Original Articles

Enhancing community resilience in arid regions: A smart framework for flash flood risk assessment

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ABSTRACT

This paper presents a novel framework for smart integrated risk management in arid regions. The framework combines flash flood modelling, statistical methods, artificial intelligence (AI), geographic evaluations, risk analysis, and decision-making modules to enhance community resilience. Flash flood is simulated by using Watershed Modelling System (WMS). Statistical methods are also used to trim outlier data from physical systems and climatic data. Furthermore, three AI methods, including Support Vector Machine (SVM), Artificial Neural Network (ANN), and Nearest Neighbours Classification (NNC), are used to predict and classify flash flood occurrences. Geographic Information System (GIS) is also utilised to assess potential risks in vulnerable regions, together with Failure Mode and Effects Analysis (FMEA) and Hazard and Operability Study (HAZOP) methods. The decision-making module employs the Classic Delphi technique to classify the appropriate solutions for flood risk control. The methodology is demonstrated by its application to the real case study of the Khosf region in Iran, which suffers from both drought and severe floods simultaneously, exacerbated by recent climate changes. The results show high Coefficient of determination (R²) scores for the three AI methods, with SVM at 0.88, ANN at 0.79, and NNC at 0.89. FMEA results indicate that over 50% of scenarios are at high flood risk, while HAZOP indicates 30% of scenarios with the same risk rate. Additionally, peak flows of over 24 m³/s are considered flood occurrences that can cause financial damage in all scenarios and risk techniques of the case study. Finally, our research findings indicate a practical decision support system that is compatible with sustainable development concepts and can enhance community resilience in arid regions.

1. Introduction

Natural disasters, such as floods, often lead to devastating impacts on people and the environment. According to the Internal Displacement Monitoring Centre (IDMC) report, natural disasters have caused an average of 20 million people to be displaced worldwide between 2008 and 2019, with the most significant displacement occurring in 2010 when more than 40 million people were affected by weather and geophysical disasters (Statista.com). Besides, the Centre for Research on the Epidemiology of Disasters (CRED) reports that countries such as Indonesia, the United States, and China have experienced the most natural disasters in 2020, with Iran and Mexico ranking eighth in the number of disaster occurrences (Statista.com). In 2020, the highest flood damage costs occurred in China, India, Japan, and Pakistan, with estimated losses amounting to 32, 10, 9, and 2 billion U.S. dollars, respectively, according to the India Spend report (Statista.com). Sustainable smart flood management is essential for addressing the risks and impacts of flooding. It involves integrating advanced technologies, data
analytics, and real-time monitoring systems to make informed decisions and optimize resources. Nature-based solutions such as wetland restoration, green infrastructure, and floodplain zoning are prioritized, providing flood protection and additional benefits like improved water quality and biodiversity. Engaging communities and adopting participatory approaches empower residents to contribute to flood prevention and preparedness. By embracing sustainable smart practices, it can be addressed climate change challenges, reduce risks, and create resilient communities in flood-prone areas (Hu et al., 2018; Chao et al., 2018; Liu et al., 2021). According to statistical data, there is a pressing need for smart and sustainable approaches to statistical flood disasters in Asia.

Flash floods are a common type of disaster that can have devastating consequences, particularly in arid regions. Iran, in particular, has been facing severe drought and flash floods, with a significant increase in their frequency, intensity, and impacts due to climate change in recent years. Traditional methods for assessing flood risk typically rely on historical data and statistical approaches, which are insufficient for predicting and managing flood risks in the face of the current climate crisis. Flooding is one of the most significant challenges faced by human civilisation, and its impact is expected to worsen due to climate change and rapid urbanisation. Changes in vegetation, temperature, and rainfall patterns have resulted in unpredictable flood behaviour (Mahato et al., 2021), making flood forecasting, particularly in real-time applications, a subject of widespread attention globally (Piadeh et al., 2022). Developing a reliable prediction model with practical capabilities is an optimistic goal (Wasko et al., 2021). However, the lack of historical data on extreme flash floods, which are becoming more common due to climate change and typically occur in modern cities, is a major obstacle to effective flood management (Islam et al., 2021). Recent flash floods have been sudden, unpredictable, and highly destructive (Talukdar et al., 2020), and the scales are beyond the range of historical records that conventional statistical approaches will not be able to predict such extreme events. Therefore, flood management frameworks need to include hydrologic models and intelligent prediction systems to address the possibility of future flash floods (Arora et al., 2021). Geographic Information System (GIS), Watershed Modelling System (WMS), Artificial Intelligence (AI), and other contemporary tools are often used individually in scientific studies related to flood risk management (Hashim and Sayl 2021). It is crucial to develop a comprehensive framework that integrates these tools to achieve effective flood risk assessment and management in arid regions (Karami et al., 2022).

In recent times, the well-being of society has been threatened by a range of hazards, including natural disasters, particularly floods. From 1998 to 2017, floods were found to be the most harmful climate-related disaster to humans, with a significant amount of attention being given to the severity of the matter, leading to the creation of various flood management approaches (Wallemaaq and House, 2018). Among these, Artificial Intelligence (AI) has emerged as the flagship technology in flood management and prediction techniques, with several experts highlighting its potential (Goyal et al., 2021). For instance, Wang (2021) introduced AI as a tool that enhances the ability to observe flood behaviour, while Liu et al. (2021) proposed a comprehensive flood management schedule that addresses the crisis from beginning to end. Moreover, many scientists have explored the prediction capabilities of AI, such as Kunverji et al. (2021), who used three algorithms, including Decision Tree, Random Forest, and Gradient Boost, to develop an early warning system. Zalnezhad et al., (2023) used three different Neuro-fuzzy Inference System (ANFIS) to conduct regional flood frequency analysis for ungauged catchments in Australia. Also, Zabibi et al., (2023) employed a smart decision support system to propose a unique framework for flood management in three steps i.e., monitoring, prediction and control the flood. Fig. 1 provides an overview of the methods and tools used in AI and flood management to illustrate their relationship between the years 2019–2021.

While AI has been a popular method recently for flood risk management, other tools such as GIS and WMS are also utilised in this field. For instance, Erten and Çelik (2021) employed GIS to examine the impact of urbanisation on floods in the context of climate change. Similarly, Mourato et al. (2021) proposed a Web-GIS system that incorporates rainfall, hydraulic, and hydrologic models for flood warning and forecasting. This system is capable of updating itself every six hours and provides a prediction of potential floods. Additionally, GIS can be combined with other decision-making concepts such as multi-criteria decision analysis, as demonstrated by Hosseinzadeh et al. (2023), to identify flood management solutions based on several sustainability criteria. WMS is also utilised in modelling flash floods worldwide by various experts (Abd El Shafy and Mostafa, 2021).

A plethora of flood management tools such as AI, GIS, and WMS have been used for flood prediction and modelling, as mentioned in the
literature (Feng et al., 2021). While these methods have proven to be effective, a knowledge gap has been identified in their implementation individually without considering climate and land changes in the lead-up to flooding (Avand and Moradi, 2021). Therefore, a comprehensive flood management system should integrate the three main components of Flood Modelling and Simulation, Flood Prediction and Flood Risk Assessment and Management. To fill this gap, the research aims to develop a framework that integrates various methods, including flood simulation modelling, statistical methods, AI, geographic evaluations, and decision-making modules, to enhance community resilience and reduce the negative impacts of flash floods in arid regions. The abovementioned three components of the flood framework will be described and analysed in the following sections.

1.1. Flood modelling and simulation

Fig. 2 shows a schematic of the flood modelling and simulation research area, divided into four periods: before 2006, 2006–2010, 2010–2021, and 2022. Prior to 2006, early studies mainly focused on 1D and 2D flood simulations, as evidenced by works such as O’Brien et al. (1993), Haile and Rientjes (2005), Lin et al. (2006); and Stelling and Verwey (2006). Applicable software for flood simulation was also developed between 2006 and 2010, with platforms such as ArcGIS, LISFLOOD, and others utilized for estimation purposes in studies by Begnudelli et al. (2008), Knijff et al. (2008), Luino et al. (2009), and Pistriki et al. (2010). From 2010 to 2021, research increasingly utilized the integration of 1D/2D programming and professional platforms, as seen in studies by Hu et al. (2018), Chao et al. (2018), Liu et al. (2021); and Jadouane and Chaouki (2022). More recently, flood simulation and modelling have been enhanced through the application of metaheuristic algorithms and machine learning computations in works by Sedighkia and Datta (2022), Zhou et al., 2022a, 2022b, Quintana-Romero and Leandro (2022) and Wand et al. (2022). More recently, Liu et al., (2023) used a model to simulate the waterlogging process for flat irrigation districts in the paddy fields to predict floods in various scenarios. Moreover, Chen et al., (2023) presented a new approach for quick estimation of the risk of urban flooding by using a numerical model with great computing efficiency and a Long-Short Term Memory (LSTM) artificial neural network model.

1.2. Flood forecasting

The R-Studio software and Scopus databank are used to evaluate flood prediction studies through the Bibliometrics toolbox. The Sankey diagram in Fig. A.1 shows that prediction models are often used in Decision Support Systems (DSS). From 2000 to 2017, hot topics included flood prediction, DSS, risk management, uncertainty, flood management, remote sensing, and climate change. In recent years, data-driven and mining techniques have been commonly used for computations based on time series data. Flood forecasting has been evaluated at different spatial and temporal resolutions, with some studies using convolutional neural networks to analyse radar echo maps. For example, Dtissibe et al., (2020) utilized discharge data as input-output variables to create a flood forecasting model using a multilayer perceptron algorithm. Puttinaovarat, and Horkaew (2020) developed a new flood forecasting system based on combining massive, crowdsourced data with meteorological, hydrological, geospatial, and hydrological information. Ma et al., (2021) validated when and where dike breaks occurred during Typhoon Hagibis which caused catastrophic flooding in Japan in 2019. To accomplish the study’s objective, they coupled a hydrodynamic model with statistical analysis while being forced by a 39 h forecast from the Meso-scale model Grid Point Value (MSM-GPV) of the Japan Meteorological Agency. They then got dike-break times for all flooded locations for validation. To construct and assess a forecasting model to anticipate the occurrence of flood events in the future, Moishin et al., (2021) developed a hybrid deep learning (ConvLSTM) algorithm by integrating the predictive benefits of Convolutional Neural Network (CNN) and LSTM Network. Zhou et al. (2022a, 2022b) developed a flood prediction system that combines deep learning computations with Bayesian optimization techniques to evaluate computational time and

![Flood Modelling and Simulation](image-url)
model efficiency. Similarly, Chen et al. (2022a, 2022b) assessed the performance of deep learning for short-term flood forecasting, incorporating both spatial and temporal features into the model. Sikorska-\-Senoner (2022) presented a clustering model for the hydrological specifications of case studies used for risk analysis of flood disasters, and the optimal number of clusters was obtained by flood frequency analysis. Zabihi et al., (2023) employed three AI algorithms including Logistic Regression, Neural Network, and Support Vector Machine to predict the flood disasters by clustering rainfall data. Saint-Fleur et al., (2023) also developed a deep artificial neural network for forecasting flash floods, which would enable it to better account for regional variability, scales of rainfall, and hydrological reactions due to its unique architecture.

1.3. Flood risk assessment and management

This study evaluated the use of risk assessment for controlling flood disasters, using Scopus databank and Bibliometrix toolbox in R-Studio (see Fig. A.2). There are some known analytical risk assessment methods such as Failure Mode and Effects Analysis (FMEA) and Hazard and Operability study (HAZOP) that have been used in construction projects (Ahmadi et al. 2017) and structural engineering (Yeganeh et al. 2022). However, our literature review shows FMEA and HAZOP have been rarely used for flood risk management. Most studies instead identified high-risk areas by integrating GIS and hydraulic computations. For instance, Quesada-Román et al. (2022) developed a model for risk assessment of flood events based on flood frequency evaluations at peak discharging points, using Topographic Wetness Index (TWI) for risk assessment at different points. Rincón et al. (2022) presented a stochastic model for flood risk assessment in different climates by first analysing the flood hazards in their case study then detecting the high-risk regions, and finally estimating risk functions. Zhang et al. (2022) created a flood risk assessment model to develop a warning system in the Brahmaputra River floodplain of Bangladesh, by integrating HEC-HMS (Hydrological software) and HEC-RAS (Hydraulic software). Brawlewska and Brawlewska (2022) applied the Poland’s national risk assessment methodology to control flood hazards in a case study by categorising risk points. Yang et al., (2023) sought to reduce flood losses brought on by drought and floods and to identify drought and flood hazards in rainfed agriculture using conditional probabilities. They produced an index using the meteorological data to create four time-scale drought indicators. For flood risk assessments on a wide spatial area, Kelly et al., (2023) created a unique way of index-based analysis employing a multi-criteria decision-making (MCDM) method. Based on flood hazard, flood exposure, and flood vulnerability indices, an overall Flood Risk Index (FRI) for the Hawkesbury-Nepean Catchment was generated using an MCDM technique. By combining the Interpretative Structural Modeling Method (ISM) with the Bayesian Network (BN) framework, a risk assessment model was presented by Li et al., (2023) that would result in an integrated ISM-BN simulator for accurate flood assessments.

Based on the literature review outlined above, no previous work has conducted a comprehensive analysis of flood risk management that combines flood predictions with risk assessment and decision support systems (DSS). Therefore, this study aims to develop a new DSS framework for flash flood mitigation by integrating GIS-WMS simulation, artificial neural network (ANN) predictions for flash floods, and flood risk assessment and scenario building for decision-making on flood risk mitigating measures. This framework will utilise both smart tools like ANN and digital technologies such as GIS, as well as human experience, to analyse flood predictions and associated risk, feeding the DSS to make informed decisions. The methodology is demonstrated by its application to a real-world case study in Iran, representing an international collaboration for flood simulation, risk assessment, and prediction worldwide (see Fig. A.3). The next section details the methodology, including data gathering, mathematical calculations, software modelling, and AI settings. Results are presented, along with critical discussion and comparison to a similar previously published study. The conclusions draw key findings and provide recommendations for future work.

2. Material and methods

2.1. Methodology

This study proposes a novel framework for smart flood risk management and flood forecasting, which is based on integrated GIS, WMS, and AI algorithms. The framework is illustrated in the flowchart shown in Fig. 3 and includes various components such as data collection, hydrologic and hydraulic modelling of the catchment, and flood simulation and forecasting.

Data collection involves gathering descriptive and digital information, topographic layers, vegetation land cover, geotechnical, rainfall, and climatic data to form a comprehensive database. GIS software is then used to pre-process the above-mentioned data to prepare inputs for flood modelling. This is followed by hydrologic and hydraulic modelling of the catchment using the WMS software to simulate surface runoff and estimate flood flow in the case study. AI algorithms are then utilized to identify effective parameters for future flood predictions and identify key performance indicators for evaluating flood resilience. The estimated damages of flood occurrences are then used to analyse flood risk assessment based on FMEA and HAZOP methods. Finally, the Classic Delphi (CD) method is employed to identify the best solutions for mitigating flood risk. The steps involved in this framework are further explained in the following sections.

2.2. Hydrologic modelling process in GIS and WMS

The digital map created by GIS includes various layers such as topographic, vegetation, geotechnical, and geo-hydrological data (Pareta and Paretta, 2012). This map is used as input data to create a hydraulic model in WMS software version 7.1. The WMS model estimates various parameters based on the physical characteristics of the catchment (Al-Zahrani et al., 2017), such as Sin (the sinuosity factor of the stream which is meandering conditions between any two points in the stream that is defined by the ratio of the maximum stream length to the direct length), MFD (the maximum flood distance within the catchment), CSD (the average distance between the centroid of the catchment and the points with maximum flow), CSS (the slope of the CSD), MFS (the slope of the catchment), AVEL (the mean catchment elevation), SF (catchment shape factor), P (the catchment perimeter), and A (the area of the catchment). These parameters are used to simulate and predict flood discharge, depth, and velocity.

Note that the WMS model was configured with additional parameters, including a Primary Infiltration (PI) time of 0.2 s, 10% Impenetrable Percentage (IP), Mean Curved Number (MCN) of 78 (www.hec.usace.army.mil), and maximum potential losses to runoff can be calculated based on (Garen and Moore, 2005; Hawkins et al., 2008):

\[
MCN = \left( \frac{\sum A_i}{100} \times CN \right)\]

\[
S = \frac{25400}{MCN} - 254
\]

\[
A_i = \text{The percentage of area of the basin whose curved number is } CN,
\]

The time of concentration (Tc) is computed using the Soil Conservation Service (SCS) method as (Grimaldi et al., 2012):

\[
T_c = \left( \frac{0.871L}{\Delta h} \right)^{0.365}
\]

where L is the flow length (m), and \( \Delta h = H_{\text{max}} - H_{\text{min}} \) is the difference between the maximum and minimum level of the catchment.
2.3. AI computations

The AI developed in this study is primarily designed to undertake two main tasks: (1) binary prediction of flood occurrence and (2) estimation of flood damages. The computations of the AI use four machine learning (ML) algorithms, including Support Vector Machine (SVM) used for flood mapping (Bera et al. 2022), Neural Network (NN) (Mahesh et al. 2022), Nearest Neighbours Classification (NNC) (Avand et al. 2022) and Linear & Polynomial Regression (LPR). The algorithms are written in Python language and are configured with the settings illustrated in Table 1 (the programming codes in the Python platform are available in the supplementary file).

The input layer of all ML algorithms consists of five variables, including vegetation land cover, temperature, precipitation, and flash flood flow. The output layer includes the two tasks of flood occurrence and flood damage. The flood flows computed by the WMS simulation are used as the historical data for the input layer, along with corresponding data from other input layer variables in various times of the historical years. Fig. 4 illustrates the structure of input and output layer data in this study. As can be seen in the figure, both data gathering and simulation processes are used to prepare the databank for the ML computations.

For all AI models, 80% of the total historical data is used for model training, while the remaining 20% is reserved for testing. The general setting of the AI models includes sklearn.model_selection.train_test_split (*arrays, test_size = None, train_size = None, random_state = None, shuffle = True, stratify = None) in Jupiter notebook (Hishinuma and Iiduka, 2019). The specific parameters and settings of the ML algorithms are given in Table 1. The coefficient of determination ($R^2$) is used as the performance indicator to identify the best AI algorithm in this case study (Gheibi et al., 2019). Note that the historic input data used in this study can be divides into three distinct groups as shown in Figs. S10–12 based on precipitation and temperature. The first group (Fig. A.10) is related to flood occurrence (0 as no flood and 1 as flood detection). The second group (Fig. A.11) classifies the data according to the integer values of MUSD (between 1 and 5) representing the extent of damages. The last

Table 1
The specific parameters and settings of the utilised AI algorithms in the Jupiter notebook.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Settings</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Support Vector Machine (SVM)</td>
<td>C = 1.0, break_ties = False, cache_size = 200, class_weight = None, coef0 = 0.0, decision_function_shape = ‘ovr’, degree = 3, gamma = ‘scale’, kernel = ‘rbf’, max_iter = 1, probability = False, random_state = None, shrinking = True, tol = 0.001, verbose = False</td>
<td>(Shahzadi et al., 2021)</td>
</tr>
<tr>
<td>Neural Network (NN)</td>
<td>MLPClassifier (activation = ‘relu’, alpha = 0.0001, batch_size = ‘auto’, beta_1 = 0.9, beta_2 = 0.999, early_stopping = False, epsilon = 1e-08, hidden_layer_sizes = 100, learning_rate = ‘constant’, learning_rate_init = 0.001, max_fun = 15000, max_iter = 250, momentum = 0.9, n_iter_no_change = 10, nesterovs_momentum = True, power_t = 0.5, random_state = None, shuffle = True, solver = ‘adam’, tol = 0.0001, validation_fraction = 0.1, verbose = False, warm_start = False)</td>
<td>(Kalantar et al., 2021)</td>
</tr>
<tr>
<td>Nearest Neighbor Classification (NNC)</td>
<td>KNeighborsClassifier (algorithm = ‘auto’, leaf_size = 30, metric = ‘minkowski’, metric_params = None, n_jobs = None, n_neighbors = 18, p = 2, weights = ‘uniform’)</td>
<td>(Shahabi et al., 2020)</td>
</tr>
<tr>
<td>Linear &amp; Polynomial Regression (LPR)</td>
<td>copy_X = True, fit_intercept = True, n_jobs = None, normalize = False</td>
<td>(Ling et al., 2022)</td>
</tr>
</tbody>
</table>
2.4. Flood risk assessment

Two risk assessment methods, FMEA and HAZOP, are used in this study to evaluate risk levels of flash floods. Different steps in FMEA method is illustrated in Fig. 5 (Chang and Cheng, 2010), and the same is illustrated for HAZOP method (Siddiqui et al., 2014) in Fig. 6. Both methods involved eight experts with relevant expertise, including three experts in crisis management and five experts in water management. Each expert had at least a Master degree in a field related to civil engineering, HSE engineering, hydraulic engineering, environmental engineering, or crisis management, and had more than ten years of experience in their respective fields (Gheibi et al., 2019; Akbarian et al., 2022a). Furthermore, all the experts had experience dealing with at least one flood crisis. The experts were responsible for scoring points in the risk assessment process.

The FMEA algorithm (Fig. 5) requires three parameters: Detectability rate (D), Occurrence rate (O), and Severity rate (S) (Peddi et al., 2023), which are first specified by GIS modelling, WMS simulation, and experts’ opinions, respectively. These parameters are then scored by participating experts, and the score-weighted multiplications of the three parameters are used to calculate the Risk Priority Number (PRN), which can be used to evaluate the risk level of flash floods. More specifically, the D factor is determined by assessing the distance of the risk point from the flood zones in the GIS environment, while the O factor is determined by comparing simulated flash flood flows in WMS to the average flow of the catchment. The S factor is estimated based on the experts’ knowledge of previous flood experiences (Ouyang et al., 2022).

On the other hand, the HAZOP algorithm (Fig. 6) requires two factors: Risk Intensity (RI) and Risk Possibility (RP), which are evaluated and scored based on experts’ opinions and available data (Moezzi et al., 2023). The multiplication of these score-weighted average factors generates Risk Matrix (RM) which is used for flood risk assessment and categorisation in different regions and conditions.

2.5. The classic Delphi (CD) decision-making

In this study, the CD method is utilised for decision-making, as illustrated in the flowchart in Fig. 7 (Elmer et al., 2010). The CD method in this study involved 15 experts from three Iranian universities: Ferdowsi University of Mashhad (FUM), Birjand University of Technology (BUT), and the University of Tehran (UT) (Gheibi et al., 2018). These experts are alumni and faculty members with postgraduate degrees in relevant fields. The decision-making process comprises three stages. First, all possible flood risk mitigation strategies are collected and compiled in an archive. Second, the experts are presented with each strategy and asked to provide their opinions and score each one based on their individual expertise. Third, the experts analyse and evaluate each strategy, and their viewpoints both for and against each strategy are recorded and shared with all experts. Strategies with more than 60% support from the experts are approved and selected, while those with less support are not. This step is repeated three times, and finally, all
Fig. 6. The HAZOP algorithm used in this study for flood risk assessment.

Fig. 7. The CD algorithm used for decision making in this study.
accepted strategies are prioritized based on their importance.

3. Case study

The methodology presented in this study is applied to a case study in the arid and semi-arid region of Khosf, located in the South Khorasan province of Iran (Fig. A.4). This region has been affected by severe floods in recent decades and has been the subject of various research studies (Mikaniniki et al., 2019). Despite being mostly a desert, the region has a limited ground cover, with seven species including *Seiditisa Rosmarinus, Peganum Harmalla, Haloxylon Aphyllon, Heliotropium Europaceae, Hordeum Bulbosum, spp Alhaji, Gundelia Toriforti-Stipa Barbata, Artemisia Sieberi, and Artemisia Oucheri-Poa Bulbosa.* (Izanloo et al., 2019). The ground cover in Khosf is classified into four categories, as shown in Fig. A.5 with varying levels of flood resilience: strong, semi-strong, average, and weak.

Over the past forty years, the average monthly rainfall in South Khorasan province has been only 9.1 mm. In comparison, the central plateau of the country, which is geographically similar to this province, receives more than 18.5 mm of rainfall on average each month. Despite the low rainfall, the Khosf region of South Khorasan has experienced four destructive floods in 2005, 2010, and 2015. Table 2 shows the average monthly rainfall for those years and the estimated flood damage caused each year, as reported by the Water Management Organisation of South Khorasan.

4. Results and discussion

The study used GIS to create a digital map of the Khosf region for WMS modelling, based on geo-statistical data and the integrated GIS-WMS platforms as the steps shown in Fig. 8. The WMS software was used to compute a hydrological map of the catchment based on the average rainfall data (Fig. A.6a). The hydrograph (Fig. A.6b) showed a peak flow of 28.35 (m³/s) for a total duration of 420 min, resulting in a flood volume of 474,900 (m³). These results suggest that the Khosf region is vulnerable to flooding, and hence the WMS modelling outputs can be used for managing and mitigating flooding risks in the region.

The rainfall data used in this study were recorded daily as the average value of hourly data. However, to accurately compute flood flow in the WMS model, hourly precipitation data is required. To account for this, we employed a sequential WMS modelling approach that incorporates hourly flood precipitations to estimate the flood flow.

The data required for ML computations in this study are obtained as described below (variations of recorded data can be seen in Fig. A.7). We used the outputs of the WMS simulation as flood data for the input layer in the ML computations for various catchment conditions. Using hydrologic modelling in WMS, we collected flood flow data (m³/s) for 210 records in the Khosf region, along with data related to catchment and environmental characteristics, including temperature (°C), vegetative ground cover (type), precipitation (mm), and the corresponding damage costs (MUSD in millions of US$) resulting from flood occurrences. Fig. 9 presents the heat maps of the correlations between different effective data in the case study as a pair-wise comparison of the correlation coefficient where lighter colours show a higher amount and darker colours show a lower range of amounts. Fig. 9 demonstrates that the occurrence of floods depends more on damage cost and flood flow, with correlation coefficients of 0.87 and 0.86, respectively, than on other parameters. In contrast, the temperature has the lowest correlation with flood occurrence.

The key features of the input layer data are summarised as follows: temperature ranging between 12 and 22 °C, four types of vegetative ground cover, precipitation ranging from 0 to 15 mm, flood flow ranging between 10 and 30 m³/s, and damage cost ranges up to 5 MUSD (the box plot of these data is available in Fig. A.8). The output layer includes a binary flood occurrence with values of 0 and 1 indicating no flood and flood occurrence, respectively. In this case study, the four types of vegetative ground cover were scored by experts between 1 and 4, with each score representing a different level of flood resilience. Resilience is influenced by various parameters, and among them, vegetation cover type and density play a significant role. The ability to modify vegetation cover through operational activities in the field with relatively low investments underscores the importance of this feature in enhancing resilience. Vegetation cover serves as a natural protective barrier against environmental hazards and contributes to the overall stability of ecosystems. The type of vegetation, such as forests, grasslands, or wetlands, determines its specific characteristics and functions. Different types of vegetation can offer distinct benefits in terms of erosion control, water regulation, biodiversity support, and climate regulation. Furthermore, the density or extent of vegetation cover greatly influences its effectiveness in mitigating risks and promoting resilience. Dense vegetation cover acts as a formidable shield against soil erosion, reduces surface runoff, and enhances water infiltration. It helps to stabilize slopes, prevent landslides, and minimize the impact of flooding events. The advantage of vegetation cover lies in its adaptability and relatively low-cost implementation. Through operational activities such as afforestation, reforestation, or the establishment of green infrastructure, it is possible to modify and enhance the existing vegetation cover. This can be achieved by planting trees, promoting the growth of natural vegetation, implementing agroforestry practices, or restoring degraded ecosystems. Investments in vegetation cover can yield multiple benefits, both in terms of short-term risk reduction and long-term sustainability (Dahri and Abida, 2017). These levels are classified as strong, semi-strong, average, and weak (a picture of each typical vegetative ground cover is available in Fig. A.5).

Once the hydrologic modelling was completed and data were collected for developing AI, machine learning was built in two parts. The first part used three classification algorithms - SVM, NN, and NNC - to determine whether a flood would occur or not. The second part used the LPR algorithm to estimate the corresponding damage caused by the possible flood and to suggest safe measures for mitigating flood risk. Coefficient of determination (R²) indicator is a widely recognised and easily interpretable metric that represents the proportion of the variance in the dependent variable (outcome) that is explained by the independent variables (features). The high coefficient of determination (R²) of the three algorithms – SVM, NN, and NNC given in Table 3 demonstrates their efficiency in predicting flood occurrence. In addition, the model performance for other error indicators of flood occurrence including root mean square error (RMSE), mean absolute error (MAE), or smooth absolute error (SAE) are also shown in Table 3. While SVM and NNC present the best correlation coefficients in comparison to SVM with respect to R², the error function results demonstrate that the NNC algorithm has the best performance for prediction of flood occurrence. Fig. 10a-e depict partial residual plots that display the estimated relationships between various flood variables and the status of flood or non-flood occurrence for different types of vegetative ground covers. These plots are accompanied by confidence bands and highlight the impact of various factors on flood occurrence and damage costs. Note that the status of flood or non-flood occurrence is based on the definition

<table>
<thead>
<tr>
<th>No.</th>
<th>Average Rainfall (mm)</th>
<th>Estimated damages (Million US $)</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.9</td>
<td>1</td>
<td>2005</td>
</tr>
<tr>
<td>2</td>
<td>7.3</td>
<td>3</td>
<td>2010</td>
</tr>
<tr>
<td>3</td>
<td>10.4</td>
<td>5</td>
<td>2015</td>
</tr>
</tbody>
</table>
of the Water Company when flooding and flow spills over rivers result in specific damage to properties and agricultural lands. The plots reveal that for the state of no reported flood (denoted by blue colour) in Fig. 10a, the damage costs for various precipitations are almost uniform in the first three types of land cover (i.e., independent from precipitation). However, for the cases of reported flood occurrence, higher precipitation results in higher damage cost only for land cover type 2 and 3, while the damage costs remain constant for land cover type 1.

The estimated linear regression in Fig. 10b shows that flood flow is either directly or inversely proportional to precipitation in vegetation cover types 1 (in non-flood condition) and 4 (in flood condition), with different rates for various land covers. This relationship may be due to the impact of the vegetative ground cover type on the overland runoff and flood flow, especially when it is located in the highest resilience against flood disaster (i.e., vegetative ground cover type = 1). The impact of vegetative ground cover is more pronounced between flood and non-flood occurrences. For example, flood flows are directly proportional to precipitation in flood occurrences, while non-flood occurrences.
occurrences are inversely proportional to precipitation. The impact of vegetative ground cover type has also been reported by other research works (Fazel-Rastgar., 2020; Psomiadis et al., 2019). The estimated relationship between flood flow and temperature is shown in Fig. 10c. For vegetative ground cover type 1, the plots reveal an inverse proportional relationship between the variables. This indicates that no classic

Fig. 10. Partial residual plots and estimated relationship between the flood variables with associated confidence band based on four vegetative ground covers for (a) precipitation vs damage cost; (b) flood flow vs precipitation; and (c) flood flow vs temperature; note the blue denotes non-flood occurrences and red denotes flood occurrences based on the definition of the Water Company. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 11. The relationship of flood flow & precipitation for each vegetative ground cover type; note flood = 0 indicates non-flood occurrence and flood = 1 indicates flood occurrence (a-h).
relationship can be defined between these flood variables and hence ML tools can be useful in identifying this relationship.

Fig. 11a-b depict the relationship between flood flow and precipitation for different types of vegetative ground cover to determine when flooding is likely to occur. More specifically, flooding occurs when the flow rate exceeds 15 m$^3$/s, regardless of the type of ground cover. Additionally, higher levels of rainfall (over 10 mm) are generally associated with greater occurrences of flooding in the region, as indicated by the corresponding flow rates although flood occurs for small rainfall depth in some cases as indicated in Fig. 11b.

Regression algorithms based on AI are utilised to predict damage costs. Table 4 presents the R$^2$ scores, RMSE, SAE and MAE for four different LPR regression methods that were tested to predict overall damage costs. These LPR algorithms consist of one linear regression model and three polynomial regression models with various orders ranging from 1 to 3. The results indicate that the linear model is the most effective, followed by the polynomial model with a second order. Based on the model performance for forecasting flood in different orders of LPR algorithm occurrence, the second order has the best performance compared to other orders in all four indicators. Additionally, higher-order models may result in a slight reduction in the correlation rate, making them less appropriate for this task. Table 5 shows the coefficients of the LPR models that were developed, indicating the most significant parameters for forecasting cost damage. Flood occurrence, precipitation, vegetative ground covers, and flood flow are found to be the most impactful parameters, in that order.

This study presents a statistical model using multiple linear regression analysis to predict flood occurrence based on temperature and precipitation data with regards to performance indicators such as the R$^2$-squared and adjusted R$^2$-squared values. In addition, the flood risk is then evaluated based on defining three risk level of high, medium, or low for predicted flood values as below:

High risk: Flood prediction $\geq 0.5$.
Medium risk: $0.2 \leq$ Flood prediction less than 0.5.
Low risk: Flood prediction less than 0.2.

To evaluate the model performance (i.e., the accuracy of the flood predictions), this study applies confusion matrix concept based on the calculations of true positives, true negatives, false positives, and false negatives for flood predictions (Piadeh et al., 2023). The accuracy metric measures the proportion of correctly predicted instances out of the total dataset. Precision represents the proportion of true positives out of all the predicted positives, while recall represents the proportion of true positives out of the actual positives. The combination of precision and recall into a single metric is called the F1 score, as an overall measure of prediction quality (Fig. 12). In this case, the overall model accuracy is calculated as 0.70952 representing the proportion of correctly predicted instances (both floods and non-floods) out of the total dataset. In other words, approximately 70.95% of the flood occurrences were correctly predicted by the model. The precision of the model is calculated as 0.73196. Precision measures the proportion of true positives (correctly predicted floods) out of all the predicted positives. In this case, the model predicted 97.95% of the flood occurrences were true flood occurrences.

To assess the performance of the model in terms of precision, recall, and F1 score, the performance metrics for each order of LPR models were calculated. The F1 score is the harmonic mean of precision and recall and provides a balanced measure of the model's performance. An F1 score of 0.69951 suggests a reasonable balance between precision and recall, indicating that the model performs reasonably well in predicting both floods and non-floods. The total precipitation value is determined to be 1552. This suggests a reasonable balance between precision and recall, indicating the model's ability to effectively predict both floods and non-floods.

The online prediction system developed in this study should also be utilised to send temporal alarms to human resources and managers. Based on Fig. 15, the results of the HAZOP and FMEA techniques confirm that critical situations in high-risk points occur at flood flows exceeding 24 m$^3$/s. These points cover large areas with agricultural and rural land use, and therefore, all crisis management measures and facilities should be used to control the damage during high-risk situations. The online prediction system developed in this study should also be utilised to send sent segmental alarms to human resources and managers. In point A, flood flows ranging from 15-24 m$^3$/s (with a 3C risk value) result in the second level of damages and require implementation of controlling activities in the next step. All other risk situations are considered manageable, and the crisis management system has sufficient time to control the damages. However, according to the HAZOP and FMEA techniques, points A, C, and C are highly dangerous and have low resiliency. Therefore, to approve controlling activities before and during flood disasters using the CD method, there are two categories: High-Risk Regions (HRR) including points A and C, and High Resilience Areas (HRA) including point B.

Table 4

<table>
<thead>
<tr>
<th>Regression type</th>
<th>Order</th>
<th>R$^2$</th>
<th>RMSE</th>
<th>SAE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>1</td>
<td>0.81</td>
<td>0.53</td>
<td>17.93</td>
<td>0.42</td>
</tr>
<tr>
<td>Polynomial</td>
<td>2</td>
<td>0.82</td>
<td>0.52</td>
<td>18.35</td>
<td>0.43</td>
</tr>
<tr>
<td>Polynomial</td>
<td>3</td>
<td>0.82</td>
<td>2.03</td>
<td>63.44</td>
<td>1.51</td>
</tr>
<tr>
<td>Polynomial</td>
<td>4</td>
<td>0.80</td>
<td>5.60</td>
<td>173.46</td>
<td>4.13</td>
</tr>
</tbody>
</table>
Table 5
The coefficients of the regression equation in this study.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Temperature (°C)</th>
<th>Vegetative Ground Cover (type)</th>
<th>Precipitation (mm)</th>
<th>Flood Flow (m³/s)</th>
<th>Flood Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Coefficients</td>
<td>-0.008</td>
<td>0.087</td>
<td>0.097</td>
<td>0.029</td>
<td>1.527</td>
</tr>
<tr>
<td>Polynomial Coefficient</td>
<td>-0.011</td>
<td>0.116</td>
<td>0.097</td>
<td>0.016</td>
<td>1.698</td>
</tr>
</tbody>
</table>

Fig. 12. The hydro-statistical risk assessment of this study.

Fig. 13. High-risk points (A, B and C) in the case study with the following key features for L1 and L2; L1: (A = 15.43 km², P = 9092.38 m, Shape = 2.87 m⁻², Sin = 0.41 (MSL/L), AVEL = 1756.41 m, MFD = 9226.58 m, MFS = 0.0392 mm⁻¹, CSD = 997.49 m, CSS = 0.0401 mm⁻¹) and L2: (A = 1.15 km², P = 4747.6 m, Shape = 38.23 m² m⁻², Sin = 0.15 (MSL/L), AVEL = 1741.20 m, MFD = 7396.24 m, MFS = 0.0161 mm⁻¹, CSD = 712.13 m, CSS = 0.1429 mm⁻¹).
both HRR and HRA, and the results are presented in Fig. 16. Additionally, Table 6 provides a comprehensive list of all approved strategies, which were collected based on the input of experts. The information presented in Fig. 16 indicates that the CD method prioritises flood risk management in HRR1, HRR2, and HRR5 for A and C regions, as supported by Iqbal et al. (2021), Ghosh et al. (2022), and Parvez et al. (2022), respectively. In addition, for point B, HRA2 and HRA4 are identified as the most important priorities, as also suggested by Pally and Samadi (2022) and Hong and Abdelkareem (2022), respectively.

The Flood Action Plan (FAP) has been developed and presented from various perspectives and scales in different studies. Some studies have aimed to increase citizen responsibility and government performance in flood damage prevention (Brammer, 2010), while others have focused on irrigation, animal livelihood, and pollution control in more developed countries (Newson et al., 2022). In this study, the FAP concentrates on local operation functions and short reaction times, with a focus on utilising all facilities for human health control in developing countries (Akbarian et al., 2022b). The presented plan considers hydrological, social, economic, and political factors as well as available human resources.

Another approach to the FAP is the online assessment of water volume in natural channels using satellite images, as seen in El Faid City, Morocco (Ali et al., 2022). However, this study’s crisis management approach is based on available facilities and potential risks, which can
be further supported by experts and managers. The methodology used in this study is based on endogenous solutions, with experts serving as the executive trustee board for accurate implementation during a flood. In the other approach, Khamutova et al. (2022) developed an idea for the presentation of dynamic FAP based on the volume of damage in different regions. Likewise, in the present research, and risk analysis, the corresponding solutions are conveyed in different scenarios and conditions. In fact, the model developed in this study covers all hydrological, social, economic, political and available human resources.

In the present study, the crisis management approach is based on the available facilities and potential risks that can be more supported by experts and managers. In other words, the policy applied in this study was based on endogenous solutions (Kumar et al., 2022). However, the limitations of the present study can be divided in three sections, model uncertainty, data limitations and representativeness and, simplified assumptions. About the model uncertainty, the methodology relies on the use of various modeling techniques, including flash flood simulation modeling, statistical methods, and artificial intelligence algorithms. These models have inherent uncertainties and limitations. The accuracy of the flash flood simulation model (WMS) depends on the representation of hydrological processes and the input data used. The statistical methods applied for data trimming may introduce subjectivity and potential bias in the data selection process. The AI algorithms (SVM, ANN, and NNC) used for flood prediction and classification are based on assumptions and trained on available data, which may not capture all the complex factors influencing flash floods. These uncertainties in the models can affect the reliability and robustness of the results and should be considered when interpreting the findings. Data limitations and representativeness could be subjected to the dependence of the methodology on the data collection from the Khosf region in Iran. The representativeness of this data for the broader population or other arid regions is unclear. The data used for flood simulation modeling, statistical analysis, and AI training may not fully capture the range of environmental and climatic conditions that can exist in different regions. Consequently, the generalizability of the results and the applicability of the framework to other arid regions may be limited due to the specificity of the data used in the study. Moreover, the availability and quality of historical data may also impact the accuracy and reliability of the models and subsequent analyses. Also, the methodology involves the use of simplified assumptions and techniques to evaluate and assess risks in vulnerable regions. The geographic evaluations utilizing GIS and the application of FMEA and HAZOP methods may simplify the complexity of risk factors and their interdependencies. These simplifications can overlook certain nuanced aspects of risk, such as socio-economic factors, local knowledge, and institutional dynamics, which are critical for comprehensive risk management. Consequently, the framework’s ability to capture and address the full spectrum of risks and their impacts may be limited by the assumptions and simplifications made in the methodology.

The Monte Carlo method is also used in this study to perform sensitivity analysis using Sobol’s indices in MATLAB (2019b). This analysis aims to assess the individual contributions of input variables (temperature, vegetation cover, precipitation, and flood flow) to the occurrence of floods. The input variables are combined into a matrix called X, which serves as the basis for the subsequent analysis. The Sobol’s indices are then calculated using the Sobol function. This function employs a permutation-based approach, iterating over each input variable. For each variable, its values are permuted while keeping the other variables constant. A linear regression model is fitted using the permuted input matrix and the output variable (flood occurrence). The resulting R-squared values, representing the proportion of variance in flood occurrence explained by each input variable, are stored as Sobol’s indices in an array that is shown as a Tornado diagram demonstrated in Fig. 17.

Flood flow, with a Sobol’s index of $4.7 \times 10^3$, holds significant importance in flash flood occurrences. Flash floods are sudden and localised rises in water levels and flow rates in rivers and streams. Various factors, such as watershed size, land use changes, channel morphology, and river network properties, influence the magnitude of flood flow. Accurate flood forecasting and warning systems require understanding the relationship between flood flow and flash floods. Timely monitoring of river levels, flow rates, and hydrological conditions enables anticipation of flash flood events and early warnings to at-risk communities. Analysing flood flow patterns helps hydrologists and emergency management agencies make informed decisions on.
storms, frontal systems, or orographic lifting. The precipitation index, primarily driven by intense and localized precipitation events. These events result from various meteorological phenomena, such as convective storms, frontal systems, or orographic lifting. The precipitation index, with a value of $2.9 \times 10^{-3}$, emphasises its strong influence on flash flood occurrences. Understanding the characteristics of precipitation events is crucial for effective flash flood risk assessment and forecasting. This includes evaluating factors such as the intensity, duration, and spatial distribution of rainfall. By improving precipitation monitoring systems, early warning capabilities, and predictive models, it becomes possible to enhance flash flood preparedness and response. Timely and accurate information about precipitation patterns, including the identification of heavy rainfall events and their potential impacts, can help authorities issue appropriate warnings, implement evacuation measures, and coordinate emergency response efforts. Furthermore, ongoing research and technological advancements in precipitation forecasting can contribute to the development of more robust and reliable flash flood prediction models, ultimately leading to enhanced resilience in flash flood-prone regions (Chiang et al., 2007).

Vegetation cover plays a vital role in flash flood dynamics. Vegetation acts as a natural buffer by intercepting rainfall, promoting infiltration, and reducing surface runoff. It helps regulate water flow and prevents the rapid generation of runoff during intense rainfall events, mitigating the risk of flash floods. Additionally, vegetation cover contributes to the overall stability of slopes and reduces soil erosion, which can further minimise flash flood hazards. Changes in land use, such as deforestation or urbanisation, can substantially alter vegetation cover, resulting in decreased infiltration rates, increased surface runoff, and elevated flash flood risks. Therefore, protecting and restoring vegetation cover in flash flood-prone areas is crucial for reducing vulnerability to flash floods and maintaining the natural hydrological balance. Strategic land management practices, afforestation efforts, and land-use planning that prioritise vegetation conservation can contribute to effective flash flood mitigation strategies and enhance overall resilience to flash flood events (Mohamed and Worku, 2021).

In the sensitivity analysis, the temperature has a weight of $-0.95 \times 10^{-3}$, indicating a reverse relationship with flood occurrence, according to the Monte Carlo assessment. Flash floods are often triggered by intense rainfall events, and temperature plays a crucial role in modulating the meteorological conditions that lead to such events. Higher temperatures can increase the evaporation rate, potentially resulting in more moisture in the atmosphere. This increased moisture availability, combined with other atmospheric factors, can contribute to the formation of convective storms that generate heavy rainfall and, consequently, flash floods. The significant Sobol’s index for temperature ($-0.95 \times 10^{-3}$) indicates that changes in temperature can have a substantial impact on flash flood occurrences. As temperatures rise due to climate change or natural variability, the likelihood of extreme rainfall events and flash floods may also increase. Therefore, understanding the relationship between temperature and flash floods is crucial for effective flash flood management and adaptation strategies (Gámez et al., 2016).

Precipitation plays a critical role in the occurrence of flash floods, as they are primarily driven by intense and localized precipitation events. These events can result from various meteorological phenomena, such as convective storms, frontal systems, or orographic lifting. The Sobol’s index for precipitation, with a value of 0.73, emphasizes its strong influence on flash flood occurrences. Understanding the characteristics of precipitation events is crucial for effective flash flood risk assessment and forecasting. This includes evaluating factors such as the intensity, duration, and spatial distribution of rainfall. By improving precipitation monitoring systems, early warning capabilities, and predictive models, it becomes possible to enhance flash flood preparedness and response. Timely and accurate information about precipitation patterns, including the identification of heavy rainfall events and their potential impacts, can help authorities issue appropriate warnings, implement evacuation measures, and coordinate emergency response efforts. Furthermore, ongoing research and technological advancements in precipitation forecasting can contribute to the development of more robust and reliable flash flood prediction models, ultimately leading to enhanced resilience in flash flood-prone regions (Chiang et al., 2007).
5. Managerial perspective and decision support systems

The findings of the present study need to be put into practice for study to be useful. More specifically, this area of Iran is prone to destructive floods, and sustainable development can serve as a reliable guide for managing this issue effectively (Gheibi et al., 2022). The study is closely linked to two parameters of sustainable development: good health and well-being (Mohammadi et al., 2021; Erfani et al., 2019) and sustainable cities and communities (Gheibi et al., 2018; Shahsavar et al., 2021).

As there has been an increasing trend in the use of decision support systems (DSS) in recent years (2014–2022) (see bibliographic analysis in Fig. A.9), we propose a DSS as illustrated in Fig. 18 based on the findings in this study. DSS platforms generally have a wide range of applications and can be particularly useful for rapidly detecting problems and pursuing sustainable management practices. The DSS proposed in this study involves weather and field monitoring to collect historical data, which can be used to develop AI models for forecasting future conditions. The accurate data gathered through digital modelling applications such as GIS and WMS serves as the basis for various AI equipment used to build ML models. The system also involves analysing potential crisis scenarios with the help of experts to better manage them and ensure the safety and security of cities. It is important for managers/decision makers to consider using these smart systems to better manage flood crises by prioritising flood risks and implementing appropriate solutions to mitigate them.

The other aspect of the work concerns sustainable development in terms of good health and well-being. The decision support system proposed by the study can be environmentally friendly in terms of flood and water storage management, increasing safety and stabilising the economic conditions of the area (Shahsavar et al., 2022). Ultimately, by providing a reliable and accurate database, experts and decision-makers can make informed decisions that promote good health and well-being and sustainable cities and communities.

6. Future research

This study employs several AI methods (e.g., SVM, NNC and ANN) to predict and classify flash flood occurrences. However, there are plenty of other AI algorithms that are yet to be applied for solving challenging decision problems about this study. For example, to simplify the berth scheduling at marine container terminals and reduce the overall vessel service cost, a novel memetic method with deterministic parameter control has been developed by Dulebenets (2017). The study employed a local search heuristic that uses the first-come, first-served principle at the chromosomes and during the initialisation of the population stage in the developed memetic algorithm. Moreover, a learning approach is suggested by Zhao and Zhang (2020) in order to improve generalisation capabilities to solve many objective problems. A learning automaton (LA) is incorporated into the algorithm on the foundation of a many-objective optimisation framework based on decomposition. Furthermore, in order to help with the cross-docking terminal trucks (CDT) operations planning, a new Adaptive Polyploid Memetic Algorithm (APMA) has been developed by Dulebenets (2020) for the issue of...
scheduling CDT vehicles. Kavoosi et al., (2019) developed a novel island-based metaheuristic algorithm to solve the marine transportation berth scheduling problem and reduce the total cost of accommodating arriving boats at the marine container terminals. To search for islands, four different population-based metaheuristics are used in this study, including the evolutionary algorithm (EA), particle swarm optimization (PSO), estimation of distribution algorithm (EDA), and differential evolution (DE). In addition, in order to discover the best order of routes for each ambulance and reduce the latest service completion time as well as the number of patients whose conditions deteriorate as a result of obtaining delayed medical care, Rabbani et al. (2021) employed a mixed-integer linear programming model. Finding high-quality solutions quickly is done using Multi-Objective Particle Swarm Optimisation (MOPSO) and Non-dominated Sorting Genetic Algorithm II (NSGA-II). Pasha et al., (2022) created a novel multi-objective optimisation model for the vehicle routing problem with a factory-in-a-box that tries to reduce the overall cost associated with traversing the network’s edges and the total cost associated with visiting network nodes. As a solution strategy, a customised multi-objective hybrid metaheuristic solution algorithm that explicitly considers problem-specific features is devised. This study also suggests conducting a comparative analysis of different flood simulation modeling tools, such as Watershed Modelling System (WMS), with other available models to assess their accuracy and suitability for arid regions. This aims to compare their performance in different geographical and climatic contexts to identify the strengths and limitations of each model. This analysis can also provide insights into the most appropriate modeling tool for different regions and improve the reliability of flood simulations. Furthermore, exploring the integration of diverse data sources, including satellite imagery, remote sensing data, climate models, and social data, to enhance the accuracy and reliability of the risk management framework. By incorporating a wide range of data types and sources, the framework can capture a more comprehensive understanding of the factors influencing flood risks in arid regions and improve the effectiveness of risk assessment and decision-making processes. In addition, integrating socio-economic factors into the risk management framework for better understanding of the impacts of flash floods on communities in arid regions plus considering aspects, such as population density, infrastructure vulnerabilities, economic indicators, and social dynamics. Furthermore, conducting in-depth stakeholder engagement activities is crucial to ensure the framework’s relevance and acceptance by local communities, policymakers, and other relevant stakeholders. Additionally, exploring the integration of participatory decision-making approaches and stakeholder feedback mechanisms can enhance the inclusivity and effectiveness of the decision-making module in the framework.

7. Conclusions

This study developed a smart framework for assessing flash flood risk to improve community resilience in arid regions. The framework consists of three components: (1) integration of GIS-WMS computations to create flash flood predictions using soft-sensors; (2) development of a valid decision databank through the integration of Classic Delphi method and risk assessment techniques for flash flood events; (3) combination of WMS simulation with FMEA/HAZOP risk models to identify hazardous sites during flash flooding. The main objectives of the study were to: (1) assess the feasibility of using AI-based soft-sensors for early flood warning; (2) minimise the time required for decision-making during flash flood events through smart flood risk management; (3) provide useful managerial insights by proposing a DSS in flash flood disasters.

The GIS-WMS model proved to be highly accurate in providing values for flash-flood flow, which were used to populate the databank of AI systems. Regression evaluations revealed that precipitation and vegetative ground covers had the most significant effect on flash flood damage costs in the study. The most efficient algorithms for classification and prediction were found to be NNC (with an $R^2$ value of 0.89) and two-–three degrees of polynomial regression (with an $R^2$ value of 0.82).

The results in the case study showed, using both FMEA and HAZOP risk analysis methods, points A and C were classified as HRR, and the CD method identified the best solution for reducing flood damage costs at these points as HHR1. This solution involved the installation of surveillance cameras equipped with image processing systems to detect rising water in the seasonal riverbed quickly, with 86% of experts agreeing in the first cycle. Point B was classified as HRA, and the most effective solution for this point was similar to the previous points (A and C) and involved the implementation of image processing technology, with 66% of experts agreeing in the first cycle. This framework and the findings of this study can help in developing better early action and fast reaction flood control systems for the areas that are at high risk of flash floods especially in developing countries by providing valuable managerial insights in flash flood disasters. This can also help for better early action and fast reaction of flood control systems.

Comparing different geographical lands in terms of hydrologic modelling and AI application would provide valuable insights and help create a more comprehensive decision support system. Additionally, using AI-computer vision techniques could be a promising alternative to the current integration of WMS and GIS. Furthermore, the combination of CD and risk analysis online could lead to an even more efficient flood control system. Additionally, the application of System Dynamic models could be an attractive option for smart decision-making in flood risk control. Lastly, the idea of coupling System Dynamic models with knowledge management in flash-flood control approaches and creating Dynamic Knowledge Management is an innovative concept that could lead to improved decision-making in the field. These suggestions could inspire future research and help advance the field of flood risk management.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110457.

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