM and FSM publications were selected from different journals globally. The key search words applied in gathering works of literature include machine learning, flood susceptibility, flood hazard, statistical, and multi-criteria decision. The inclusion criteria include publications available from the last two decades. The scope of this study was limited to flood hazard and flood susceptibility-related flood mapping. The database explored for the search was the Scopus and Science Direct. Over the years, the database has provided relevant and ground-breaking publications that have contributed a lot to problem-solving and new investigative areas. The search process is presented in Fig. 2 and details of the results systematic review analysis are presented below. An overview of several past related studies on FHM and FSM was made possible by analyzing relevant scholarly articles.

A total of 84 papers were reviewed shown in Fig. 2 after narrowing down the review scope and eliminating papers with similar contributions. Forty-six papers (55%) of the reviewed papers applied the MCDM method in FHM/FSM exceeding the utilization rate of the other methods as shown in Fig. 3. This might imply that more than half of the papers used a qualitative-based empirical modeling technique in FHM/FSM

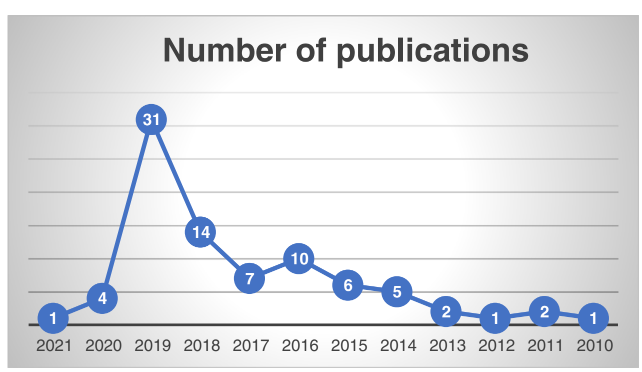


Fig. 4 Trend in the publication of the reviewed paper

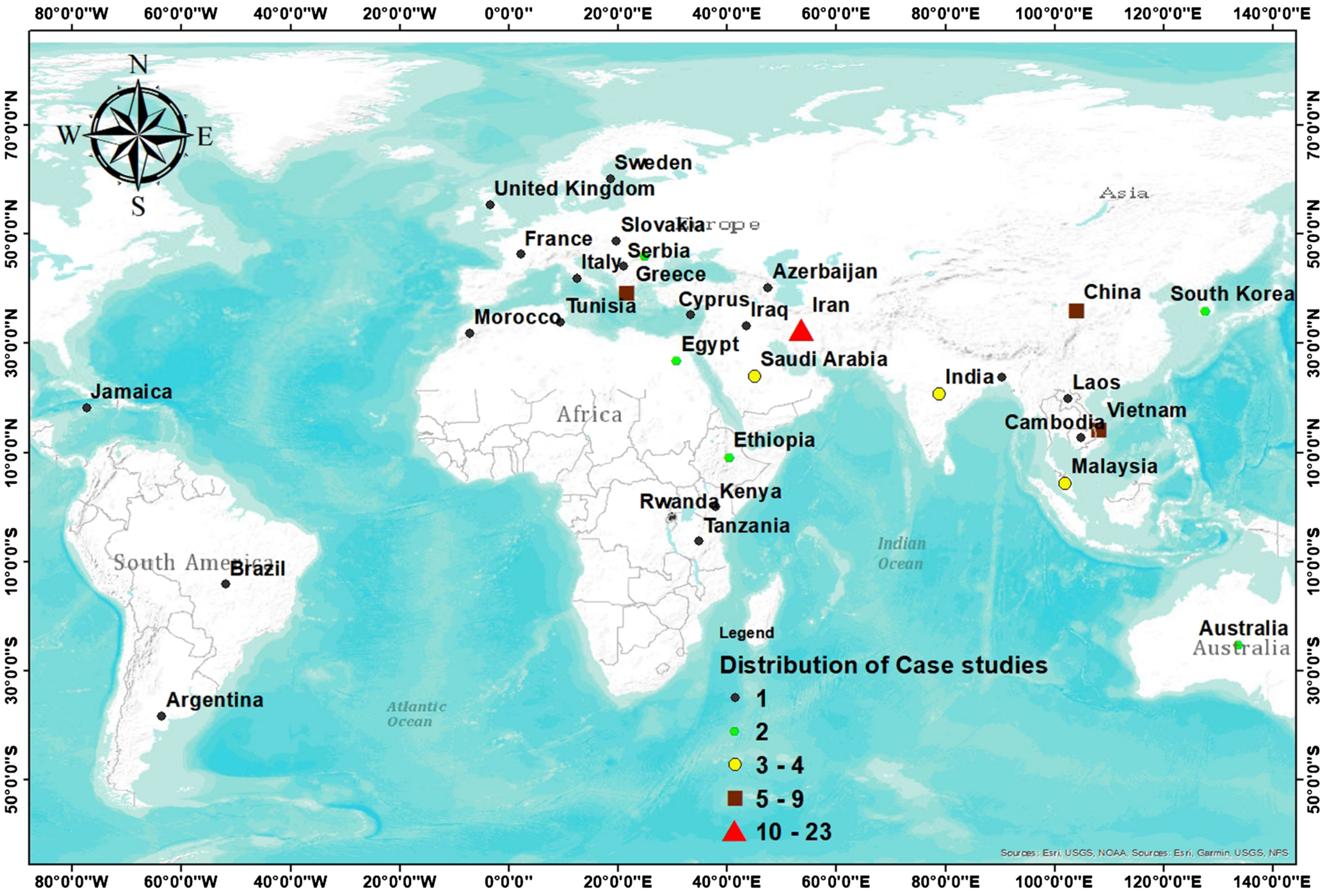
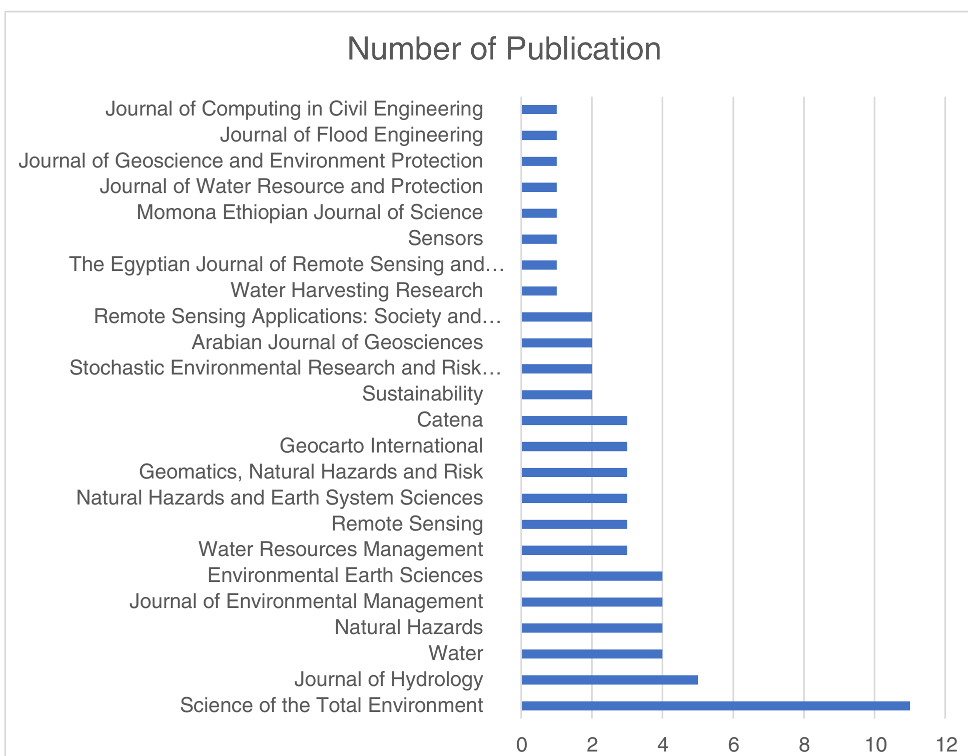


Fig. 5 Spatial distribution of identified case studies of FHM/FSM

Fig. 6 Articles with significant publication numbers in FHM/FSM



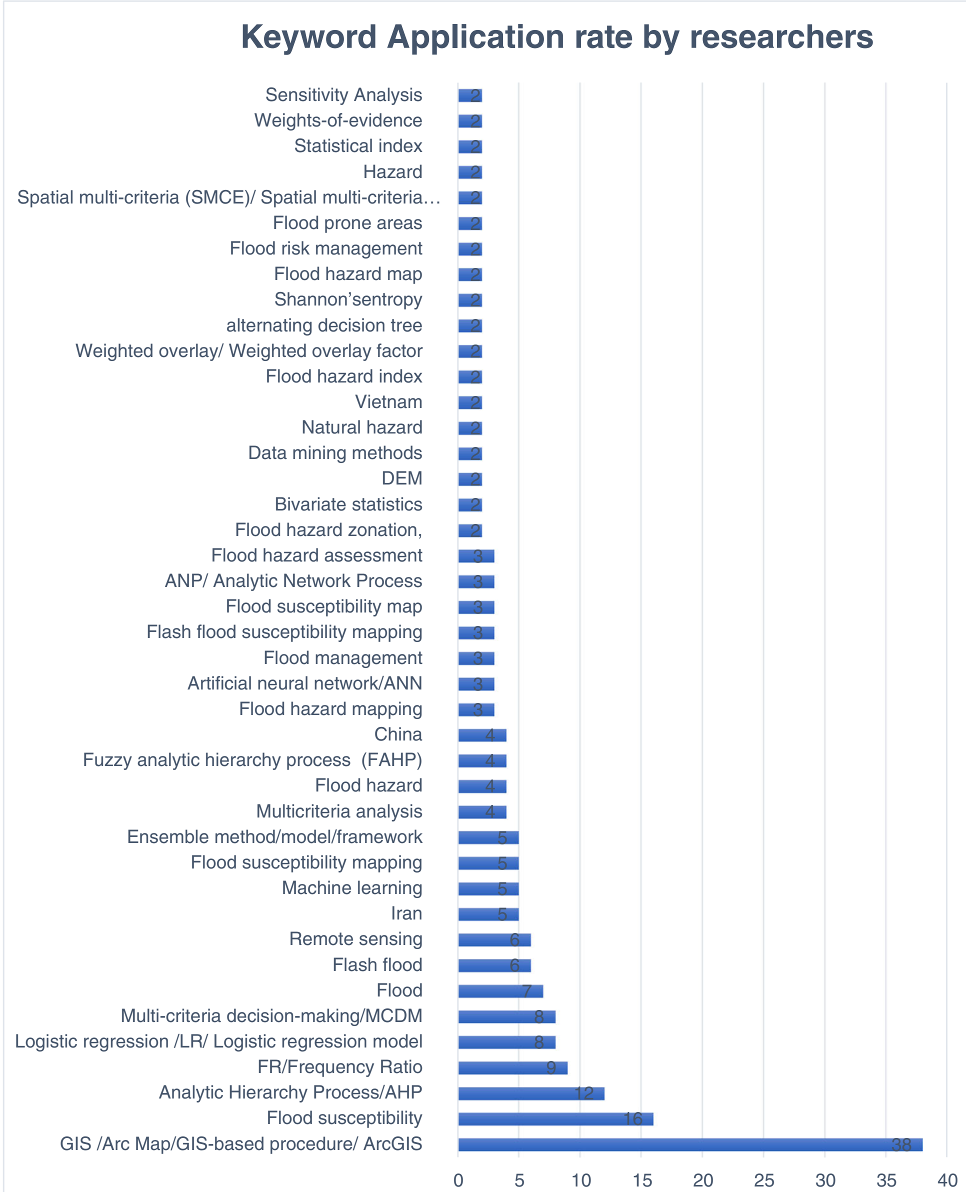


Fig. 7 Keywords application record amongst researchers

which is related to the ease of implementation and understanding (Parhizgar et al. 2017) of the method. Thirty percent of the reviewed paper utilized the ML in modeling flood hazard/susceptible areas while 15% applied the statistical modeling method. Analyzing the trend in the reviewed papers as presented in Fig. 4 signifies a positive trend in the publication rate of FHM/FSM with 31% growth in publication between the years 2019 and 2010. This positive trend might be related to the reliability of the quantitive and semi-quantitative methods in FHM/FSM. The spatial distribution of case studies indicated in Fig. 5 showed Iran had the highest distribution of publications followed closely by China, Greece, Vietnam, Malaysia, and Saudi Arabia respectively. The Science of the Total Environment had the database for the highest number of publications followed closely by the Journal of Hydrology as indicated in Fig. 6. An extraction of all keywords in the selected publication for review indicates GIS, flood susceptibility, and AHP had the highest record of appearances as indicated in Fig. 7. Supplementary data for the systematic review analysis is presented as an online Appendix.

Overview of quantitative and semi-quantitative methods in FHM/FSM

In this section, the concepts of the three methods are discussed, including flood contributing factors, the uncertainties, strengths, and limitations of the methods.

Interpretation of FHM/FSM based on three approaches by researchers

A closer look at the term FHM amongst researchers based on the quantitative and semi-quantitative methods indicates the context of the assessment of flood hazard/tends towards analysis that recognizes the areas at risk of flooding and the level of the risk. This differs from the flood hazard maps created through the popular numerical modeling that shows information about flood depth, velocity, and sometimes the probability of occurrence in varying return periods. For example, Kim et al. (2019) referred to FHM as a tool that provides users with information on the probability of the extent of flood damage and disaster mitigation activities. Stefanidis and Stathis (2013) referred to the identification and analysis of flood hazard zones as a critical element required for a reasonable watershed management. Patrikaki et al. (2018) affirmed that determining flood hazard areas is relevant for policymakers in designing flood mitigation strategies and in the implementation of flood risk management. Phrakonkham et al. (2019) referred to FHM as a tool applied in empowering decision-makers in prioritizing schemes for flood mitigation, formulating response measures, and in the identification of flood-prone areas. Fernández and Lutz (2010) define urban FHM as a process of creating maps that are relevant tools for planning prospects for urban city development and also in the identification of key areas with water discharge structure needs.

On the other hand, significant similarities can be found in the interpretation of FSM and FHM based on the context of the quantitative and semi-quantitative methods. This is apparent in the study by Rahman et al. (2019) which mentioned that the identification of flood susceptible areas is very important in reducing the risk of loss of lives and properties. Chen et al. (2019) also added that FSM is the right management tool required in the identification of areas at risk of flooding which is important in reducing the risk of lives, properties, and the environment to the flooding disaster. Samanta et al. (2018) defined FSM as a major task for EWS and emergency responders in preparation for strategic management of flood prevention and control of future flood occurrences. Similarly, Chapi et al. (2017) and Tehrany et al. (2015) categorized FSM as an important process in the prevention and management of future flood occurrences. Souissi et al. (2019) listed FSM as the first and essential process (Chapi et al. 2017; Lappas and Kallioras 2019) in evaluating the probability of occurrence of a flood (Wang et al. 2019a) and risk analysis. FSM is essential for the appropriate and timely management of flood hazards (Khosravi et al. 2018). Furthermore, Costache and Tien Bui (2019) mentioned that FSM as a non-structural flood mitigation measure should be considered in flood risk management.

The flood hazard map generated shows a graded evaluation of flood hazard areas based on different flood scenarios. The authors applied flood indices derived from a 2D hydraulic model in generating flood hazard maps through the use of the fuzzy MCDM method.

Different approaches in FHM/FSM

There has been a rising interest concerning flood mitigation measures to decrease flood-related losses for decades. FHM/FSM remains a key tool in flood mitigation scheme and management. Researchers have proposed and applied various methods in the evaluation of flood hazard/ susceptible areas. Before the 1970s, physical modeling of flood scenarios was prominent (Do Carmo 2016, 2020) but subsequent years witnessed the dominance of the numerical models which are capable of simulating flood processes. Recently, there is an increasing trend in the application of semi-quantitative and quantitative methods in FHM/FSM.

Overview of the MCDM methods

This semi-quantitative method provides a structure for the decision-making process and carries out an integrated spatial analysis for flood hazard /susceptibility mapping. The MCDM method has proven effective when solving a large number of technical and complex issues with a variety of conflicting and subjective criteria (Mikhailov 2003). The MCDM methods can improve the standard of decisions through effective, simplified, and rational processes that result in better and reasonable choices. Besides, the MCDM methods improve the parts played by decision-makers in the process of decision-making and allows all stakeholder to express their opinions, preferences, and alternatives.

The above-mentioned characteristics of MCDM allow actual inclusive processes that are significant for effective flood management practices (De Brito and Evers 2016). Most MCDM methods are usually made up of five processes which include model development, assigning scores, scores standardization/ normalization, accumulating weights, and sensitivity analysis (Ishizaka and Labib 2011).

The first step of the MCDM is problem structuring which involves the expert giving detailed assessment in the decision making to aid in the effective assigning of weights to the criteria. Hierarchical order structuring is very important because the method affects the result. The decision tree is constructed in the manner where the main goal is situated at the uppermost level, closely followed by the factors on which the target depends, and typically at the lowest level, the factors on which the criteria rely are situated (Saaty 2008). The subsequent step involves the assigning of score to criteria according to the decision-makers' choice of it over another criterion.

The major categorization technique in MCDM is through its weight derivation methods. In MCDM, techniques for obtaining criteria weights include ranking, rating, analytic

Table 1 Frequently applied MCDM methods in FHM/FSM studies

MCDM type	Explanation	Subjective/ objective	Numbers	Source
AHP	One of the most effective MCDM techniques which are based on pairwise comparison and evaluate decision-making problems by allowing varying alternatives in varying scenarios to be compared	Subjective	Crisp	(Le Cozannet et al. 2013; Radmehr and Araghinejad 2014; Saaty 1987)
ELECTRE	This method applies several mathematical functions in describing the level of relevance of a particular alternative relative to other alternatives and it applies three steps which are the preference, indifference, and the veto thresholds	Subjective	Crisp	(Chitsaz and Banihabib 2015)
FUZZY AHP	Expert's opinion is described by fuzzy numbers founded on the theory that human choices are usually accompanied by uncertainties and cannot be efficiently described by crisp numbers	Subjective	Fuzzy	(Parhizgar et al. 2017)
WLC	A practical method based on decision theory for creating integrated maps applying GIS tools. The technique is very common because it is easy to process and implement	Subjective	Crisp	(Malczewski 2000)
ANP	Similar to AHP but considers multiple dependencies and interdependencies in a network	Subjective	Crisp	(Dano et al. 2019)
TOPSIS	The method follows the theory that the highly preferred alternative is represented by the alternative that is recognized by the difference of the nearest positive and farthest negative ideal solution	Subjective	Crisp	(Levy 2005)
FUZZY TOPSIS	This method is applied to evaluate the uncertainty of weighting and input data values in MCDM	Objective	Fuzzy	(Çelikbilek 2018; Radmehr and Araghinejad 2015)
DEMATEL	This method evaluates relationships between criteria and the weight of each interconnected relationship. It enables the evaluation of complex decision problems in clustered groups	Subjective	Crisp	(Kanani-Sadat et al. 2019; Wang et al. 2019a)
PROMETHEE	This method is associated with applying the probabilistic technique for handling MCDM models under uncertainty	Subjective	Crisp	(Su and Tung 2014)
VIKOR	This method is applied in the identification of compromising solutions and estimating appropriate intervals. It is usually applied in modeling complex issues for an optimized outcome	Subjective	Crisp	(Khosravi et al. 2019)

hierarchy process (AHP) pairwise comparison, and trade-off analysis methods (De Brito and Evers 2016; Malczewski 1999; Malczewski and Rinner 2015). Weight estimation enables a clearer insight into an expert's preference or choice. The weight refers to the value given to specific criteria under evaluation which describes its relative significance over other criteria under consideration.

Aggregating weights in MCDM involves the determination of the overall weight for criteria examined in the analysis through the addition of the product of each factor's features by their weights (De Brito and Evers 2016; Malczewski et al. 2003). The general techniques applied in MCDM for adding weights of factors include the weighted linear combination and order weighted average methods such as ordered weighted average (OWA). According to De Brito and Evers (2016), several techniques cannot be specifically assigned to a category of MCDM type. It relies on the basic principles of MCDM by adapting, improving, modifying the MCDM technique, and incorporating hybrid techniques. A brief description of these methods (applied in FHM/FSM studies) is given in Table 1.

Review of MCDM methods A past review by De Brito and Evers (2016) provided a state-of-the-art review of MCDM methods in flood risk management. The review indicated the most popular of the methods was the analytic hierarchy process (AHP) method. Additionally, a review of GIS-MCDM methods by Malczewski (2007) showed the interdependence of the method on GIS. Major national-scale FHM has been successfully carried out through the application of the MCDM method and such case studies can be found in the FHM for Laos by Phrakonkham et al. (2019) and Greece by Kourgialas and Karatzas (2017). Basin and regional scale FHM case studies have also been evaluated through the use of MCDM as reported in studies by Patrikaki et al. (2018) and Wang et al. (2019a).

Stefanidis and Stathis (2013) indicated a high level of accuracy in the application of AHP because constraints and some other factors considered by MCDM and the analysis was free from raw data input which reduced the uncertainty in the mapping results. Rahmati et al. (2015) highlighted the reliability of both AHP and hydrodynamic modeling in FHM. Patrikaki et al. (2018) adapted the FIGUSED method by Kazakis et al. (2015) and extended the methodology with a sensitivity analysis that came up with FIGUSED-S which enabled the identification of high flood-prone zones in the lowland areas.

Rahmati et al. (2015) showed the AHP performed better than Fuzzy AHP when compared both methods were compared in FHM. Kim et al. (2019) analyzed failure in a levee using a 2-D hydraulic model and factorizing three FCFs for FHM. The 3 flood indices were predicted by the model based on 3 fuzzified scenarios before integrating all three indices using the Fuzzy TOPSIS technique and finally developing a flood hazard map. The methodology used in the study was an improvement to the one applied in producing flood map of the study area by the (Ministry of Land, Infrastructure and Transports) that did not consider uncertainty analysis (triangular fuzzy membership functions for the flood indices). The improved methodology produces a more accurate flood hazard map in comparison to the actual and recent FHM of the study area. Parhizgar et al. (2017) indicated that the FHM obtained using Fuzzy AHP was consistent with the historical flood event record in comparison to the AHP.

Wang et al. (2019a) applied an ensemble of DEMATEL, IR-Numbers, WLC, and ANP in generating FSMs by using flood inventory data and 12 FCFs. The result of the new hybrid approach showed high prediction accuracy. The result of the study proved very reliable when it was validated with historical flood events. Kanani-Sadat et al. (2019) applied an integrated fuzzy-DEMATEL with ANP in generating FSM while considering 10 FCFs. An accuracy of more than 80% was achieved for the integrated method. The study highlighted the applicability of the method in the data-scarce region and the relevance of DEM in the analysis and other considered FCFs. Mahmoody and Jelokhani-Niaraki (2019) applied GIS-OWA in producing flood hazard maps by applying two weighting methods. The resulting flood hazard maps the study showed that the map produced using the subjective-objective weighting method predicted better than the ordinary normalized method. The study established that the subjective-objective approach should be considered as it considers risk components in the mapping process.

Table 2 Frequently applied statistical methods in FHM/FSM studies

Statistical model	Type	Application areas	Source
Certainty Factor (CF)	Bivariate	FSM	(Costache 2019a)
Evidential Belief Function (EBF)	Bivariate	Spatial FHM	(Althuwaynee et al. 2012; Bui et al. 2019a, b, c)
Frequency Ratio (FR)	Bivariate	Spatial FHM & FSM	(Costache and Tien Bui 2019; Nandi et al. 2016; Shafapour Tehrany et al. 2017)
FUZZY WOE	Bivariate	FSM	(Hong et al. 2018)
Logistic Regression (LR)	Multivariate	Flood susceptibility and risk zones	(Shafapour Tehrany et al. 2017)
Poisson	Bivariate	FHM	(Azizat and Wan Omar 2018)
Shanon's Entropy	Bivariate	Spatial FSM	(Khosravi et al. 2016; Siahkamari et al. 2018)
Statistical index (SI)	Bivariate	Flash-flood, flood hazard, FSM	(Azizat and Wan Omar 2018; Costache 2019a; Liuzzo et al. 2019; Shafapour Tehrany et al. 2019)
Weight of evidence (WOE)	Bivariate	Flash-flood & flood susceptibility	(Tehrany et al. 2014b)

Overview of the statistical methods

Statistical methods are quantitative methods in flood hazard/susceptibility mapping (Morjani 2011). It can be classified into bivariate and multivariate statistical methods.

The bivariate analysis represents a category of statistical methods applied in evaluating the relationship between a pair of variables. The evaluation enables the knowledge of a co-existing relationship, the weight of this relationship, and the difference between the variables (Cui and Greatorex 2014). The bivariate methods enable independent variables to be structured according to the evaluated weight relative to each variable feature class impact on flood generation.

While the multivariate statistical method allows the simultaneous analysis of more than two variables (Wuensc 2019), it also evaluates the interconnection between both the predictor variables represented by FCFs and the explainable variable represented by flooding, but is unable to evaluate the influence of each class feature on flooding (Tehrany et al. 2014a). Furthermore, the bivariate statistical methods enable the estimation of the percentage of the probability of occurrence and non-occurrence of flooding.

The statistical methods apply remotely sensed data for flood hazard/susceptibility mapping. The statistical methods make use of historical flood events to forecast and delineate flood hazard regions. This method allows evaluation of flood hazard/susceptibility index through the integration of evaluated weights of flood causing factors' thematic layers and flood points. Table 2 shows some frequently applied statistical methods in FHM/FSM studies. The major procedures in flood hazard/susceptibility mapping in statistical methods include:

i. Sourcing for flood data through historical archives or remote sensing,
ii. The historical data is trained and applied in the proportion of 70:30 respectively,
iii. In the case of bivariate statistical methods, the probability of both flood and non-flood occurrence is evaluated for each feature class of FCF under consideration. The higher the probability, the greater the relationship between the FCF and its occurrence, and
iv. In the case of multivariate statistical methods, flood events are analyzed by identifying the interrelationship between the event and the flood-causing factor.

Review of statistical methods Recently, there has been a developing trend to improve statistical-based methods in FHM/FSM to enable delineation of flood hazard/susceptible regions through the application of various relevant and non-

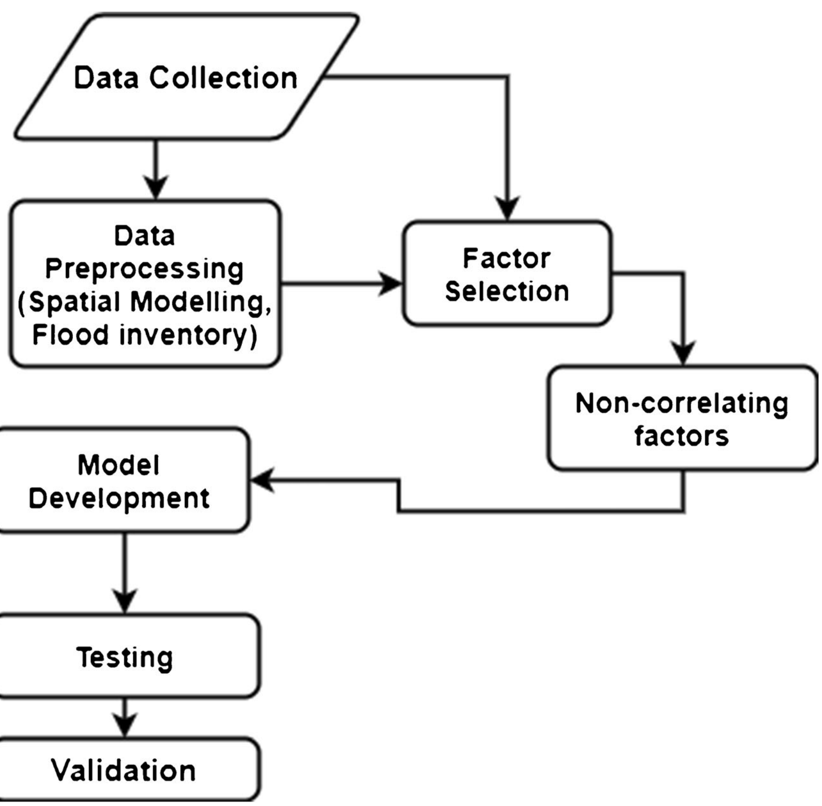


Fig. 8 Flow chart for generating a ML model for flood hazard/susceptibility map

correlating FCFs like antecedent, anthropogenic, hydrologic, geologic, and geomorphologic factors of the basin (Nandi et al. 2016). Cao et al. (2016) applied FR and SI models to develop flash flood susceptibility maps from the estimated index values of individual flash FCFs. The results from both models were tested for accuracy using the area curve method (AUC). The flash flood susceptibility map generated from the FR model based on natural classification breaks was more outstanding, although both results were found reliable. Bui et al. (2019a, b, c) applied a statistical bivariate model individually and combined each with LR in producing flood susceptibility maps. The predictive performance of the EBF was the most outstanding. The study was able to identify that Topographic Wetness Index (TWI) has the greatest impact on flood occurrence amongst the ten FCFs applied.

Mind'je et al. (2019) applied LR in modeling FSM using flood inventory records and 10 FCFs. The result showed a good performance of the model. The study was able to establish the highest flood occurrence influencers as rainfall normalized difference vegetation index (NDVI). El-Magd (2019) applied frequency ratio in developing flood susceptible maps using six FCFs and flood inventory records of the study area. The model recorded about 70% in prediction accuracy performance. The study was also able to identify areas prone to high flooding risk. (Shafapour Tehrany et al. 2019) applied SI, LR & FR in generating flood susceptible maps using flood inventory of the year 2011 and thirteen FCFs. The result of the investigation showed that the statistical index model outperformed others. The study established that the statistical index method was easier to understand, implement, and cheaper in mapping operation. Youssef et al. (2016) combined FR and LR in FSM using seven FCFs and flood inventory records. The result showed an excellent model performance and was able to identify slope as the most contributing factor in flood occurrence.

Overview of ML methods

ML is a branch of artificial intelligence that is applied to ascertain efficiency and structure in flood hazard/susceptibility mapping to enable a less complex implementation, testing, validation with high-performance output in comparison to the traditional numerical, physically based, and statistical models (Mekanik et al. 2013).

The improvement in the methods over the years has shown their outstanding performance in flood hazard/susceptibility mapping in comparison to other methods. It also can generate large spatial maps to enable the identification of regions at risk of flooding. The process of building a ML model for FHM/FSM entails applying historical flood records and/or remote sensing data, geospatial analysis of selected FCFs, correlation of FCFs and flood events, training, and validation of the datasets. A flow chart showing the ML prediction model in FHM/FSM is described in Fig. 8. These are the highlighted steps required to build flood hazard/susceptibility maps using ML:

i. Development of thematic layers through geospatial analysis for FCFs and past flood events through remote sensing derived data and /or field surveys, topographic maps, soil maps, climatic data, and historical data,
ii. Creation of the ML models,
iii. Training and validation of prediction ML models,
iv. Building of the flood hazard/susceptibility maps (Janizadeh et al. 2019).

Review of ML methods In the last two decades, ML methods have significantly influenced the improvement of flood hazard/susceptibility analysis and forecasting by finding cost-effective and accurate solutions through simulation of complex mathematical formulations that represent the physical processes of the flood. The ML methods are more dominant amongst hydrologists, researchers, and geospatial modelers due to its effectiveness and predicting capabilities. Furthermore, researchers are finding huge benefits in integrating the ML models through hybrid ML models to achieve accuracy and efficiency in flood hazard/susceptibility mapping (Mosavi et al. 2018).

A lot of researchers have applied ensemble ML models in mapping flood hazard/susceptibility with the target of improving the predicting and accuracy capabilities of these models. Tien Bui et al. (2019) combined a fuzzy rule-based algorithm and GA in the evaluation and selection of factors considered in developing FSMs through the use of three decision tree ensemble models. The study showed that the FURIA-GA-Bagging was excellent in predicting classification, specificity, and sensitivity with 93.37% prediction accuracy. Zhao et al. (2018) derived flood susceptibility maps using historical flooding records and eleven FCFs through modeling by RF. The study was able to indicate the most contributing factors to flood generation and establish that the RF model applied predominated ANN and SVM models with 93% prediction accuracy.

Tehrany et al. (2015) applied four types of SVMs in the prediction of flood susceptible areas and classification of flood susceptible maps. The result obtained for the four SVM kernel models were more accurate than the model prediction result of FR. (Chapi et al. 2017) applied the Bagging-LMT model to produce flood susceptible maps by integrating flood inventory maps and 12 FCFs. The result of the study was outstanding when compared with results from four soft computing models (Bui et al. 2020). The study compared the prediction capability of three new proposed algorithms with four previous models using eleven flood influencing variables. The result showed the new algorithms (SIA & DNN) integrated with DNN outperformed the four conventional methods. The study was able to propose a more robust methodology in FSM.

Chen et al. (2019) applied a reduced-error pruning tree model with two sampling ensembles to produce flood susceptibility maps using 363 flood records and thirteen flood influencing factors. The result of the evaluation showed the ensemble with a random subspace outperformed the bagging ensemble in the prediction of flood susceptible areas. The newly developed approach was found to be very efficient and better than other new models. Dodangeh et al. (2020) applied a new integrated approach of RS and BT algorithms in combination with GAM, BRT, and MARS ML models by using an average of ten run times for the models used in producing flood susceptible maps which considered flood inventory records and nine FCFs. The results showed the new approach of resampling enhanced the prediction efficiency of the three ML models. The result of this study can be applied at an urban scale.

Tien Bui et al. (2019) applied new soft computing based on (PSO and MARS) approach in FSM using 654 flood records and 12 FCFs to produce flood susceptibility maps. The prediction capability of the new method was compared with ANN, SVM, and CTree ML models and the result showed that the new PSO-MARS was outstanding under various statistical tests. The model showed high efficiency and accuracy in FSM. Janizadeh et al. (2019) applied QDA, FT, KLR, ADT, and MLP ML models in developing flood susceptibility maps using 320 flood records and eight flood influencing factors. Indications from the result showed that the ADT exceeded all other four ML models in terms of prediction accuracy. The study stated that all five models tested are effective and reliable in FSM. Bui et al. (2019a) applied a newly proposed method that integrated both ELM and PSO in FSM by using 654 flood inventory records and 12 FCFs to produce flood susceptibility maps. The new PSO-ELM method was compared with three other ML models (MLP, SVM, and C4.5 DT) results and the PSO-ELM performed better when compared to the rest. The hybrid method was also capable of mapping susceptible areas in tropical typhoon regions.

Ngo et al. (2018) applied a newly proposed ML named FA-LM-ANN model in FSM prediction using Sentinel-1 imagery for inundated area detection and twelve FCFs. The new model performed excellently when compared with other ML models. The methodology highlighted the benefit of choosing sentinel-1 imagery for flash flood detection. Al-Abadi (2018) compared the predicting performance of three ML models in FSM under six different statistical tests. The AdaBoost model outperformed others which included the RF and RTF. The study was the first to apply the MLs in FSM and was found to be very useful and reliable in FSM. Razavi Termeh et al. (2018) applied the ANFIS with three optimization models in modeling FSM by applying flood inventory records of the study area nine FCFs. The ensemble of ANFIS with PSO generated flood susceptibility maps related to the historical records. The models applied in the study and the approach helped manage the data scarcity problem and produce an outstanding outcome.

Integration of all three methods Researchers often explore the combination or comparison of some or all the three methods discussed in this review. Such case study can be found in the study by Samanta et al. (2018) which applied the FR model and MCDM to identify flood-prone regions in the area of investigation by considering 10 FCFs derived from geospatial data and flood points generated from historical flood inventory maps to obtain flood susceptibility maps. The result of the FR methodology obtained in the study was compared to MCDM applied in the same study area and the results showed that the FR's model output was better. Shafizadeh-Moghadam et al. (2018) applied eight machine models that were implemented with seven statistical models (ensemble) for comparison of prediction performance in FSM. The result showed that the Enmedian, i.e. the median probability of all 8 ML models, performed best. The authors recommended the state-of-the-art ensemble approach in the study in other FHM/FSM studies. Khosravi et al. (2019) applied three MCDMs (VIKOR, TOPSIS, and simple additive weighting methods) and two ML models (NB and NBT) to develop flood susceptibility maps by considering eleven FCFs and flood inventory records. The result showed all models performed well but the Naïve Bayes Tree was outstanding in developing flood susceptible maps. Rahman et al. (2019) applied ANN, AHP, FR, LR, and several combinations of the models in FSM using flood inventory records and nine FCFs to produce flood susceptibility maps. The results showed LR outperformed others individually and the ensemble of LR and

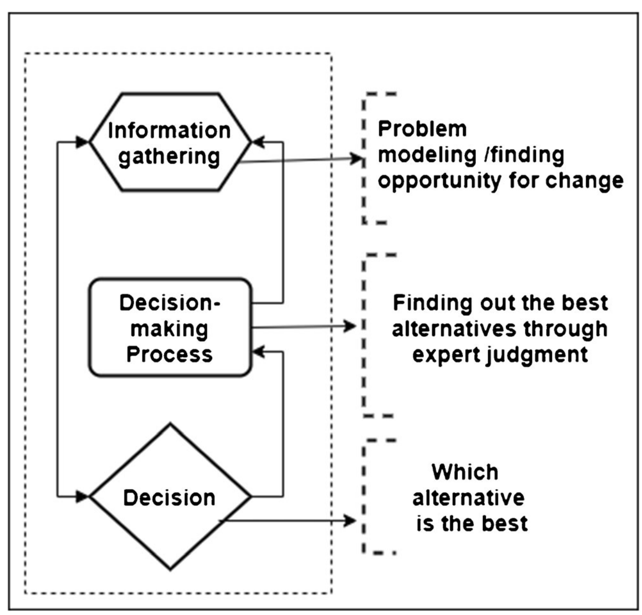


Fig. 9 Framework of GIS-based MCDM analysis

FR was outstanding amongst all other model integration. The method is highly efficient and can be reliable in a data-sparse region. Costache (2019b) applied two new ML (ANFIS and fuzzy SVM) models and two statistical models (CF and SI) in FSM using flood inventory records and nine FCFs. Results from the study showed that the fuzzy SVM and CF models performed best. The fuzzy SVM was novel and its performance was excellent in creating flood susceptibility maps. Costache and Tien Bui (2019) proposed six new ensembles of bivariate statistical and Artificial intelligence models (MLP-WOE, RTF-WOE, MLP-FR, RTF-FR, CART-WOE, and CART-FR) in FSM using 132 flood inventory records and thirteen FCFs. All ensemble models performed well but RTF-WOE was very outstanding in the generation flood susceptibility map. Hong et al. (2018) applied WOE and FR alongside three ML models (LR, RF, and SVM) in producing flood susceptible maps using eleven FCFs and flood inventory records. The result showed that fuzzy WOE-SVM outperformed all other models in their respective predictive capabilities. The method applied made the analysis much easier to evaluate the criteria's weights and much easier to comprehend.

Role of GIS in the implementation of FHM/FSM

In this section, a description of the relevance of GIS in the implementation of flood hazard/flood susceptible maps generation through the years for the three methods is given:

i. MCDM Methods: Several spatial decision problems result in the GIS and MCDM analysis (GIS-based MCDM analysis) which are both unique subjects for research that rely on each other (Chandio et al. 2013; Malczewski 2007). The GIS approach and processes have a significant role in evaluating decision-making problems. It has been identified as a key decision-support system in synthesizing spatially referenced information in an analytic environment.

   GIS has remained significant in its capability of computing and evaluating various spatial information since the 1970s. It is capable of producing both hard and digital formats of maps from which the decision-making process can be dependent for creating a solution. It also can synthesize information from multiple sources. Furthermore and more recently, GIS has displayed high efficiency and capability in the building of a set of alternatives decisions based on spatial relationship concepts of proximity, adjacency, connectivity, and the overlay method (Malczewski et al. 2003; Saragih 2020).

   The general predominant framework for the GIS-MCDM analysis has been classified into three major steps- problem design, decision-making process, and outcome of the decision (Malczewski 2007). The GIS-MCDM analysis framework is described in Fig. 9.

ii. Statistical & ML Methods: GIS is applied in the delineation of sub-catchments, evaluation of drainage system, building geospatial database, evaluation of parameters, and recognition of flood extents and depths (Hou and Du 2020). Application of GIS has played a significant role in the evolution of environmental sciences through the provision of innovative ideas in flood assessment studies. The statistical and ML modeling methods are some of the various methods developed by researchers which apply GIS in the zoning/delineating/identifying of flood hazard/ susceptible areas alongside other tools (Khosravi et al. 2016). The ability of the GIS in handling and integrating an enormous volume of spatial information makes it a reliable tool in FHM/FSM. This can be confirmed based on the (highest) record of the appearance of GIS amongst other keywords applied by researchers in the selected review publications as shown in Fig. 6.

Flood contributing factors

Floods are a result of runoff caused in most cases by rainfall, and sometimes from sea level rise or dam failures. Flash flood characteristics from the time it reaches the earth's surface can be affected by meteorological factors such as evaporation, wind, temperature, and topographic factors of the catchment once runoff occurs (Benson 1962). The spatial extent and frequency of runoff leading to a flood event rely on physical, hydrological, geomorphological, geological characteristics of the basin, and also human activities. Identifying these factors and categorizing them is significant in flood planning and mitigation measures (Pirnazar et al. 2017).

The characteristics of flood and events leading to its generation are highly dependent on these factors, therefore characterizing them in flood inundating studies is very needed (Kanani-Sadat et al. 2019). In flood modeling studies, it is very important to investigate the spatial connection between flood occurrences and influencing factors (Pradhan 2009). It is crucial to identify these influencing factors which may vary with the catchment's characteristics (Zhao et al. 2018), and select the factors with the least interdependency relationship (Benson 1962).

Correlation analysis is one of the evaluations which is necessary for finding the multicollinearity of flood contributing factors (FCFs) and possible solutions. It is important to test for multi-collinearity between these factors before carrying out any MCDM, statistical analysis, and ML/regression modeling (Tehrany et al. 2019a). Chen et al. (2019) successfully applied

Table 3 FCFs from past studies relating to MCDM

S/No	Area of application	Criteria applied (FCFs)	No. of criteria applied	Source
1	FHM	Land use, Climate change, and flood	3	(Phrakonkham et al. 2019)
2	FHM	Depression area, river network, permeability ratio, rainfall, detention ponds, and elevation	6	(Chen et al. 2015)
3	FHM	Slope, Soil Conservation Service Curve-Number (SCS-CN), density of depression area, elevation, dike density, elevation standard derivation, flow accumulation, pumping station density, and Topographic Wetness Index (TWI)	10	(Mudashiru et al., 2019; Xiao et al. 2017)
4	FHM	Peak flood depth, velocity, and flood arrival time	3	(Kim et al. 2019)
5	FHM	Drainage texture, slope, geology, distance to main channel, Land use/land cover (LULC)	5	(Franci et al. 2016)
6	FHM	Flow accumulation, geology, rainfall intensity, slope, land use, and elevation	6	(Kourgialas and Karatzas 2011)
7	FHM	Geology, distance from the drainage network (DFDN), flow accumulation, rainfall, elevation, and land use	6	(Patrikaki et al. 2018)
8	FHM	Slope, DFRN, lithology, runoff depth, land use, flow accumulation, and vegetation cover	7	(Khaleghi and Mahmoodi 2017)
9	FHM	Mainstream slope, rock permeability, land use, rock erodibility, watersheds slope, watershed shape, and drainage density	7	(Stefanidis and Stathis 2013)
10	FHM	Vertical overland flow distance, Modified Fournier Index (MFI), flow accumulation, DEM, slope, aspect, horizontal overland flow distance, TPI, wetness Index, and SCS-CN	10	(Papaioannou et al. 2015)
11	FHM	Water table, elevation, slope, the distance from the water surface, distance to the sewage network, and land use	6	(Gigović et al. 2017)
12	FSM	Stream Transport Index (STI), rainfall, slope, lithology, soil type, curvature, land use, Distance from River (DFR), elevation, TWI, Normalized Difference Vegetation Index (NDVI), and Stream Power Index (SPI)	12	(Khosravi et al. 2019)
13	FSM	Drainage density, elevation, distance from the drainage system, geology, flow accumulation, runoff, slope, LULC, soil type, and annual rainfall	10	(Mahmoud and Gan 2018)
14	FHM	Drainage density, vegetation, geology, slope, land use, erosion rates, soil texture, and average annual rainfall	8	(Arianpour and Jamali 2015a)
15	Flood Hazard & Flood Risk Vulnerability Mapping	Flow accumulation, Population density, water table, elevation, building density, LULC, rainfall, slope, rainfall, flow direction, and road density	11	(Nigusse and Adhanom 2019)
16	Flash FHM	Drainage density, land use, runoff, surface slope, distance to main channel, surface roughness, and soil type	7	(Elkhrachy 2015)
17	Urban FHM	Groundwater table depths, slope, elevation, distance to the drainage channels, and urban land use	5	(Fernández and Lutz 2010)
18	FHM	Flood duration and depth	2	(Luu et al. 2018)
19	FHM	Geology, slope, MFI, land use, flow accumulation, distance from drainage, TWI, soil type, and elevation	10	(Lappas and Kallioras 2019)
20	Flood Hazard susceptibility	SPI, soil type, NDVI, lithology, TWI, elevation, slope, plan curvature, distance to stream, drainage density, aspect, and LULC.	13	(Arabameri et al. 2019)
21	FHM	Slope, DFR, LULC, and elevation.	4	(Rahmati et al. 2016b)
22	Flood Susceptibility Assessment	Slope, horizontal overland flow distance, TPI, TWI, NDVI, DEM, CN, flow accumulation, vertical overland flow distance, and MFI	10	(Kanani-Sadat et al. 2019)

the correlation attribute evaluation (CAE) method in selecting FCFs for their study. Cohen's kappa index was also successfully applied by Arabameri et al. (2019); Hosseini et al. (2019); Kumar (2016) in evaluating classification accuracy. The variance inflation factor and tolerance tests are very common methods and have been successfully applied by various researchers in analyzing the existence of collinearity amongst FCFs (Al-Juaidi et al. 2018; Arabameri et al. 2019; Costache 2019a; Hong et al. 2018; Khosravi et al. 2018; Rahman et al. 2019; Tehrany et al. 2019a). The number of

Table 4 FCFs from past studies relating to ML models

S/No	Area of application	FCFs applied	No. of FCF applied	Source
1	FHM	Rainfall, aspect, TPI, slope, topographic roughness index(TRI), TWI, flow accumulation, NDVI, elevation, DFR, lithology, drainage density, soil type, land use, and soil depth	15	(Hosseini et al. 2019)
2	Flash FSM	NDVI, slope, TWI, rainfall, altitude, DFR, curvature, SPI, river density, lithology, and land use	11	(Khosravi et al. 2018)
3	Flash FSM	River density, lithology, TWI, slope, NDVI, curvature, SPI, elevation, rainfall, aspect and soil type	11	(Bui et al., 2019b)
4	FSM	Drainage density, peak daily rainfall, CN, elevation, frequency of intense rainfall, soil moisture, latitude, longitude, relative elevation, peak annual daily rainfall, vegetation cover	11	(Zhao et al. 2018)
5	FSM	Geology, TWI, altitude, DFR, slope, SPI, soil type, LU/LC, surface runoff, and curvature	10	(Tehrany et al. 2015)
6	FSM	Slope, SPI, geology, TWI, curvature, DEM, rainfall, DFR, LU/LC, and soil type	10	(Tehrany et al. 2014b)
7	FSM	Distance to river (DTR), slope, SPI, elevation, TWI, land use, curvature, river density, lithology, NDVI, and rainfall	11	(Chapi et al. 2017)
8	FSM	DTR, DEM, curvature, TWI, aspect, river density, SPI, slope, NDVI, rainfall, and Normalized Differentiated Built-up index (NDBI)	11	(Bui et al. 2020)
9	FSM	Elevation, SPI, slope, STI, lithology, slope aspect, TWI, curvature, NDVI, soil type, rainfall, soil type, and land use	13	(Chen et al. 2019)
10	FSM	Curvature, altitude, NDVI, slope, land use, aspect, river density, lithology, and rainfall	9	(Dodangeh et al. 2020)
11	Flash FSM	Elevation, TWI, slope, SPI, lithology, curvature, NDVI, aspect, river, soil type, and rainfall	11	(Bui et al., 2019a, b, c)
12	FSM	Elevation, DTR, slope, rainfall, aspect, soil type, land use, and lithology	8	(Janizadeh et al. 2019)
13	Flash FSM	Lithology, river density, TWI, slope, SPI, elevation, NDVI, curvature, soil type, aspect, and rainfall	11	(Bui et al., 2019a)

Table 5 FCFs from past studies relating to statistical models

S/No	Area of application	FCFs applied	No. of FCF applied	Source
1	Flash FSM	Elevation, SPI, geology, subsidence risk area, intense rain, TWI, soil texture, slope, curvature, and land use	10	(Cao et al. 2016)
2	Flash FSM	DFR, altitude, NDVI, slope, LU/LC, aspect, SPI, distance from fault, soil type, TWI, geology, distance from road, STI, rainfall, and curvature	15	(Shafapour Tehrany et al. 2017)
3	FHM	Elevation, TWI, drainage density, land use, road density, soil type, slope, and catchment length	8	(Kalantari et al. 2014)
4	FSM	Elevation, plan curvature, TWI, slope, SPI, geology, DFR, rainfall, land use, and NDVI	10	(Bui et al., 2019a, b, c)
5	FSM	Elevation, profile curvature, TWI, slope, DFR, aspect, rainfall, distance from road, Normalized Difference Soil Index (NDSI), and NDVI	10	(Mind'je et al. 2019)
6	Flash FHM	Elevation, DFR, slope, curvature, geology, land use, and soil type	7	(El-Magd 2019)
7	FSM	Altitude, LU/LC, slope, TWI, aspect, SPI, curvature, soil type, DFR, geology, and topography roughness index	11	(Shafapour Tehrany et al. 2019)
8	FHM	Flow accumulation, TWI, elevation, DFR, flood depth, slope, rainfall, and aspect	8	(Nandi et al. 2016)
9	Flash FSM	Slope, DFR, soil drainage, land use, elevation, curvature, and geology	7	(Youssef et al. 2016)
10	FSM	Lithology, DFR, soil texture, land use, slope angle, TWI, plan curvature, altitude, and slope aspect	10	(Rahmati et al. 2016a)

FCFs applied in FHM/FSM studies varies and is oftentimes selected based on the researcher's recommendation from previous studies. The identification of these relevant FCFs that are generally applied in similar flood hazard/susceptibility evaluation studies will be conducted by reviewing several related works of literature relating to MCDM, ML, and statistical models as presented in Tables 3, 4, and 5.

Flood inventory maps

Past flood information is a basic requirement in flood hazard & susceptibility analysis because it forms a crucial part in spatial future prediction (Liu et al. 2019; Rahmati and Pourghasemi 2017). A flood inventory map is needed to identify the correlation between FCFs and flood occurrences. When developing a flood hazard & susceptibility map, it is necessary to have accurate information about past flood events (Shafapour Tehrany et al. 2019). The general approach applied in generating flood inventory maps in the papers is to obtain flood reports through field investigation (Youssef et al. 2016), aerial photographs, historical records (Bui et al., 2019a, b, c) and delineating the areas affected by flood from the unaffected areas through topographic maps obtained from aerial imagery (Costache 2019a). The flood inventory datasets are then subdivided by the ratio of 70% to 30% for training and testing for modeling purposes (Tehrany et al. 2014b).

Remote sensing data

Remote sensing data is a crucial part of the semiquantitative and quantitative methods in FHM/FSM as the majority of applied study regions do not have historical climatic data or insufficient data. Therefore, researchers find alternatives in data retrieved through remote sensing. One common thing the papers considered in this review share is the application of remote sensing data in their analysis. The empirical-based modeling methods in flood hazard & susceptibility mapping enable the use of remote sensing data and often with the combination of historical flood data, topographic maps, soil maps. This approach is very relevant in data-scarce or ungauged areas. The hydrodynamic models operate successfully on more data and produce accurate results (Teng et al. 2017) while the quantitative and semi-quantitative-based methods such as MCDM, machine learning, and statistical methods need fewer input data and produce adequate results (Kanani-Sadat et al. 2019). Chapi et al., (2017) and Nigusse and Adhanom (2019) highlighted the importance of GIS, remote sensing (RS), and image processing in FHM & FSM.

Recently, high-resolution advanced remote sensing data have been increasingly applied in flood analysis studies. A series of these databases (the sentinel-1, 2, Landsat 7 &8 OLI, Phased Array L-band Synthetic Aperture Radar (PALSAR), Advanced Land Observing Satellite-2 (ALOS-2), Synthetic Aperture Radar (SAR) images like the

Table 6 Summary of some applied dataset FHM/FSM studies

Input dataset	Source
Sentinel-2 Images, ASTER DEM 30m	(Hosseini et al. 2019; Msabi and Makonyo 2021)
Field Survey, IRS imagery, ASTER DEM 30m, and meteorological data	(Khosravi et al. 2018)
Digital topographic map, historical rainfall, and Sentinel-1-SAR imagery	(Bui et al., 2019b)
Historical flood records, rainfall, soil hydraulic parameters, landcover product, and NASA SRTM -90m	(Bakhtyari Kia et al. 2012; Zhao et al. 2018)
Historical flood records, field surveys, DEM-20m, Landsat 8 OLI, and Historical rainfall	(Chapi et al. 2017)
Historical Flash flood, topographic map, Landsat 8 OLI-30m, pedology map, geological &mineral map	(Bui et al., 2019a; Huang et al. 2006)
Historical flood records, google earth, field survey, ASTER GDEM 2, and Landsat 8 OLI	(Chen et al. 2019)
Historical flood records, field surveys, long-term historical rainfall data, DEM 30m, Land use map, geological map	(Dodangeh et al. 2020)
Sentinel-1A-SAR, Landsat 8 OLI, Climatic data, and topographic map	(Mohammadi et al. 2020; Ngo et al. 2018; Trung Nguyen et al. 2018)
Historical flood inventory, ALOS PALSAR DEM-12.5m, meteorological data, soil map, and lithology map	(Janizadeh et al. 2019)
"	(Shafizadeh-Moghadam et al. 2018)
Historical flood records, rainfall data, DEM 10m, and land-use/landcover map 1;100,000	(Razavi Termeh et al. 2018)
Sentinel-1A, Lnadsat 8 OLI, and DEM 30m	(Bui et al. 2020)
Flood inventory records, ASTER GDEM, Landsat 7 ETM, and rainfall data	(Wang et al. 2019b)
Resource Sat-2 (56m), SRTM 30m, Digitization of hard copy land use, soil and lithology maps	(Al-Abadi 2018)

TerraSAR-x, Moderate-Resolution Imaging Spectroradiometer (MODIS)) available for flood records have been explored by various researchers to allow identification of flood locations and non-flood locations. In the absence of historical flood event records from the field, researchers have sought alternatives in readily available remote sensing data. Some studies have also highlighted the importance of the date of flood occurrence in correlation with satellite imageries and DEM applied in flood hazard/ susceptibility analysis (Shafizadeh-Moghadam et al. 2018). Much advanced application of remote sensing through cloud computing can be found in the FSM study by Swain et al. (2020). A brief of some databases for FSM/FHM studies is highlighted in Table 6.

Uncertainties relating to the semi-quantitative and quantitative methods in FHM/FSM

Flood maps are meant to present accurate information as a lot of key decisions rely on the information provided by these maps. Accurate flood hazard maps enable the undertaking of significant, reasonable, and cost-effective flood control measures that can decrease flood damage, impact, losses, improve adaption measures, and prediction of the disaster. Uncertainties in the process of analysis of FHM/FSM, in general, include data quality and accessibility, assumptions made while modeling, user-bound errors, and the technique applied.

i. MCDM methods

Despite all the capabilities of the MCDM, it is highly susceptible to uncertainties that are associated with the weight assigning and derivation, input data characteristics, the judgment process, and the MCDM model assumptions (de Brito et al. 2019). In the MCDM process, priority is given to the weight assigning, derivation, and evaluation processes. Although the MCDM addresses the complexity and uncertainty associated with the processes that lead to the flood generation well, researchers are hassled with the subjectivity nature of the entire decision-making process involving various experts' opinions (Kanani-Sadat et al. 2019; Mahmoody and Jelokhani-Niaraki 2019). Each expert has a varying opinion of the problem, therefore, introducing bias into the decision process for the flood assessment due to subjectivity in human reasoning. It is therefore very important to choose a reasonable MCDM tool and also consider performing a sensitivity and/or uncertainty analysis of the MCDM model. Generally, for the AHP method, the inconsistency index is widely recognized as a mode of assessing the uncertainty associated with the weight assigning and derivation process (De Brito and Evers 2016). Souissi et al. (2019) applied a single parameter sensitivity analysis to validate the MCDM weight derivation process in their study. Jun et al. (2013) fuzzified all the criteria weights for assessing vulnerability due to flood damage to address the uncertainty associated with all the MCDM methods applied in their study. Gigović et al. (2017); Wang et al. (2019a) applied interval rough and fuzzy numbers in addressing uncertainty associated with group decision making when mapping flood susceptible regions. Kanani-Sadat et al. (2019) applied a hybrid of fuzzy and DEMATEL to address a group of experts' decision-making processes for FSM. Several authors have considered fuzzifying various MCDM methods due to its closeness in characteristics with human reasoning with the intent of reducing associated uncertainty of the MCDM methods (Arianpour and Jamali 2015b; Kim et al. 2019; Papaioannou et al. 2015; Wang et al. 2011; Xiao et al. 2017).

ii. Statistical methods

Uncertainty in statistical methods is usually originated from major input data such as the FCFs and flood records. Therefore, researchers have focused on evaluating the impact of the variation of these factors on the prediction outcome through various methods of sensitivity analysis and model validation (Arabameri et al. 2019; Tehrany et al. 2019b). Although uncertainty is inevitable in most analyses, it is very crucial to incorporate them in process of FHM/FSM analysis to produce models with accurate and optimum prediction capabilities. Furthermore, certain statistical methods such as EBF and Shanon's entropy are known to address uncertainty.

The EBF method evaluates the probability of certainty of theory and measures the model outcome to ascertain the level of closeness to the hypothesis. The measurement in EBF includes the level of belief, level of uncertainty, level of disbelief, and the level of plausibility (Shafapour Tehrany et al. 2019; Tehrany et al. 2019b). Shanon's entropy on the other hand estimates the degree of disorder, unevenness, and uncertainty in a system (Khosravi et al. 2016). Khosravi et al. (2016); Shafapour Tehrany et al. (2019); Tehrany et al. (2014a) applied the receiver operating characteristics (ROC) to evaluate the model outcome through true and false-positive values where the area under the curve (AUC) is capable of quantitatively estimating the models prediction accuracy. Cao et al. (2016) applied the AUC to assess the capability of the model applied in predicting flash flood susceptible areas. Nandi et al. (2016) applied the ROC to validate the LR and FR models applied in identifying flood hazard regions in Jamaica. El-Magd (2019) also applied the AUC to estimate the capability of the FR model applied in analyzing flash flood hazard zones in Egypt.

iii. ML methods

Uncertainty in ML methods originated from sources that include the process of selecting FCFs, subjective classification of the FCFs, quality of resolution of applied datasets, the training and validation datasets, and the selected efficiency

Table 7 Advantages and disadvantages of the semi-quantitative and quantitative methods in FHM/FSM

Method	Strengths	Limitations
MCDM	a. Ability to integrate spatial and nonspatial data within a decision-making process b. Easy implementation within the GIS environment c. Consistency in the expert's judgment that represents human reasoning d. Allows all stakeholder to express their opinions, preferences, and alternatives e. Less data input requirement f. Simple computation process g. Ability to assign varying significance of alternatives to scalar values (crisp, fuzzy, grey numbers) simultaneously h. Easier characterization and structuring of the preferences i. Suitable for regional studies	a. With AHP, pairwise comparisons are based on very practical uncertain criteria b. Generally, subjective evaluation due to human reasoning which is sometimes found to bias c. With AHP, large pairwise comparisons overwhelming participating experts leading to uncertainty in the judgment process and high consistency ratio d. Loss of information due to the subjectivity of the method e. Results can be influenced by dominant stakeholders and noise in the responses f. Reliance on a group of experts' or expert's opinion
Statistical	a. Improve predictive capability than other methods b. Easy computation and implementation c. Applies a straightforward concept d. Bivariate methods can evaluate the relationship between a dependent (flood) and independent (FCFs) e. Multivariate methods do not necessarily require normally distributed data and can easily implement continuous or discrete dataset f. Ability to address uncertainty within the predicted flood and flooding region outputs g. Yields realistic estimates h. Easy implementation within the GIS environment i. Does not require a large capacity computing system to operate j. Ability to manage incomplete dataset k. Reasonable operation cost	a. The inability of the multivariate method to analyze the relationship between individual flood contributing factor and flood b. Large numbers of FCFs will require a longer computation process and duration c. Complex processing required to transform independent factor layers into evidential belief layers (with EBF) d. Longer processing time for models such as EBF e. Statistical model such as FR is not capable of modeling complex flood terrains f. Bivariate methods usually infer that flood is generated due to the combination same FCFs for an entire study area
ML	a. High computing and automation level b. Ease in the recognition of trends and structures within flood dataset c. Ability to incorporate multi-variety and highly complex flood dataset d. High prediction efficiency e. Ability to combine other models (ensemble) for better output f. High computation speed g. Accurate learning h. Efficient mapping into feature spaces i. Good generalization capabilities j. Ability to incorporate large datasets k. Easy implementation within the GIS environment l. Suitable for regional and large-scale study areas	a. Large and long-duration data required for training and validation b. Difficult to optimize c. Complex network architecture d. Requires highly trained manpower to perform accurate predictions e. Prone to input data uncertainty f. Requires high-capacity computer system to operate g. Reliance on remote sensing datasets for ungauged areas

metrics (Janizadeh et al. 2019). Similar to the statistical methods in FHM/FSM, researchers have focused on assessing uncertainty in the applied model's performance through validation and sensitivity analysis. Also, researchers have worked on improving predicting capabilities and accuracy in models for FHM/FSM through the application of high-resolution datasets (Chapi et al. 2017; Janizadeh et al. 2019; Razavi Termeh et al. 2018; Tehrany et al. 2019b), application of datasets related to the date of flood events in mapping flood (Hosseini et al. 2019), and improving models through ensemble ML models. Most researchers that apply ML models have evaluated the degree of uncertainty through the application of the ROC and AUC methods (Al-Juaidi et al. 2018; Bui et al., 2019b; Costache 2019a; Ngo et al. 2018; Pourghasemi et al. 2019; Sahana and Patel 2019; Shafizadeh-Moghadam et al. 2018). The better models with reduced uncertainty are identified through high AUC values and high classification accurate rate (CAR) values (Ngo et al. 2018).

Strengths and limitations of all three methods in FHM/FSM

The advantages and limitations of the three sub-group (the MCDM, statistical, and ML methods) discussed in this review study are highlighted in this section and presented in Table 7.

Summary, recent advances, and recommendations for future research

This section of the review study summarizes recommendations from various studies, highlighting gaps for future studies, and also providing relevant information for decision-makers and stakeholders in the field of flood management. Although the MCDM methods have proven to be a key tool in the preliminary investigation for flood vulnerability, damage, risk, and management studies, there is room for improvement to increase the reliability of the outcome. Recent developments in MCDM methods for FHM/FSM cover the application of fuzzy numbers in place of crisp numbers to reduce the subjectiveness of the method. Future studies in the MCDM are recommended to focus majorly on decreasing uncertainty associated with the decision-making and weight evaluation process. The application of objective and or a combination of subjective-objective methods that are capable of analyzing the entire process of criteria weight evaluation is highly recommended. The application of Grey-AHP has been successfully applied to evaluate the effectiveness of studies such as environmental vulnerability assessment (Sahoo et al. 2016) and groundwater potential assessment (Sahoo et al. 2017). This method can be reciprocated in MCDM methods in FHM/FSM to evaluate the decision-making to indicate the applicability of the MDCM model outcome (flood susceptible/flood hazard map).

Statistical methods have been applied in FSM as standalone models. Generally, the prediction outcomes are more on the average effectiveness and accuracy rate. Researchers have found improvement in complementing the strength and weaknesses of these models in hybrid statistical models with better predictive and accuracy outcomes. Recent advances have seen these methods combined with more complex ML models to supplement the basic assumptions of the statistical models and better outputs have been achieved. Future researchers should consider comparing the ensemble of (bivariate statistical methods and ML) and an ensemble of (multivariate statistical method and ML) to determine which present the optimum predicting model in FHM/FSM. Researchers should also consider the impact of data of varying resolution on the predictive performance in the statistical methods in FHM/FSM.

When considering ML methods in FHM/FSM, the most common ones include the (ANN, SVM, DT, MLP, ANFIS, RF, RTF)s. Some are applied as a single model and some in combination/s as ensemble ML models. Major recent advances in ML are the exploration of the capabilities of ensemble models in the prediction of flood hazard/flood susceptible regions. Other developments include an ensemble of ML with classifiers to improve the prediction efficiency, increase the degree of accuracy, reduction of uncertainty, increase computing speed, and reduction of operating time. Recommendation for future studies from past studies includes investigation of the influence of the number of classification of FCFs on the predictive performance of model output. Also, an ensemble of ANN and SVM which is characterized by different classification and learning techniques is suggested to map flood susceptible/hazard regions. Generally, the application of the ML model in FHM/FSM is at the early phases that provide a whole lot of opportunities for researchers to explore for future work with the intent of optimizing existing methods and creating new methods for the best outcome.

Conclusion

According to the EU-Directive (2007), in order to decrease the risk associated with flooding, there is a need to provide flood mitigation measures at the basin scale. Flood hazard/flood susceptibility maps provide useful information required to prepare, prevent, and plan for flood disaster. The relevance of the quantitative and semi-quantitative approach in FHM/FSM has become predominant as the shift to methods that are capable of providing better results with less uncertainty at larger scales have developed significantly. The MCDM methods have shown the capability of integrating stakeholder's input with less complex processing, less input data requirement, accurate results, and decreased uncertainty. The statistical methods are also characterized by the ability to address uncertainty, provide spatial flood maps by analyzing the relationship between a dependent (flood) and independent (FCFs). On the other hand, the ML methods are the fast emerging and reliable methods in FHM/FSM as it provide highly accurate flood maps suitable for regional and large-scale study. On the contrary, there are limitations associated with these methods such as reliance on expert's subjective opinions, inability to model complex terrains, and susceptibility to input data uncertainty. However, if necessary steps are taken to address these challenges by evaluating the decision-making process, exploring ensemble models to balance the weaknesses and strengths of models, good model choice, application quality data from a reliable source and high-resolution datasets, and performing validation these challenges can be addressed to provide optimum results with less uncertainty. This paper provides observations and recommendations to enhance the existing information for relevant knowledge in future studies and to assist stakeholders and key policy-makers in making good decisions for flood management.

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Declarations

Competing interests The authors declare that they have no known competing financial or personal interests.

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