Forecasting flood-prone areas using Shannon's entropy model

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With regard to the lack of quality information and data in watersheds, it is of high importance to present a new method for evaluating flood potential. Shannon's entropy model is a new model in evaluating dangers and it has not yet been used to evaluate flood potential. Therefore, being a new model in determining flood potential, it requires evaluation and investigation in different regions and this study is going to deal with this issue. For this purpose, 70 flooding areas were recognized and their distribution map was provided by ArcGIS10.2 software in the study area. Information layers of altitude, slope angle, slope aspect, plan curvature, drainage density, distance from the river, topographic wetness index (TWI), lithology, soil type, and land use were recognized as factors affecting flooding and the mentioned maps were provided and digitized by GIS environment. Then, flood susceptibility forecasting map was provided and model accuracy evaluation was conducted using ROC curve and 30% flooding areas express good precision of the model (73.5%) for the study area.

1. Introduction

Flood is defined as an increase in water level of rivers and floodways and flowing water along with covering plains around the river. Naturally, human activities have increased flood risk because of increasing population growth and rapid urban and rural development. Floods are regarded as the most dreadful climatic disaster in the world in terms of loss of life and property damage (Hosseini and Matlabifar 2008). Golestan province is among those regions of the country where short rain showers occur during warm seasons of the year and most of the time, these showers result in severe and devastating floods especially in the east area of this province that leaves huge property damage and life loss. Modelling flood in watersheds and reducing damages of these natural disasters is the primary objective of comprehensive management of

watersheds (Rahmati *et al.* 2016a). Employing these methods accompanies difficulties because of limitations in different hydrologic methods to determine flood-prone areas and their need for large financial resources. Therefore, in many watersheds, authors employ environmental analyses in the form of GIS for hydrologic studies. Pourghasemi *et al.* (2014) conducted zoning of landslide susceptibility using Shannon's entropy index. Results of this study demonstrate that Shannon's entropy index with an accuracy of 82.83% is a very good index for zoning of landslide susceptibility for the study area. Hosseinpour and Abbaspour (2014) improved the results of forecasting landslide using Shannon's entropy theory. Results of their study showed that the cited model was 69% accurate in forecasting landslides. A similar study by Pourghasemi *et al.* (2012) was conducted to prepare landslide susceptibility mapping of Safarood watershed in

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Ramsar using probability and Shannon's entropy models. Results of the models' evaluation suggest a high accuracy of entropy theory (86.08%) relative to probability theory (82.75%). Naghibi *et al.* (2014) employed Shannon's entropy and frequency ratio to prepare qanat potential mapping in the Moghan watershed. Results suggest that the area under the curve (AUC) for frequency ratio and Shannon's entropy models is 88.48 and 91.21%, respectively. Bednarik *et al.* (2010) employed entropy index to assess landscape susceptibility of Slovakia and their results express good precision of model (70%) using ROC curve. Jaafari *et al.* (2013) utilized frequency ratio and Shannon's entropy to prepare zoning map of landslides in Caspian forests by ArcGIS software. Their results suggest that Shannon's entropy model, with an accuracy of 75.59%, could be employed as a simple tool in evaluating landslide susceptibility compared to frequency ratio with an accuracy of 72.68%. Lee *et al.* (2012) used the frequency ratio (FR) model for predicting the flooding susceptibility map using GIS, the results of their study are expected to be used in programmes to reduce the flood and its damage. Shafapour Tehrani *et al.* (2013) in Malaysia, in a study, applied an integration of frequency ratio, logistic regression and decision tree methods for determining flood susceptibility. Results of their study showed that the use of machine learning methods such as decision trees increases the accuracy of the given methods for mapping the flood potential. Rahmati *et al.* (2016c) zoned flooding using frequency ratio and control weight in the Golestan province, the results of their research indicated that the two mentioned models were relatively similar, acceptable, as well as useful for flood risk reduction strategies.

Literature review indicates that Shannon's entropy model has been used by various researchers for modelling and analysis in the fields of hydrology and water resources management. Mishra *et al.* (2009) used an entropy-based method to measure the spatio-temporal variability of a precipitation time series in the State of Texas, USA. Singh (1997) reviewed applications of entropy concept in hydrology and water resources management and discusses their strengths and limitations. Kawachi *et al.* (2001) investigated the capability of Shannon's entropy to quantitatively measure the uncertainty of the over-a-year rainfall apportionment and to construct an isoentropy map in Japan. Their results indicated that the isoentropy map would be useful in conjunction with an isohyetal map of the average annual rainfall. Mishra and Coulibaly (2010, 2014) and Li *et al.* (2012) discussed the applicability of the entropy theory for the evaluation of an optimal hydrometric network and to identify essential streamflow stations. Recently,

Rajsekhar *et al.* (2012) used an entropy-based method for drought characterization and identification of homogenous regions based on drought duration and severity. With regard to the lack of quality information and data in watersheds of the country, it is of high importance to present a new method for evaluating the potential of flood and flood-prone areas. Flood susceptibility is among those studies with a short history in the world and it is regarded as one of the newest studies in the field of floods. In addition, Shannon's entropy model is a new method in risk assessment and it has never been used before to assess the potential of flood elsewhere. Therefore, being a new model, it should be assessed and investigated in different regions of the country in terms of determining flood susceptibility and this study is conducted for this purpose.

2. Materials and methods

2.1 Study area

The study area is one of the eastern sub-basins of Gorgan Rood River called Madarsoo watershed located in the longitude of 55°21'–56°28'N and latitude of 36°58'–37°30'E (figure 1). With an area of 2310.27 km², this watershed, which is located in three provinces of Golestan, Semnan and Khorasan, according to political divisions, is one of the most popular watersheds of Golestan province and is popular for its devastating floods.

2.2 Effective parameters in flooding

Various data are required as independent variables in flood risk assessment (Liu and De Smedt 2005). These variables are very effective in flood occurrence in a special area. On the other hand, if we employ all these parameters in the modelling process, the huge amount of information would prevent quick and extract analyses (Campolo *et al.* 2003; Sanyal and Lu 2004). No absolute guideline is defined yet. Some effective and finite parameters employed by authors to evaluate flood risk include: land use, lithology, soil type, drainage density, distance from river, topographic wetness index (TWI), altitude, slope aspect, slope angle and plan curvature (Skilodimou *et al.* 2003; Lee *et al.* 2012; Kia *et al.* 2012; Pradhan and Lee 2010; Shafapour *et al.* 2013, 2014).

2.2.1 Altitude

Different elevations change the climatic features and this issue results in changes in vegetation and soil conditions (Aniya 1985). Elevation always plays an important role in flood susceptibility maps (Rahmati *et al.* 2016b). Therefore, an elevation

Figure 1. Geographical location of study area in Iran.

Figure 2. (a) Elevation map and (b) slope angle (in degree) in Madarsoo watershed.

map of the study area is provided from topographic maps and is divided into five categories using sequential classification method (figure 2a).

2.2.2 Slope angle

Because of having a direct effect on surface runoff and opportunities for permeation, the slope is

regarded as a major factor in flood occurrence in watersheds. To prepare the map, digital elevation model (DEM) (with a resolution of 30 m) was employed along with ArcGIS 10.2 software. The resulted map was classified into five classes of 0–13.93, 13.93–27.85, 27.85–41.78, 41.78–55.72 and 55.72–69.7 (in degrees). Figure 2(b) depicts classified slope map in the study watershed.

2.2.3 Slope aspect

Slope aspect is an important factor in analyzing geomorphologic stability by controlling some climatic parameters including radiation received, wind (dry, wet), and intensity of precipitation and soil moisture. Determining the direction of water flow is one of the applications of the direction of slope map. Aspect map is drawn in ArcGIS 10.2 software using digital elevation map (DEM). This map is classified into nine groups, the levels of which are flat, north, north-east, east, south-east, south, south-west, west and north-west. Figure 3(a) depicts aspect map.

2.2.4 Plan curvature

Plan curvature is an effective factor on flood potential of watersheds. The curvature map is provided based on digital elevation model and ArcGIS 10.2. This map is categorized into three classes of concave curvature, convex curvature and flat (without curvature) (figure 3b).

2.2.5 Drainage density

Drainage density is the ratio of total length of watershed channels to the area of the basin. Waterways network in watershed shows the way water flows in the basin (Abdideh *et al.* 2011; Tahmassebpour *et al.* 2016). Finally, drainage density map was classified into four groups using 30×30 m cells (figure 4a).

2.2.6 Distance from river

An important factor in flooding of adjacent lands is the distance from the river. Map of distance from the river was prepared based on a digital layer of flow network in ArcGIS 10.2 software. The resulted map was classified into five classes of <500, 500–1000, 1000–2000, 2000–3000 and >3000 m that are shown in figure 4(b).

2.2.7 Topographic Wetness Index (TWI)

TWI map determines the effect of topography on the amount of saturated levels to create runoffs and it is regarded as a useful index in investigating flood potential of watersheds. TWI is defined as equation (1):

$$TWI = \ln \left(\frac{A_s}{\tan \beta} \right), \quad (1)$$

where A_s is the special area of watershed and β is slope (in degrees) (figure 5a) (Rahmati *et al.* 2016b).

2.2.8 Soil type

This factor plays the most important role in creating surface runoff and subsurface flow. Lithological and pedologic features have a major effect on the amount of water permeability in soil or direct runoff and consequently balance in river flow or flooding of the watershed. Pedologic layer was prepared from soil texture map of Madarsoo

Figure 3. (a) Slope aspect map and (b) curvature of the earth in Madarsoo watershed.

Figure 4. (a) Drainage density map and (b) distance from river in Madarsoo watershed.

Figure 5. (a) Topographic wetness index map and (b) soil type in Madarsoo watershed.

watershed (1:100000 scale) presented by the Ministry of Agriculture (figure 5b).

2.2.9 Lithology

Because of having a direct influence on permeability power and surface runoff, lithology is an important

factor in flooding of watershed basins. Lithological map of Madarsoo watershed was prepared and digitized using lithological 1:100000 scale maps from Geology Organization. Geology of the area was divided into age classes of Cretaceous, Devonian, Eocene, Jurassic, Miocene, Proterozoic, Cambrian, Silurian and Quaternary as shown in figure 6(a).

Figure 6. (a) Lithology and (b) land use map of Madarsoo watershed.

2.2.10 Land use

Land use is a major factor in creating surface runoff and flood potential of watersheds. The map of land use of Madarsoo watershed was prepared according to digitized land use maps from forest, rangeland and watershed management organizations. Land use map was divided into forests, rangelands, agricultural and residential lands as could be seen in figure 6(b).

2.3 Assessing the statistics of flood locations in recent decades

In order to evaluate the potential of flooding, it is necessary to analyze the floods recorded in the area (Manandhar *et al.* 2010). Thus, based on the statistics of the basis of Golestan regional water company, a map containing the geographical location of the last 70 floods that occurred in Madarsoo watershed was prepared. This set of floods was randomly divided into two groups including a group of 49 flood locations (70%) for training, and a group of 21 flood locations (30%) for validation. The locations of flood events were provided as a raster network (30×30 m) applicable in maximum entropy and frequency ratio models, then these locations were divided based on training and validation groups as shown in figure 1.

3. Flood susceptibility modelling

3.1 Shannon's entropy index

Entropy is a management approach employed in a system to prevent disorder, instability, disturbance and uncertainties available in that system (Pourghasemi *et al.* 2014). This theory was initially proposed by Stephan Boltzmann and it was finally presented quantitatively by Shannon (1948) (Pourghasemi *et al.* 2014). In fact, entropy states a way to estimate main factors among effective factors of an objective; in other words, it determines variables that are more influential in event occurrence. In general, equations (2–7) were employed to prioritize the affecting flood occurrence and to prepare its susceptibility map using the mentioned method (Bednarik *et al.* 2010; Constantin *et al.* 2011; Pourghasemi *et al.* 2012):

$$P_{ij} = \frac{b}{a}, \quad (2)$$

$$(P_{ij}) = \frac{P_{ij}}{\sum_{j=1}^{S_j} P_{ij}}, \quad (3)$$

$$H_j = - \sum_{i=1}^{S_j} (P_{ij}) \log_2(P_{ij}), \quad (4)$$

$$H_{j\max} = \log_2 S_j, \quad (5)$$

$$I_j = \frac{H_{j\max} - H_j}{H_{j\max}}, \quad I = (0, 1), \quad j = 1, \dots, n, \quad (6)$$

$$W_j = I_j P_{ij}, \quad (7)$$

where a and b are the domain and flood percentages, (P_{ij}) is the probability density, H_j and $H_{j\max}$ represent entropy values, I_j is the information coefficient, S_j is the number of classes and W_j represents the resultant weight value for the factor as a whole (figure 7).

After determining the final weight of each factor and multiplying it in classes of that factor and P_{ij} values related to each factor, weighted maps were added up and the final map of flood susceptibility was obtained.

Flood susceptibility index (FSI) was calculated using the following equations:

$$FSI = \sum_{i=1}^n (W_j P_j), \quad (8)$$

$$\begin{aligned} FSI = & (L_{P_j} \times 0.22) + (LU_{P_j} \times 0.38) + (DFR_{P_j} \times 0.53) \\ & + (St_{P_j} \times 0.9) + (S_{P_j} \times 0.18) + (SA_{P_j} \times 0.14) \\ & + (P_{P_j} \times 0.03) + (TWI_{P_j} \times 0.25) \\ & + (DD_{P_j} \times 1.44) + (A_{P_j} \times 0.94), \end{aligned} \quad (9)$$

where W_j and P_j are the final weight and the probability density for the j th feature. L, LU, DFR, St, S, SA, P, TWI, DD, and A are lithology, land use, distance from river, soil texture, slope, slope aspect, plan curvature, topographic wetness index, drainage density, and altitude, respectively.

The resulting map of the layers is classified as Quantile and this classification map would be the final Shannon's entropy model (Pourghasemi *et al.* 2012; Ozdemir and Altural 2013; Pourghasemi *et al.* 2013a, b, c, d; Regmi *et al.* 2013; Zare' *et al.* 2013).

3.2 Accuracy evaluation of flood forecasting map

To evaluate the accuracy of flood potential forecasting map, 21 flood events related to last periods were employed that were not entered Shannon's entropy model to forecast flood potential. Figure 1

Figure 7. Flowchart showing the methodology adopted in this study.

Table 1. Relationship between flood location, effective factors and determining their effects using Shannon's entropy index.

Factor	Class	Number of pixels in basin	Number of floods	P_{ij}	(P_{ij})	H_{ij}	$H_{j \max}$	I_j	W_j
Lithology	Cretaceous	130634	0	0	0	1.24	3.17	0.61	0.22
	Devonian	4162	0	0	0				
	Eocene	13377	0	0	0				
	Jurassic	1185498	15	0.66	0.21				
	Miocene	384916	3	0.41	0.13				
	Proterozoic	44221	0	0	0				
	Precambrian	33612	0	0	0				
	Quaternary	759585	31	2.14	0.67				
	Silurian	10961	0	0	0				
Land use	Agricultural land	569019	28	2.58	0.68	1.20	2	0.40	0.38
	Forests	707397	10	0.74	0.2				
	Pasture land	1282210	11	0.45	0.12				
	Urban areas	8340	0	0	0				
Distance from river (m)	<500	216190	4	0.97	0.10	1.66	2.32	0.29	0.53
	500–1000	197138	14	3.72	0.40				
	1000–2000	355363	27	3.98	0.43				
	2000–3000	329857	4	0.64	0.07				
	>3000	1468418	0	0	0				
Soil type	Alfisols	516267	2	0.20	0.03	0.94	2	0.53	0.90
	Entisols	1080624	10	0.48	0.07				
	Inceptisols	688404	7	0.53	0.08				
	Malisols	281671	30	5.58	0.82				
Slope angle (in degree)	0–13.93	1763692	35	1.04	0.42	1.46	2.32	0.37	0.18
	13.93–27.85	646449	13	1.05	0.43				
	27.85–41.78	138807	1	0.38	0.15				
	41.78–55.72	17097	0	0	0				
	55.72–69.7	921	0	0	0				
Slope aspect	Flat	17179	1	3.05	0.29	2.78	3.17	0.12	0.14
	North	418558	8	0	0.09				
	North-east	265949	3	0.59	0.06				
	East	235565	0	0	0				
	South-east	300124	4	0.70	0.06				
	South	397116	12	1.58	0.15				
	South-west	281170	6	1.12	0.10				
	West	284575	10	1.84	0.20				
	North-west	366730	5	0.71	0.07				
Plan curvature	Concave	1116224	27	1.27	0.41	1.54	1.58	0.03	0.03
	Flat	363300	8	1.15	0.37				
	Convex	1087442	14	0.67	0.22				
TWI	<5	861256	12	0.73	0.38	0.96	2	0.52	0.25
	5–12.7	1662190	37	1.17	0.61				
	12.7–20	41763	0	0	0				
	>20	1757	0	0	0				
Drainage density (km/km ²)	0.01<	1338984	0	0	0	1.01	2	0.50	1.44
	0.01–0.17	549363	5	0.48	0.04				
	0.17–0.33	598433	31	2.71	0.23				
	>0.33	80186	13	8.49	0.73				
Altitude (m)	<500	276460	32	6.06	0.82	0.84	2.32	0.64	0.94
	500–1000	272046	4	0.77	0.10				
	1000–1500	1305610	13	0.52	0.07				
	1500–2000	666306	0	0	0				
	>2000	46544	0	0	0				

shows the location of these floods. Forecasting accuracy of flood potential in Madarsoo watershed was calculated using ROC index. ROC curve is a graphical representation of equilibrium between the negative and positive rate of error for each possible value of fitness (Pourghasemi *et al.* 2014). If the index value (or area under the curve) equals 1, it shows complete fitness of the model and if it equals 0.5, it represents the lack of fitness of model (Zare' Garizi *et al.* 2012). Qualitative–quantitative correlation of the area under curve and evaluation of estimation is as follows: 0.9–1: perfect; 0.8–0.9: very good; 0.7–0.8: good; 0.6–0.7: medium and 0.5–0.6: weak (Pradhan and Lee 2010; Regmi *et al.* 2010; Pourghasemi *et al.* 2012, 2014).

4. Results and discussion

In this study, first, entropy values were calculated for effective parameters in the study area using relations presented in Shannon's entropy model, as could be seen in table 1. Results of investigating factor of elevation map indicate that the highest rate of flood has occurred in elevations that are lower than 500 m, i.e., in higher altitudes and mountainous areas, flood events are less. Gradient controls surface runoff permeability and water flow speed. In areas with medium slope, runoff flow is slow and water has much time to penetrate. The less the gradient, the more is the possibility of flooding and flood events (Rahmati *et al.* 2016c).

Aspect impacts delay in thawing resulted from temperature difference, soil moisture, evaporation, respiration and vegetation (Rahmati *et al.* 2016c). After investigating the aspect of Madarsoo watershed, it could be stated that in lands with no aspect (flat), the highest number of flood events are observed; south, north, west, north-west and south-west aspects are of medium flood rate and the lowest flood prevalence could be observed in north-east aspect. Land curvature index verifies that concave lands experience the highest flood event. Drainage density of >0.33 with highest P_{ij} value demonstrates that this class is strongly related to flood events. Distance from the river demonstrates that the highest flood event is expected up to 2000 m away from the river; i.e., there is a greater flood possibility in this distance from the river compared to other areas and as the distance from river increases, the possibility of flood event decreases significantly. TWI parameter defines the effect of topography in producing runoff assuming steady and homogenous soil conditions. Evaluating this index demonstrates that in 0–12.7 class, P_{ij} value is the highest. Mollisols have experienced the highest flood rate and features of this soil depend on the soil type of the study area. The factor of geology demonstrates that the highest flood rate has been observed in Quaternary formations, the cause of which is related to marl and conglomerate in this formation. Marl is of lowest permeability, highest runoff and highest erosion. The factor of land use represents that agricultural lands experience

Figure 8. Flood potential forecasting map of Madarsoo watershed using Shannon's entropy model.

Figure 9. ROC curve of flood potential forecasting map based on Shannon's entropy model in Madarsoo watershed.

the highest flood event, which happens because of impermeability of agricultural lands (plowing agricultural lands prevents water from permeating into the soil), increase in runoff and therefore increases in flood severity.

W_j results demonstrate that the highest weight is assigned to factors of drainage density, elevation, lithology and distance from the river (1.44, 0.94, 0.90, and 0.53), while the lowest is assigned to the factor of curvature of the earth (0.03).

According to the results obtained from analyses, flood potential forecasting map of Madarsoo watershed was provided using Shannon's entropy model based on 10 factors affecting flood occurrence that could be seen in figure 8.

As stated before, ROC curve was employed to evaluate the model. This curve is the most effective method in presenting characteristic determination, possible recognition and forecasting systems that estimates model accuracy quantitatively. According to the results of ROC curve, the area under curve value of the study area was 73.5% with standard deviation of 0.079 that represents a good evaluation of Shannon's entropy model (figure 9).

5. Conclusion

Preparing flood susceptibility map provides the background for recognizing factors affecting flood event, its occurrence, planning for risk management and risk prevention methods. In this study, flood-prone areas were recognized using Shannon's entropy model. In the first stage, the location map of flood events was provided according to data from

Golestan Regional Water Company. Then, 10 information layers of factors affecting flood occurrence (altitude, slope angle, slope aspect, plan curvature, distance from the river, soil type, drainage density, topographic wetness index, lithology and land use) were prepared in ArcGIS 10.2 software. In the third stage, flood susceptibility map was provided using Shannon's entropy theory and finally, ROC curve was prepared using validation data and then it was employed to evaluate the accuracy of maps. Results of validation demonstrate that Shannon's entropy is of good performance in recognizing flood susceptible areas in Madarsoo watershed. It could be suggested that scientific information obtained from this study could be employed by the government, planners and engineers to implement control projects in order to reduce flood damage in future.

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