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Flash flood inundation assessment for an arid catchment, case study at Wadi Al Jizzi, Oman

Eyad Abushandi* and Moza Al Sarihi

Civil Engineering Stream, Faculty of Engineering, Sohar University, Sohar, Sultanate of Oman
*Corresponding author. E-mail: eshandi@su.edu.om, eabushandi@gmail.com

EA, 0000-0001-6160-6186

ABSTRACT

Lack of high-resolution data and inappropriate integration of different data sources make modelling flash flood even more complicated. The IHACRES and AHP models were used to estimate floods for the period 1987 to 2007 for Wadi Al Jizzi arid catchment. The IHACRES model results showed that the average simulated flood was 0.36 m^3/s, while that observed for all flood storms was 0.30 m^3/s. The average readjusted AHP Simulated Flood for three statically defined clusters: low, moderate, and high rainfall was 3.55, 3.20, and 3.75 m^3/s, respectively. The average observed flooding for low, moderate, and high rainfall were 3.23, 1.54, 3.07 m^3/s. Pearson correlation between observed and simulated flood showed significant values for IHACRES and AHP with a range of 0.84 and 0.89 respectively. The Nash-Sutcliffe efficiency of the IHACRES model was 0.78, while it shows a good performance for low and high AHP re-adjusted values, which was 0.81 and 0.82.

Key words: AHP, arid catchment, flash flood, IHACRES

HIGHLIGHTS

- Identification of extreme hydrologic events for arid areas is developed.
- The applied two models were able to represent the actual flood even with limited number of storms.
- The AHP performed better than IHACRES in simulating flood events.
- For arid areas, hydrologic models require additional readjustment to better simulate flood.
- Correlation between the several hydrologic parameters is identified.

INTRODUCTION

There are many reasons for unexpected flash floods including climate change, physical and topographic complexities, and the variability of extreme conditions. They are also expected to have higher rainfall intensity and much more localized storms. Therefore, the magnitude of flash flooding during each event is a great challenge to predict flow behaviour after a rainstorm. Apart from the reasons mentioned, there are additional reasons for flood modelling difficulties in arid areas (Abushandi & Merkel 2013) such as:

i. lack of data,
ii. difficulties in access catchment area during rainy periods,
iii. great diversity in altitudes,
iv. isolation of most monitoring stations.

Evaporation also increases with an increase in bare soil surfaces in the area; hence, it is important to know the frequency and duration of droughts and severely wet conditions. Typically, evaporation and transpiration in arid regions account for at least 90% or more of precipitation (Haan *et al.* 1994). While there is a pressing need to model the flash floods accurately, it is also necessary to develop a strategy for water harvesting in the region, for direct use and recharging of ground water to reduce flood damage. Abushandi (2016) simulated flood events for a hyper-arid catchment in Saudi Arabia. In this study, two models were used. The first model was a unit identification hydrograph, formed by the components: precipitation, evaporation, and flow of water (IHACRES), while the second method was SCS-UH.

Mahmoud & Gan (2018) presented a study to categorise flooding-prone arid areas and identify the factors that cause floods. They used an analytical hierarchy process (AHP) to estimate flood magnitudes and to classify the area into five categories. Piyumi *et al.* (2021) assessed seven alternatives by utilising the AHP based on 2-hour durational precipitation. Sutradhar *et al.* (2021) used 11 influencing factors in AHP to delineate hydrologic maps. Moreover, Elkhrachy (2015) used the AHP and SCS-UH methods to determine the causative agents of flooding where all of the factors causing flooding (slope, infiltration and flow) were searched and entered into ArcMap, to create flood risk maps for each sub-catchment. Moreover, El-Magd *et al.* (2020) used the AHP method and the geographical information system (GIS) to produce a flood risk map and identify the factors causing floods. However, authors applied AHP found the runoff coefficient to estimate flood magnitudes which basically based on the consistency measures and parameter's weight using multi-criteria decision analysis (MCDA). Depending on the importance of hydrologic parameters for individual catchment, parameters were selected, and the degree of influence was evaluated.

According to the AHP methodologies conducted by many researchers, the most influential factors are soil type, slope, elevation, and drainage density.

Similarly, Abushandi & Merkel (2013) made a hydrologic study to model flash floods in Jordan and frame a new methodology to estimate flooding for a single storm event. They used two models, namely HEC-HMS and IHACRES. Hydrologic data were collected from multiple sources and the area was divided into categories according to the land use and land cover types. The HEC-HMS model showed better performance than the IHACRES model. In general, both models demonstrated the ability to simulate flow in the arid region. Ahmadi *et al.* (2019) compared three models namely SWAT, IHACRES, and ANN to simulate rainfall-runoff process in an arid watershed; however, the results showed that the performance of IHACRES model were better than the other two. Recently, Lerat *et al.* (2020) simulated rainfall data to monthly streamflow data using IHACRES model. The model showed a great applicability for selected catchment. Furthermore, El Bastawesy *et al.* (2019) studied flash flooding using remote sensing systems and estimated groundwater recharge in each sub-catchment. They used the Archydro extension in ArcGIS software to analyse the DEM of showing flow paths, creating a geological map and a laboratory flood simulation. Hussein *et al.* (2020) studied the effects of changing land use on flooding, using remote sensing and geographic systems with monthly acquired satellite images coupled with field measurements. The area was classified into five categories: mountains, sandy areas, water, vegetation, and buildings. Soil Conservation Service (SCS) or the curve number method (CN) was used to estimate surface runoff. The results showed that urbanisation causes more floods and more damage. In addition, AHP and IHACRES models were successfully applied into arid catchments where monitored data are rare. While IHACRES model is characterized by simple generic structures, AHP depends on expert opinion and its flexible to add or neglect unnecessary alternatives.

Hasanloo *et al.* (2019) studied the flood hazards based on a multi-parameter spatial set of AHP. Through this tool, the input data is categorized based on the possibility of being a member of a specific group where 0 indicates that the specified sites are not a member of the specified group, and 1 is assigned to those that are a member of the specified group. The results of the study showed that the effective factors in the occurrence of floods were best evaluated, and the sub-categories weighed for each layer, during which the flood area was divided according to the flooding of the area and the abundance of torrential events.

Wijitkosum & Sriburi (2019) analysed and assessed the risks of desertification in the upper Phetchaburi River basin through AHP tools. They compared the values of individual criteria in each hierarchy such as climate, soil, land cover type, and slope. The specific relative weight of each drought factor was calculated using pairwise comparison data between each pair of criterion risks in the same hierarchy.

Heavy rainfall and thunderstorms occurred in Wadi Al Jizzi causing serious damage to the infrastructure of Sohar City located at the catchment outlet. In the recent 20 years dramatic flooding events occurred in Wadi Al Jizzi in the years 2002, 2007, 2008, 2010, 2011, 2014, 2015, 2016, 2018, 2019, and 2021 showed that the frequency of extreme floods rate is increasing with time.

However, limited number of hydrologic studies have been conducted in Oman to estimate flood magnitudes and damage severity. Therefore, the aims of this research are to identify the causes of flash flood and assess the feasibility of applying AHP and IHACRES models for storms in the Wadi Al Jizzi catchment. In addition, critically analyse the selected model's performance in the study area. Furthermore, the research provides a platform on which future projects can be developed using the present methodology.

Study area

Wadi Al Jizzi catchment is the major wadi flowing from Al Hajar Al Gharbi Mountains in the west to Sohar city in the east (Figure 1). Sohar is the largest city of the Al Batinah North Governorate in the Sultanate of Oman and lies along the Gulf of Oman. The population is approximately 140,000 and the main economic activities are agriculture, fishing, and industry. Sohar climate forecasts are primarily based on the influence of two major climate systems, the Oman Gulf climate (or Oceanic Climate) in the East and Arid Climate, in the West of Oman. Both climate systems are characterised by a narrower annual rainfall gradient and high temperature gradient. In addition, the transient climate is not only expressed by the Oceanic or hyper-arid climate but by rapid variations of temperature, precipitation, and other aspects over a time scale. A climograph combines the selected monthly average rainfall data and minimum temperature line graph, as in Figure 2. In arid areas, the rainfall and flood events occurred when the temperature is minimum.

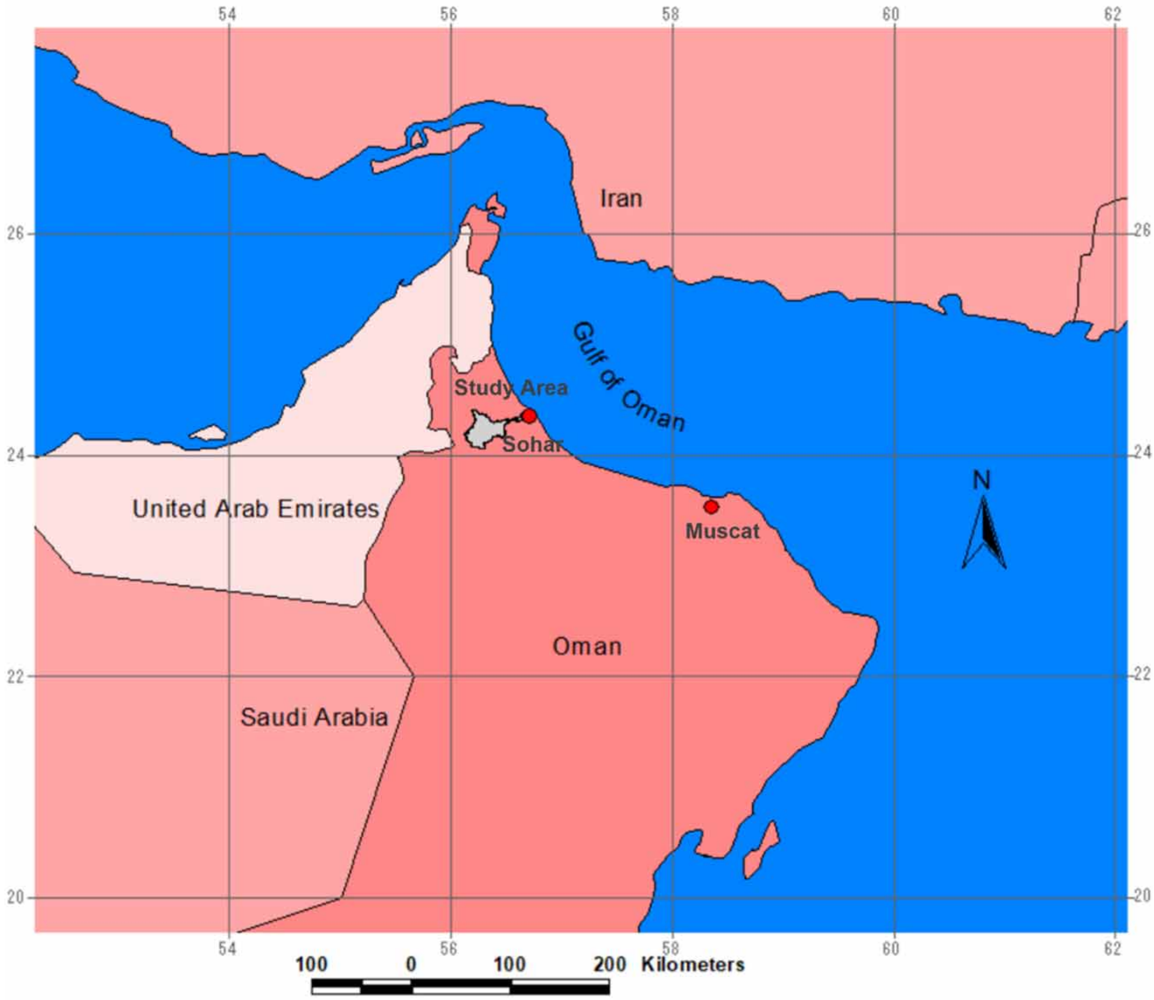

Figure 1 | Wadi Al Jizzi catchment area location within the region.

The catchment is characterised by hot and humid summers and moderate temperatures, with an average rainfall of 113.7 mm/year. The average number of rainstorms is nine per year, while only one to two storms may create flash flooding each. It is, therefore, potentially important to include those variables in the methodology that explores the impact of rapid weather change on flood risk. Different types of rocks and sediments share the geological structure of the Sohar Catchment. The mountainous parts, parallel to the Sea of Oman and United Arab Emirates (the Al Hajar Al Gharbi mountains), contain impermeable formations that are oceanic crystalline rocks (such as basalt), while in the lower area, close to the coastal line, there are mainly oceanic basin sediments (such as shale). In fact, the impermeable rocks of the Al Hajar Al Gharbi mountains will increase

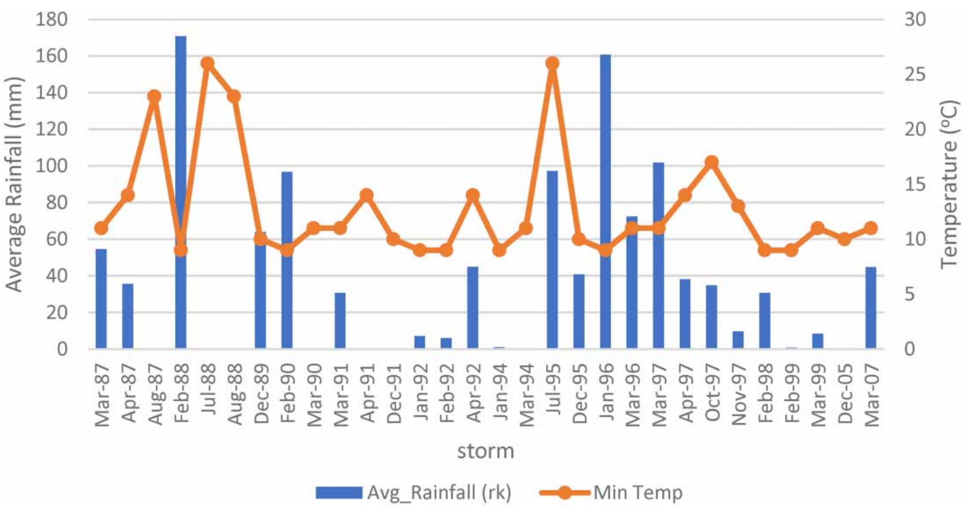

Figure 2 | Monthly average climograph for Wadi Al Jizzi Catchment, Oman.

the opportunity of accumulated flooding in the lower catchment area where the city is located. This is hydrologically important because flash flooding is common and of unexpected magnitudes. The catchment elevation varies from 1,058 m, of the Al Hajar Al Gharbi summit, to 28 m, at the coastal line. In addition, the mean slope of the study area is 9%, whereas the general slope of the land decreases from west to east, towards sea level (Figure 3). Based on double ring infiltration tests, conducted in the catchment area, the predominant soil type in the Wadi Al Jizzi Catchment is loamy soil (64%) whereas sandy soil covers approximately 36% (Figure 3).

Land use and land cover map shows that the catchment is dominated by mountain and submountain (Figure 4). The catchment plays an important role in feeding ground water aquifers, which are the only source of irrigation. The water use per sector in the Wadi Al Jizzi area (Al-Kindi 2014) indicates that the major activity is agriculture with use around 95.59%, while domestic and household is around 3.88%, livestock is 0.45%, and the lowest use was for industrial and commercial sector with percentage of 0.09. The total water requirement for the catchment is around 29.3974 million m^3/year.

The catchment is gauged and the highest value of observed flooding was in February 18th 1988, when the flow reached 44.6 m^3/s. The drainage area is around 870.6 km^2, with an average slope of 9%. The catchment is geographically divided into three areas:

1. Mountainous series (68%).
2. The plain (30%).
3. The coastal strip (2%).

METHODOLOGY

In the present study, there were two research models: IHACRES and AHP. IHACRES is a simple, lumped model, developed by Jakeman *et al.* (1994). It has two linear modules (quick and slow components) to perform the identification of hydrographs. The model has two meteorological inputs, namely daily rainfall and temperature, transformed into a nonlinear loss module to produce effective rainfall (Figure 5). The model can be modified to meet the goal of the research. For instance, Borzì *et al.* (2019) added groundwater recharge and losses as a new theme to the model, while Abushandi & Merkel (2011a, 2011b) added snow phase precipitation as a new parameter in an arid catchment.

In the initial stage, the drying rate τw must be determined for each time interval through the following equation:

$$\tau w = \tau w\ (const) e^{(20-t_k)} \times f \tag{1}$$

where: τw (*const*) is the rate at which catchment wetness declines in the absence of rainfall.

t_k is The temperature at time step k.
f is a temperature modulation parameter (C^{-1}).

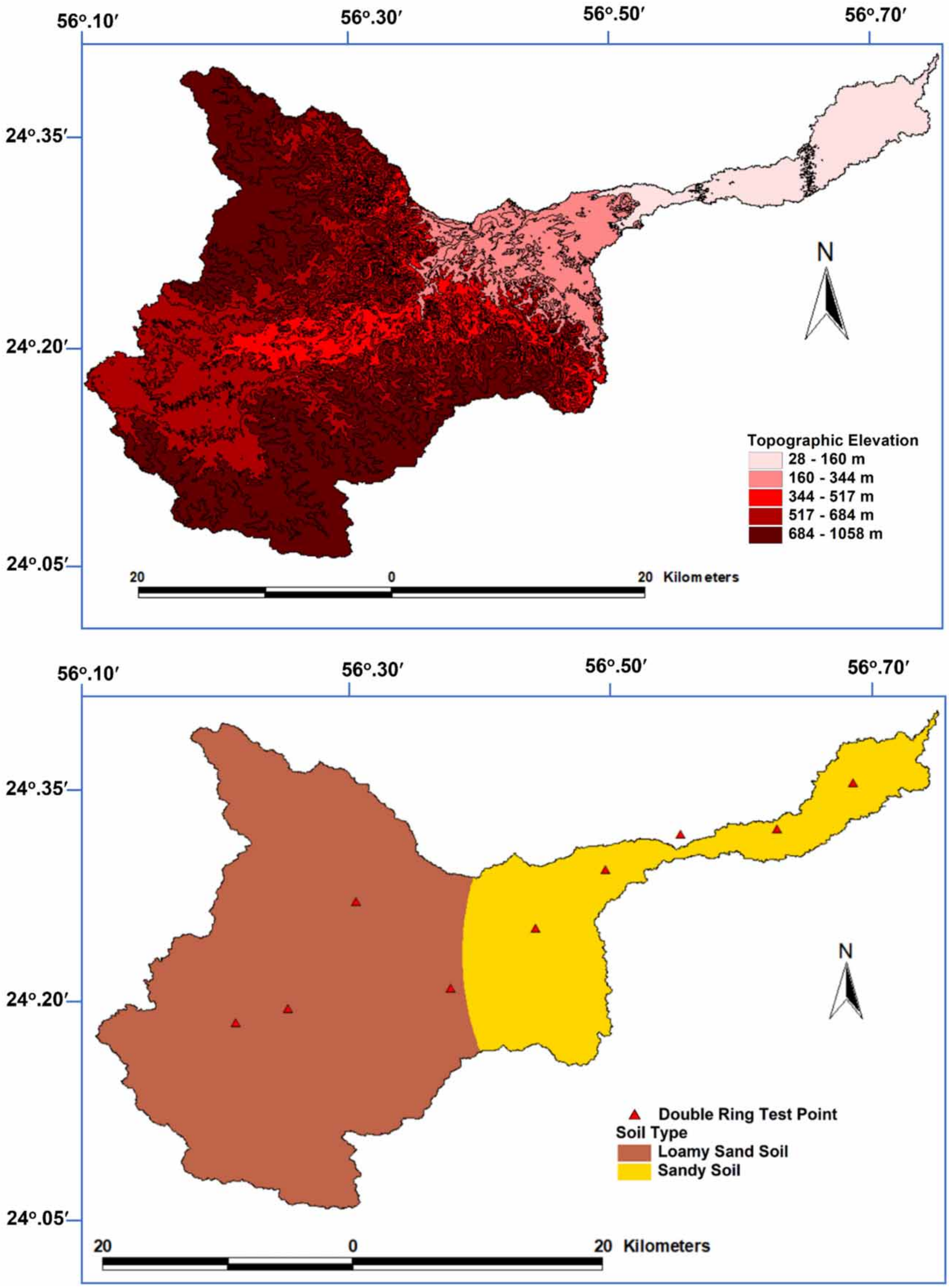

Figure 3 | Wadi Al Jizzi Catchment: topographic elevation (ASTER DEM) and soil type based on double ring tests.

The catchment moisture index S_k characterises the behaviour of arid hydrologic structures and must be determined at each time interval through the following equation:

$$S_k = cr_k + \left(1 - \frac{1}{Tw(k)}\right)S_{k-1} \tag{2}$$

where: c is the adjustment parameter and controls the amount by which S_k is increasing by a rainfall event.

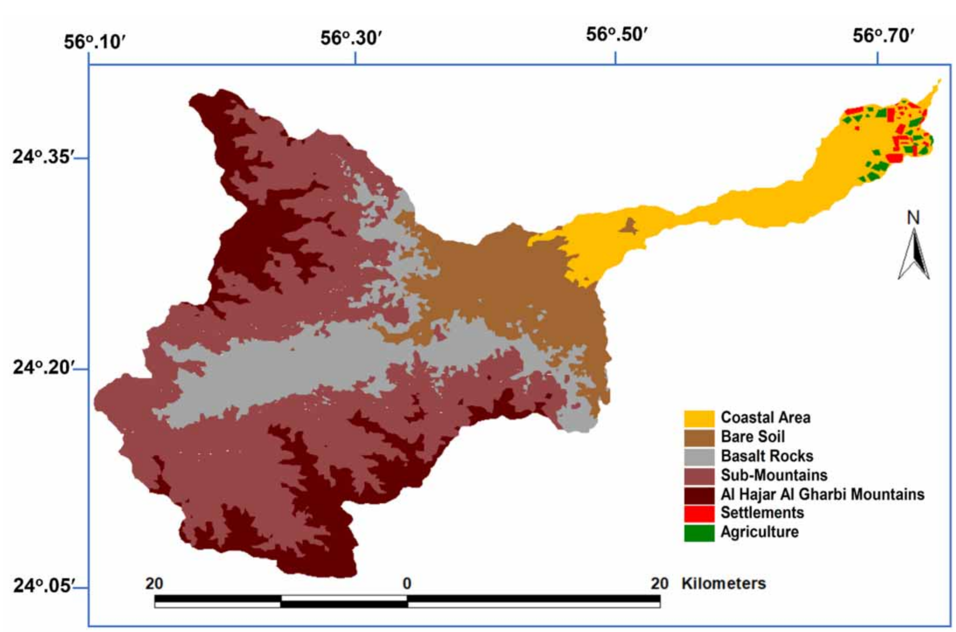

Figure 4 | Land use and land cover map Wadi Al Jizzi catchment.

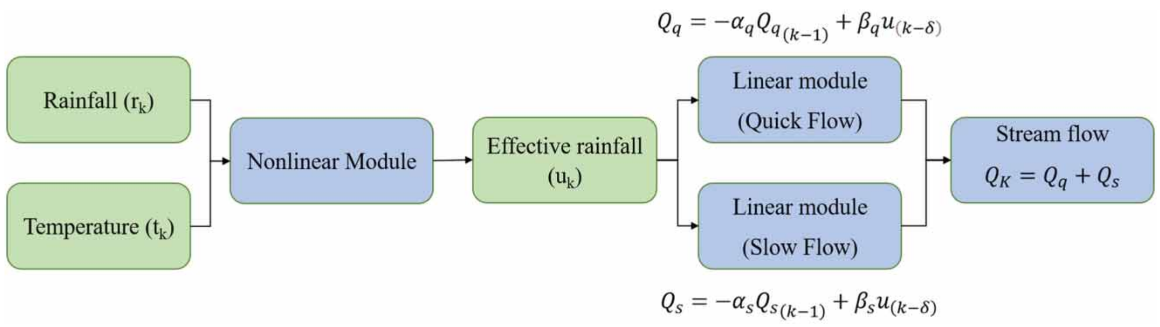

Figure 5 | IHACRES model structure.

r_k is the rainfall at time step $Tw(k)$.

The effective rainfall u_k that produces the possible flow must be determined for the model, using the following equation:

$$u_k = r_k \times s_k \; > 0 \tag{3}$$

where: u_k is the effective rainfall.

The quick and slow stream flow components will be calculated using the following two equations:

$$Q_q = -\alpha_q Q^q_{(k-1)} + \beta_q u_{(k-\delta)} \tag{4}$$

$$Q_s = -\alpha_s Q^s_{(k-1)} + \beta_s u_{(k-\delta)} \tag{5}$$

where: Q_q and Q_s are the quick and slow stream flow components.

$\beta_q u_{(k-\delta)}$ is the delay between rainfall and stream flow response.
α_q and α_s are the recession rates for quick and slow storage.
β_q and β_s are the fractions of effective rainfall.

To compare the IHACRES model with another conceptual methodology, the AHP was used to define the weights of flood parameters including rainfall intensity, slope, soil type, temperature, and land cover types.

This will help in evaluating the influence degree for each parameter. At the first stage, the parameters were defined to configure the relative importance through the creation of a matrix. Then the parameters are determined and arranged according to importance from the least to the most important and the weights of each parameter are determined. The values in the table were based the standard priorities and levels of consistency developed by Saaty & Vargas (2013), as in Table 1.

Table 1 | Scale for comparison (Saaty & Vargas 2013)

Scale	Definition	Explanation
1	the two criteria are equally important	two criteria contribute to one objective in the same way
3	one criterion is less important relative to another	experience and personal appreciation slightly favour one criterion over another
5	high or significant importance	experience and personal appreciation highly favour one criterion over another
7	very high and corroborated importance	one criterion is strongly favoured and its dominance is supported in practice
9	absolute importance	evidence supporting one criterion over another is as convincing as possible
2, 4, 6, 8	values related to intermediate judgments	when a compromise is required

The default Saaty's scale from 1 to 9 is based on a consistency test, which is closely related to a normalised, positive eigenvector method. The outcomes of paired comparisons for n attributes are ordered in a positive reciprocal matrix (n x n).

The surface runoff coefficient was estimated using the hierarchy tool. In the beginning, the parameters that affect the floods were determined. Then it was compared in a binary way, ie two by two as in Table 1 and by using an appropriate scale as in Table 2.

Table 2 | Comparison matrix

Parameter	Slope	Soil group	Rainfall Intensity	Temperature	Land Cover Types
Slope	1	7	9	4	6
Soil group	0.143	1	5	4	4
Rainfall intensity	0.11	0.2	1	9	4
Temperature	0.25	0.25	0.11	1	2
Land cover type	0.167	0.25	0.25	0.5	1
Total	1.67	8.70	15.36	18.50	17.00

Table 2 includes the matrix of environmental attributes and the values chosen for weighting the classes used in AHP. However, since this research examines an arid catchment, containing limited urban and vegetative areas, rainfall intensity and soil group have a higher influence in flood occurrence compared to other parameters. Through the catchment area, rainfall intensity is indirectly associated with slope and elevation, which explains its lower importance. Soil type can be critical important for the occurrence of flooding because of the infiltration rate, especially with sparse vegetation cover. Each parameter's weight was computed using MCDA, where experts' ratings were combined using geometric mean technique.

Each entry is then divided by the column sum to yield its normalised score. The sum of each column is 1, as shown in Table 3.

Table 3 | Normalised matrix

Parameter	Slope	Soil Group	Rainfall Intensity	Temperature	Land Cover Type
Slope	0.59858	0.8046	0.5859	0.21622	0.35294
Soil group	0.08551	0.11494	0.3255	0.21622	0.23529
Rainfall intensity	0.06651	0.02299	0.0651	0.48649	0.23529
Temperature	0.14964	0.02874	0.00723	0.05405	0.11765
Land cover type	0.09976	0.02874	0.01627	0.02703	0.05882
Total	1	1	1	1	1

Furthermore, the consistency measure is a primary component in the AHP, which is important to decision making, allows pairwise comparison, and prioritises criteria. The consistency measure was determined using the following equation (Saaty 1977):

$$CR = \frac{CI}{RI} \tag{6}$$

where:

CR is the consistency ratio.
CI is the consistency index.
RI is the random index, which is dependent on the number of factors used in the pairwise matrix (from Table 4).

Table 4 | Random index (RI) for each number of criteria (Seejata *et al.* 2018)

N	1	2	3	4	5	6	7	8	9	10
Random index	0	0	0.55	0.89	1.11	1.25	1.35	1.40	1.45	1.49

The CI was calculated using the following equation (Saaty 1977):

$$CI = \frac{\lambda MAX - n}{n - 1} \tag{7}$$

where:

n is the number of criteria.

λMAX is the average values of the consistency factor.

For further flood magnitude estimation, runoff coefficient (RC) was calculated using the following equation (Saaty 2014):

$$RC = Pv\ .\ Nv + Pt\ .\ Nt + Pp\ .\ Np \tag{8}$$

where:

N: are values between 0 and 10; they represent the impact of the variation of each criterion
Pv: invariant values between 0 and 1; they represent the weight of each criterion.

The AHP model major outputs are presented in Table 5 including and consistency ratio (CR).

RC was calculated as required, for the AHP model using the following formula:

$$\begin{gathered} = (\mathrm{Ps}\ .\ \mathrm{Ns} + \mathrm{Pc}\ .\ \mathrm{Nc} + \mathrm{Pr}\ .\ \mathrm{Nr} + \mathrm{PT.NT} + \mathrm{PL}\ .\ \mathrm{NL}) : 10 = \\ (0.5116 \times 0 + 0.1954 \times 7 + 0.1752 \times 2 + 0.0714 \times 2 + 0.0461 \times 1) : 10 = 0.1908 \end{gathered} \tag{9}$$

Table 5 | AHP model major outputs

Parameter	Slope	Soil group	Rainfall Intensity	Temperature	Land Cover Type	Average	Consistency Measure	Consistency Index (CI)	Random Index (RI)	Consistency Ratio (CR)
Slope	0.60	0.80	0.59	0.22	0.35	0.51	7.86	0.40	1.11	0.36
Soil group	0.09	0.11	0.33	0.22	0.24	0.20	8.26			
Rainfall Intensity	0.07	0.02	0.07	0.49	0.24	0.18	6.27			
Temperature	0.15	0.03	0.01	0.05	0.12	0.07	5.04			
Land cover type	0.10	0.03	0.02	0.03	0.06	0.05	5.63			

Ps, Pc, Pr, PT, and PL are the weights of the criteria, i.e. slope, soil group, rainfall intensity, temperature and land cover type, respectively. Likewise, Ns, Nc, Nr, NT, and NL represent the degree of influence from the same criteria, respectively.

Nash–Sutcliffe Efficiency (E_f) was also used to assess how good a fit the simulated flow using IHACRES and AHP models in comparison to the observed floods as per the following equation (Nash & Sutcliffe 1970):

$$E_f = 1 - \frac{\sum (q_i - \hat{q}_i)^2}{\sum (q_i - \bar{q})^2} \tag{10}$$

where q_i is observed flow, $\hat{q}_i$ is simulated flow and $\bar{q}$ is the mean value of observed flow.

The range of Ef lies between 1.0 (perfect forecast) and $-\infty$. Values closer to 1.0 indicate that the model has more predictive skills while values less than zero articulates that the average of observed flood have a better predictor than modelled values.

Furthermore, index of agreement (IoA) was used to additional measure of a goodness-of-fit models (Willmott 1981) as per the following equation:

$$IoA = 1 - \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (|x_i - \bar{x}| + |y_i - \bar{x}|)^2} \tag{11}$$

where n is the sample size, x_i and y_i are the individual sample points indexed with i of observed and modelled values. While $\bar{x}$ is the mean value of observed records.

To assess the efficiency of the observed and simulated flooding, Pearson correlation was used to evaluate the relationship between the two different flows, based on the following formula (Pearson 1895):

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{(x - \bar{x})^2 (y - \bar{y})^2}} \tag{12}$$

The values of Pearson correlation are always between -1 and 1, and if x and y are not related, the correlation is equal to zero.

RESULTS AND DISCUSSION

Most rainfall storms ranged between a few millimetres to 114 millimetres. Rainfall intensity records show that, every 10 years, the catchment suffers an extreme value, greater than 320 mm/hr. This means that the catchment will receive around 278 million cubic meter of water in a short period of time.

The flood events were modelled using two lumped, conceptual flow representations, IHACRES and AHP. The highest rainfall magnitudes usually occur in January, February, and March each year. The highest value of observed flooding was in February 18th 1988, when the flow reached 44.6 m^3/s, rainfall intensity was 341 mm/hr., and low temperatures reached 9 °C.

The IHACRES model was based on rainfall and temperature and determined ephemeral, event-based flood magnitudes. The input parameters were identified as in Table 6. Those two inputs affect soil moisture and drying rates, respectively. The results obtained from the model were proportional to the observed results. The E_f efficiency of the model was 0.78 while an Io similarity coefficient was about 0.84.

Table 6 | Parameters used in IHACRES

Parameters	Value
c	0.0008
$Tw_{(const)}$	0.800
f	0.000
a(q)	−0.250
b(q)	0.070
a(s)	−0.990
b(s)	0.009067
Area	870.6
Delay	0.3

The IHACRES model results showed that the average simulated flood was 0.36 m^3/s, while that observed for all flood storms was 0.30 m^3/s. Figure 6 shows the observed flood from Sallan gauging station located at the outlet versus simulated. The simulation was appropriate in all storms (Figure 6(a)) except for two storms in February from the years 1988 and 1990 (Figure 6(b)) indicating that the IHACRES model has difficulties in simulating extremely high flood events. These difficulties may occur due to many reasons:

(i) The meteorological station did not record the storm precisely since the storms in arid areas are extremely localised.
(ii) Rainfall intensity is too high, which gives no opportunity for water penetration.
(iii) The storm occurred in the mountainous area, covered by basaltic rocks.

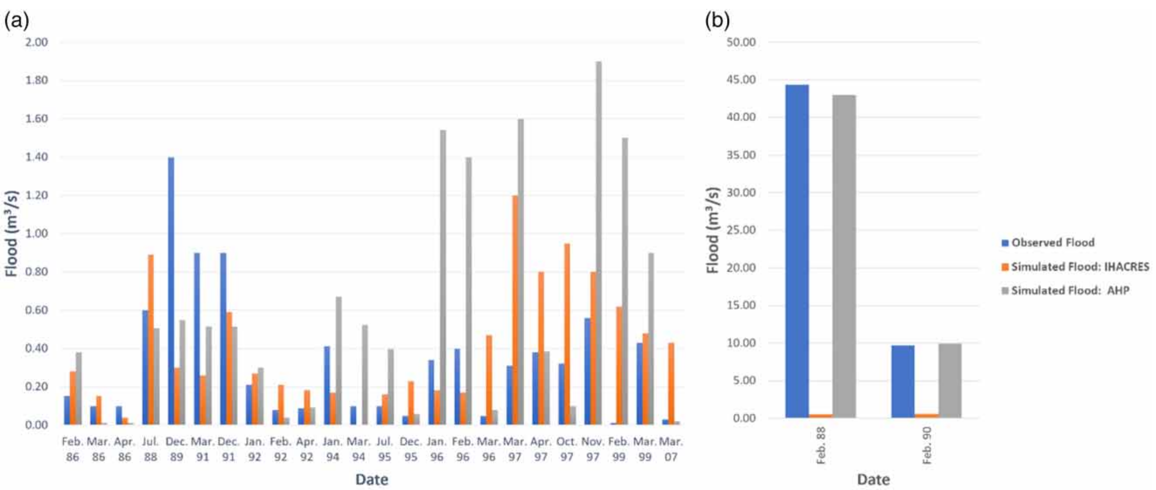

Figure 6 | Observed flood from a gauging station located at the outlet versus simulated flow using IHACRES model and AHP tools.

Abushandi & Merkel (2013) used the IHACRES model to determine the runoff of Wadi Dhuliel in Jordan, using precipitation and temperature data. The results obtained from the model were proportional to the observed results where the average runoff magnitude between 2001 and 2008 was 1.2 m^3/s. This might be due increasing agricultural activities and building dams in the upper part of the catchment. In addition, estimatation of runoff for a single storm event in the year 2008 showed a slight overestimation where observed runoff was 0.11 m^3/s while modelled runoff was 0.13 m^3/s. The E_f of the model was 0.5, which is lower than the present research. The reason for that is that observed data from Jordan is much more fluctuated.

To implement the AHP model, rainfall rates were classified into three clusters: less than 5 mm (low), 5 mm/hr to 10 mm/hr (medium), and greater than 10 mm/hr (high). Furthermore, multiple linear regression model was used to readjust AHP model results by fitting a linear equation to observed data. The concept formula of the multiple linear regression model used for arid catchment readjustment (Abushandi & Merkel 2011a, 2011b) is given by:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_{12} x_{i2} + \ldots + \beta_p x_{ip}$$

where y_i is the modelled value of the flood in m^3/s

$x_{i1}, x_{i2}, \ldots, x_{i3}$ are explanatory variables (e.g. rainfall).
$\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ are the fitting values, based on a linear relationship.

As for the results of the AHP model, direct results showed an over estimation of all records, therefore, a readjustment process based on linear regression was made in order to meet observed records which conserved as a reference data. The values were readjusted for the amount of rain less than 5 mm/hr (low), the following equation was used:

$$\text{Readjusted AHP Flood} = 0.383 + (\text{rainfall} * 13.81) - (\text{AHP Simulated Flood} * 70.794)$$

The E_f shows a good performance of readjusted values, which was 0.81, while an IoA similarity coefficient was about 0.87.

To find the readjusted AHP Simulated Flood of rainfall between 5 to 10 mm (medium) the following equation was used:

$$\text{Readjusted AHP Flood} = -6.163 + (AHP\ \text{Simulated Flood}) * 0.84$$

The E_f shows a good performance of readjusted values, which was 0.66 while an IoA similarity coefficient was about 0.71.

Furthermore, re-Adjusted AHP Simulated Flood of rainfall greater than 10 mm (high) can be calculated from following equation:

$$\text{Readjusted AHP Flood} = -6.8 + 5.335 * (AHP\ \text{Simulated Flood})$$

The E_f shows a good performance of readjusted values, which was 0.82, while an IoA similarity coefficient was about 0.88.

In fact one readjustment equation didn't represent the flood behavior as arid catchments are characterized by rainfall fluctuation. From previous experience, similar arid catchments are classified into three cluster.

Generally, the AHP tool is not able to simulate flooding when the records are less than 0.3 m^3/s for all cases.

In general, the IHACRES model and AHP tool were able to represent and assess the amount of flood magnitudes in arid catchment with some difficulties, due to the lack of high resolution data and extreme behaviour of rainfall magnitudes. The performance of the two models were compared based on E_f, which shows the performance of readjusted values of AHP are better than IHACRES.

However, based on evaluation tools adjusted AHP simulation showed better performance in comparison to the IHACRES model.

Similar results have been found by Lallam *et al.* (2018) using AHP model in determining the surface runoff parameters of Wadi Bou-Kiou arid catchment. Generally, AHP results were able to explain runoff behaviour.

However, saturated soil increases the flow, while dry soil helps absorb water, thus reducing flood risk. Therefore, it is recommended that soil moisture data is included in the modelling of floods in arid catchments. Furthermore, the economic aspect of solving flood problems must take two dimensions:

(i) Above ground: the cost saved from damages caused to the area, such as traffic accidents and property destruction.
(ii) Under ground: the cost of producing fresh water by increasing ground water recharge rates.

A flood risk map based on AHP produced using the ArcGIS environment (Figure 7) shows a pattern of flood influenced by slope, land over type, soil type, and rainfall intensity parameters due to the high weight assigned by the consistency measure. Due to a sharp slope, impermeable volcanic rocks, and relativity low infiltration rate, the upper parts of the catchment is subject to high risk of flood. In addition, rainfall rates at the mountains area is higher than lower catchment area It has been found that mountains and submountain areas are suspected as high risk of flood. Similarly, Seejata *et al.* (2018) selected six physical parameters to identify flood risk level.

AHP depends on expert subjectivity, which can be an advantage in some cases and disadvantage in many other

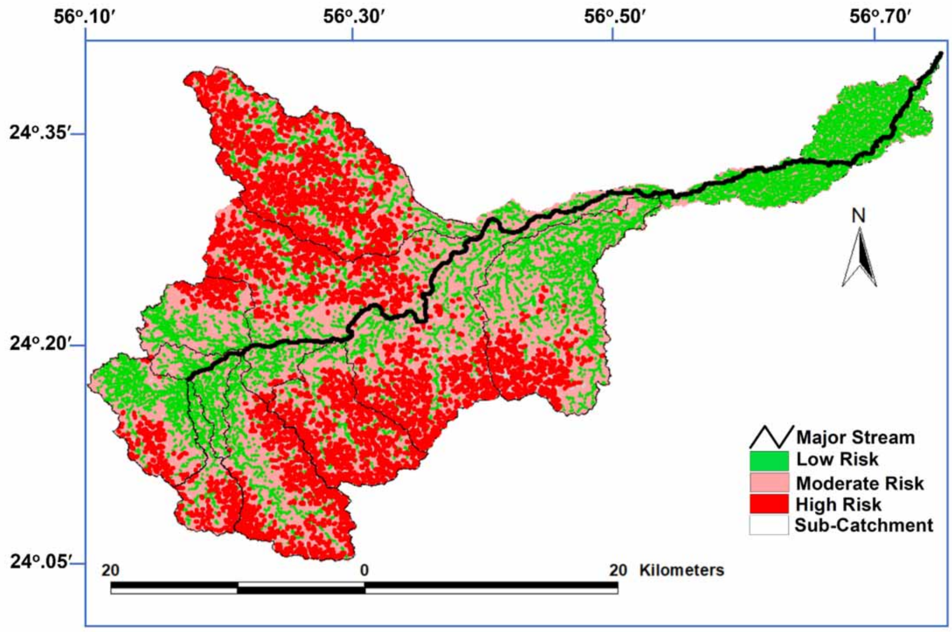

Figure 7 | Flood risk map from low to high range.

cases as the expert knowledge plays a major role in pairwise prioritisation. There are many researchers (e.g. Wang *et al.* 2006; Nefeslioglu *et al.* 2013) who have tried to minimise expert subjectivity using combined techniques such as Fuzzy-AHP and Modified-AHP. This integration helps in decision support systems.

The model simplicity and model few input data requirement of IHACRES give a great advantage to apply in arid catchments where hydrologic data is limited. However, application of IHACRES model in dry years showed low performance and high sensitivity to any minimal changes of calibration coefficients. However, both models were able to generate time series simulation

CONCLUSION

Flood estimation is the basis for designing and planning many water structures. Wadi Al Jizzi is exposed to one or two flood events per year, mainly in February and March. A study was conducted on Wadi al Jizzi to model floods at catchment scale. In general, the two models were able to identify and assess the amount of flooding with some exceptions, due to the lack of data and extreme behaviour of rainfall magnitudes. However, the AHP tool required an additional readjustment process to fill the gap between observed and simulated records, while IHACRES could not simulate extremely high flooding. The soil type across the catchment is mainly loamy sand (70%), while sandy soil covers the rest of the downstream area. This will increase the possibilities of water accumulation in the upper parts of the catchments. In addition, there is a clear relationship between rainfall intensity and flooding, apart from rainfall magnitudes. In another words, rainfall magnitudes might be just a few millimetres but still be able to create a huge flood due to a flash storm.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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