

Flood Susceptibility Mapping in Densely Populated Urban Areas Using Mcdm and Fuzzy Techniques

Vahid Nourani and Soghra Andaryani

EasyChair preprints are intended for rapid dissemination of research results and are integrated with the rest of EasyChair.

December 25, 2019

FLOOD SUSCEPTIBILITY MAPPING IN DENSELY POPULATED URBAN AREAS USING MCDM AND FUZZY TECHNIQUES

Vahid Nourani^{1,2}, Soghra Andaryani¹

¹Center of Excellence in Hydro-informatics, Faculty of Civil and Environmental Engineering, University of Tabriz, Tabriz, Iran

²Faculty of Civil and environmental Engineering, Near East University, Near East Boulevard 99138, Nicosia, North Cyprus, via Mersin 10, Turkey Email: vnourani@yahoo.com

Email: s.andaryani@gmail.com

ABSTRACT

Flood, as the most destructive natural phenomenon in Iran, causes a multitude of deaths and financial losses every year in different parts of the country. This study sought to determine flood-prone areas in one of the Ajay River sub-basins (Lighvan River basin), Iran using Analysis Hierarchy Procedure (AHP) for ranking, fuzzy logic (FZ) for integrating with AHP in order to rank and Weighted Linear Combination (WLC) for the combination of maps. For this purpose, the geomorphologic and hydrologic factors affecting the occurrence of floods such as slope, distance from the river, Hydrological Soil Group (HSG), Curve Number (CN), runoff, lithology, land use, drainage density, Gravilius coefficient in each of the 23 sub-basins were considered based on the literature. The desired criteria and sub-criteria were weighted by the AHP and FZ, respectively. Then, WLC aggregation method was applied to generate the flood susceptibility map in five classes. The results earned by the combination of Multi-Criteria Decision Analysis (AHP and WLC)-FZ (MCDM-FZ) show that 28% of the area is in high and very high hazard classes that these areas are located almost at the entrance of Tabriz city, which is a densely populated urban area. Basic measured need to be taken in the upstream of the basin especially in areas with the high flood zone.

Keywords: Flood risk mapping; analytical hierarchical process; fuzzy logic; MCDA; Lighvan River basin.

1. INTRODUCTION

Floods have been the most common, deadliest and most expensive hazard among natural hazards in history (Kusky, 2008). In other words, flooding is one of the few natural hazards in the world that whose rate of damage is impossible to be accurately estimated and that its risk is increasing over time (Kusky, 2008). The reason for such an increase is mainly due to the expansion of urbanization around rivers and deforestation as well (Bronstert, 2003), so that between 2000 and 2008, approximately 99 million people worldwide were affected by the effects of flooding (Shafapour Tehrani et al., 2013). In Iran, like in other flood-prone areas of the world in recent decades, the intensity of floods and the amount of damage caused by them has increased dramatically due to rainfall variations (Norouzi and Taslimi, 2012; Khosravi et al., 2016). It should be noted that more vulnerability can be prevented by identifying flood-prone areas and efficient management in these areas. A bulk of studies and methods have been conducted to identify flood susceptible areas (e.g., Ho and Umitsu, (2011) with integrating geomorphological features and satellite data; Shafapour Tehrani et al., (2013) with decision tree and logistic regression models and factors such as precipitation, land use, elevation, river strength index and soil type; Kalantari et al., (2014) using physiographic characteristics of basins extracted from satellite imagery). Multi-criteria decision analysis (MCDA) methods such as Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) (Yahaya et al., 2010; Tang et al., 2018; Dano et al., 2019) which are based on expert knowledge.

In the present study, the Lighvan River Basin located in the upstream part of Tabriz city with high population density and agricultural lands was selected as the study area. In other words, in the current study, one of the

sources of floods in Tabriz, in terms of flood sensitivity, has been investigated using MCDM and GIS. Regarding the water flows in the river of this basin which passes through a very populated city like Tabriz, identifying the flood zones of this basin and taking appropriate management measures is inevitable to prevent the occurrence of flood events.

2. MATERIALS AND METHODS

2.1. STUDY SITE

The Lighvan basin, where is located in north slope of Sahand mountain (northwest of Iran) was chosen as the study extent (Figure 1). The river flow as the permanent river passes through both topographical units (i.e., mountain and plateau) and four villages (Sefideh-Khavan, Lighvan, Beirag, Hervi, Abdel and Dizaj). After that, it flows towards Basmeng city and joins the Aji River by crossing Tabriz which is the populated city (Nearly two million). There are two hydrological gauges in Lighvan and Hervi (Figure 1). The average annual temperature is 6.8 °C, and average annual precipitation is 292 mm in the basin (IMO, 2016). The climate in the region based on De-Martonne climatic classification is semi-arid and cold winter types.



Figure 1. Location of (a) the Lighvan River basin in NW Iran, (b) the location of gauges and study site and altitude of basin.

2.2. DATA PREPARATION

46°22'30"E

To undertake a flood susceptibility area map modelling using the MCDM model, a variety of data is required, including the land topography, land use, as well as monthly climate and hydrological data for carry out of factors needed. it was therefore arranged a series of datasets from both local and global sources (Table 1).

Variables	Data source	Date/Scale
Digital Elevation	Advance Space borne Thermal Emission and Reflection Global Digital Elevation Model	27m
Model	(USGS/EarthExplorer)	
Land use maps	Landsat 8 Operational Land Imager (USGS/EarthExplorer)/ Date: 2013.07.10	30m

 Table 1. Variable used in MCDM model and data source.

Measured river flow	East & West Azerbaijan Regional Water (EWARW)	1985-2016
Measured rainfall	Iran Meteorological Organization (IMO) and EWARW	1985-2016
Geology maps	FRWMO	1:100000
Topography maps	FRWMO	1:50000

For driving out of land use map for the present the satellite imagery was classified in 2013 using base map land use (FRWMO, 2008) and the Google Earth system and Support Vector Machine (SVM) model. The comparison of some models with each other shows the SVM and ANN classifiers perform better than others. However, the SVM takes less time than ANN (Melgani and Bruzzone, 2004), so SVM was applied to classify in this study. SVM is a binary classifier and separates two classes using a hyperplane (Mirzaei et al., 2019). Necessary precipitation factor as a trigger criterion for the MCDM model was obtained from the 6 rain stations including monthly data for precipitation. Precipitation factor was derived by combining DEM data (elevation) with data from rain gauges (Figure 1). We assumed a linear relation between elevation gain and rain change and used these estimates as regression coefficient y = 0.0143x + 14.004 (y= rain and x= elevation of per pixel) with correlation coefficient of 0.77, which this method was used by Andaryani et al, (2019b). Soil Conservation Services (SCS) method was used to assess discharge in the per pixel of the basin, which

Soil Conservation Services (SCS) method was used to assess discharge in the per pixel of the basin, which uses rainfall and characteristics of watersheds to estimate flood discharge. SCS has offered the following formula:

$$SUR - Q = \frac{(PCP - 0.2S)^2}{PCP + 0.8S}, PCP \ge 0.2S$$
(1)
$$S = \frac{2540}{CN} - 25.4$$
(2)

Where SUR - Q is the surface runoff (cm), S is the potential maximum infiltration (cm), PCP is the precipitation (24 h maximum precipitation of 1985-2016 in 6 gauges), and CN is the curve number that depends on some factors such as land use, hydrologic soil groups (HSG) (Chow, 1988). CN reflects the SUR - Q generation capability of underlying surface pixel and describes the relationship between PCP and SUR - Q in a basin. Figure 2 shows the layers of HSG, PCP in 24 h maximum precipitation, CN and the potential maximum infiltration (i.e., S).

After producing the factors of altitude, slope, lithology, drainage density, Gravilius coefficient, SUR - Q, Strahler ranking, land use and proximity of the river in each of the 23 sub-basins based on literature, AHP weights were calculated for these factors based on the knowledge of 30 experts through questionnaires. Then, the sub-criteria classified according to their importance in flood generation were fuzzy-expertized and then by weighted linear combination (WLC) modeling flood prone map was earned in the study area. The method of AHP has explained in Saaty and Vargas, 2013.

The WLC method, one of various MCDM methods, namely the method, was used in flood prone Map. The purpose of multi-criteria evaluation is to select the best alternative based on their ranking through evaluating some of the main criteria. In this evaluation, the criteria were defined and categorized as factors to achieve the goal (Malczewski, 1999; Eastman, 2012). Each of factors was reclassified and standardized with the fuzzy method. In this decision-making method, the amount of each substitute was calculated according to Equation 3 (Eastman, 2012).

$$\mathbf{S}_{w} = \sum_{i=1}^{n} W_{i} \times S_{i} \tag{3}$$



where S_w is final score, W_i is the weight of each factor, and S_i is criterion rank of each factor.

Figure 2. Layers for calculating of surface runoff (a) hydrological soil groups, (b) 24 h maximum precipitation, (c) curve number and (d) potential maximum infiltration.

3. RESULTS AND DISCUSSION

River hydrograph is affected by its land use and vegetation (Andaryani et al., 2019a). Thus, rain first fills the holes and surface flow begins without water sorption by soil regarding the basins having no vegetation. While a part of rain is absorbed by the branch, leaf and root of plants in the basins possessing proper vegetation. Accordingly, the CN related to basin was considered, which involves vegetation situation and HSG with respect to their water infiltration rate. Further, potential maximum retention (S) is inversely related to curve number. In other words, the soil water retention of areas with less permeability is low as can be observed by adding CN (see Figure 2). The slope is probably considered as the most main factor of flooding in a basin and influences concentration time, flow amount, water infiltration, the pattern of groundwater level changes and soil moisture level. The flood hydrograph related to high-slope basins possesses low amplitude and base period of hydrograph and high peak point, which means the high volume of water passes through a cross section at short time. Figure 3 represents the slope of area, stream order of area by Strahler method, and their amplitude and class number. Strahler number was used as a distinct layer, along with other layers during decision-making since flood risk increases in the sub-basins having higher order.

Stream network density per unit of basin area, length of stream, basin geometric feature and shape and stream placement pattern in a basin play an important role in flooding. Regarding a basin having the high branching ratio of streams, water in basin level is rapidly drained by these channels. The stream density related to the whole basin was obtained as 1.07, while this factor was calculated in 23 sub-basins to account the index of stream density in each sub-basin (see Figure 3). The drainage density of sub-basins varied between 0.77-1.67 which can be a cause for low difference between sub-basins with respect to slope, lithology and area. Basin shape was considered by using Gravelius coefficient. Streams possess minimum path, and accordingly flood occurs in the basins having close to circle form. In low Gravelius coefficient, runoff is rapidly evacuated and concentration time decreases, leading to an increase in flood risk in these areas. The stream density and

Gravelius coefficient related to sub-basins are presented in Figure 2. The numerical amplitude of Gravelius coefficient was regarded as 1.53-2.95, indicating that these sub-basins were devoid of complete circle or pull form. In fact, the level of flood-producing in this area was determined as moderate based on this coefficient. It should be noted that the sub-basins having same class were merged (see Figure 3, stream network density and Gravelius coefficient).

The type of rock and soil cover affects infiltration capacity. Permeable soil or rock results in providing the condition of water infiltration into soil, delaying its evacuation into main stream, and reducing surface runoff. However, the high volume of surface runoff is produced in the basins having relative unfilterable bedrock or soil. Due to the placement of the study area in the northern slope of the Sahand mountain, most units are affected by volcanic activities so that most lands (57% or 211km2) of the area can be covered by the stratigraphy of Plio-Quaternary with PLQC unit (Conglomerate- tuff- lahar) (see Figure 3, Lithology). These fragments are composed of the volcanic rocks caused by the old activities of Sahand mountain and its cement is mainly regarded as loose and composed of sand, clay, and volcanic ash. Thus, the infiltration of rocks is low in most area and plays an important role in producing runoff due to weak rangeland cover.



Figure 3. Flood controlling factors for providing flood susceptibility map: a) land use (IA= irrigated agriculture, Fuzzy membership value(FMV) = 0.1, 0.6, 0.6, 0.2, 0.3, 0.9 and 0.9, respectively), b) surface runoff (FMV = 0.2, 0.4, 0.6, 0.8 and 1, respectively), c) Strahler ranking (FMV = 0.1, 0.3, 0.7 and 1, respectively), d) slope (FMV = 0.2, 0.5, 0.55, 0.8 and 1, respectively), e) stream network density (FMV = 0.1, 0.3, 0.5, 0.8 and 1, respectively), f) Gravelius coefficient (FMV = 1, 0.6, 0.4, 0.2 and 0.1, respectively), g) distance to stream (FMV = 0.1, 0.3, 0.5, 0.8 and 1, respectively), h) lithology (1= resent alluvium and FMV= 0.1, 2= alluvial fans - gravel plains and FMV= 0.1, 3= Volcanic breccia -lahar and FMV= 0.5, 4= Dacite -andesite and FMV= 0.8, 5= Dacitic-andesite-quartz and FMV= 0.8, 6= Marl -sandstone and FMV= 0.6, and 7= Conglomerate-tuff-lahar and FMV= 0.6).

In the present study, AHP method with respect to expert opinion was used to weight the individual criteria in pairs. Table 2 shows the results of weighting to effective criteria for flood risk.

Criteria	1	2	3	4	5	6	7	8	Eigen values	Consistency ratio
SUR-Q(1)	1								0/34	
Slope (2)	0/5	1							0/23	
Distance to stream (3)	0/33	0/5	1						0/18	
Lithology (4)	0/33	0/25	0/33	1					0/11	
Land use (5)	0/14	0/2	0/25	0/25	1				0/05	
Stream network density (6)	0/12	0/25	0/16	0/2	0/25	1			0/03	
Gravelius coefficient (7)	0/11	0/2	0/14	0/16	0/33	0/5	1		0/025	
Strahler ranking (8)	0/1	0/15	0/15	0/2	0/2	0/4	0/3	1	0/02	
										0/08

Table 2. Pairwise comparison matrix for factors affecting the flood.



Figure 4. (a) flood susceptibility map using MCDM and fuzzy method and (b) relative proportion of areas.

As shown in Table 2 and weighting method, the maximum effect on flooding was observed in the factors of SUR-Q and slope, respectively. The Consistency value of 0.08 represented the correct scoring of criteria, which must be less than 0.1. After weighting criteria, the numerical amplitude of 0 - 1 was assumed for subcriteria to enter into WLC model by using Fuzzy approach based on the amount of their importance in flooding (see caption of Figure 3). It should be noted that Expert's viewpoints and weighting criterion questionnaire were provided in the present study.

The site study was divided into five classes by applying the multi-criteria decision making (MCDM) of weighted linear composition (WLC) on produced layers and reclassification (Figure 4a). consideration of the zoned map for the flood risk indicated that 5.97%, 22.19%, 32.83%, 29.36%, and 9.85% of the Lighvan River basin is in the very high, high, medium, low, and very low risk class, respectively (Figure 4b).

It should be noted that the AHP method is popular as a method of criteria ranking and allows a degree of individuality in the pairwise comparisons between the criteria (see Table 2). In the other hand, the application of WLC needs the standardization of classes within the criteria to a common numeric range (e.g. 0–1). This standardization addresses the relative importance of each class in flood porn.

4. CONCLUSION

Recognizing the flood risk-sensitive areas in basins, especially in those having steady rivers, which passes through population centers and applying optimum and efficient managerial methods can reduce the losses caused by this natural hazard. The areas sensitive to flood-producing were zoned by using satellite data, observed data, remote sensing technique and geographic information system by recognizing the factors which influence flooding such as land use, elevation, SUR-Q and the like in the present study. However, in the present study, criteria and their sub-criteria were weighted by using AHP and fuzzy models by considering expert's viewpoint, respectively. Further, WLC was used for the flexible combination of maps. Based on the results, the area is flood-producing in basin downstream and entrance of Tabriz city so that more than 28% of area can belong to the areas having high and very high flood-producing potential. Considering abundance life and financial losses caused by flooding in the entrance areas of Tabriz in each year, basic activities should be conducted in basin upstream, especially in the areas with high flood-producing zone. These activities can be planned to implement the comprehensive management programs of basin and management of flood risk and watershed in order to improve vegetation situation in basin level, reduce life and financial losses during a long term, and prevent land use change in the bed and limit of flood-producing rivers and streams by flowing and enforcing available rules continuously and developing and setting new rules.

Acknowledgments

This research was partially supported by the Iranian National Elites Foundation.

REFERENCES

Andaryani, S., Nourani, V., Trolle, D., Dehghani, M., Mokhtari Asl, A., 2019a. Assessment of land use and climate change effects on land subsidence using a hydrological model and radar technique. Journal of Hydrology. https://doi.org/10.1016/j.jhydrol.2019.124070.

Andaryani, S., Trolle, D., Nikjoo, M.R., Rezaei Moghadam, M.H., Mokhtari, D., 2019b. Forecasting near future impacts of land use and climate change on the Zilbier River hydrological regime northwestern. Iran. Environ. Earth Sci. 188 (6). https://doi.org/ 10.1007/s12665-019-8193-4.

Bronstert, A., 2003. Floods and climate change: interactions and impacts. Risk Anal 23, 545–557.

Chow, V.T., 1988. Applied hydrology. McGraw-Hill book Company, New York.

Dano, U.L., Balogun, A.L., Matori, A.N., et al., 2019. Flood Susceptibility Mapping Using GIS-Based Analytic Network Process: A Case Study of Perlis, Malaysia. Water 11 (3), 615; doi:10.3390/w11030615. Eastman, R.J., 2012. IDRISI for Windows: IDRISI Selva Manual. Clark University, New york.

Ho, T.K.L., Umitsu, M., 2011. Micro-lan dform classifi cation and flood hazard assessment of the ThuBon alluvial plain, central Vietnam via an integrated method utilizing remotely sensed data. Applied Geography 31, 1082-1093.

IMO, 2016. Country Climate Analysis in year 2016. Iran Meteorological Organization, Tehran. Iranian Forest, Range and Watershed Management Organization (FRWMO)., 2008. The studies of soil in Lighvan river basin, East Azerbayjan, Iran.

Kalantari, Z., Nickman, A., Lyon, S.W., Olofsson, B., Folkeson, L., 2014. A method for mapping flood hazard along roads. Environmental Management 133, 69 -77.

Khosravi, K., Nohani, E., Maroufinia, E., Pourghasemi, H.R., 2016. A GIS-based flood susceptibility assessment and its mapping in Iran: a comparison between frequency ratio and weights-of-evidence bivariate statistical models with multi-criteria decision-making technique. Natural Hazards 83 (2), 947-987. Kusky, T., 2008. Floods: Hazards of Surface and Groundwater Systems, Facts On File publishing, New York.

Malczewski, J., 1999. GIS and Multicriteria Decision Analysis, John Wiely and sons, New york. USA. Melgani, F., Bruzzone, L., 2004. Classification of hyperspectral remote sensing images with support vector machines. IEEE Transactions on Geoscience and Remote Sensing 42, 1778–1790.

Mirzaei, M., Marofi, S., Abbasi, M., Solgi, E., Karimi, R., Verrelst, J., 2019. Scenario-based discrimination of common grapevine varieties using in-field hyperspectral data in the western of Iran. International Journal of Applied Earth Observation Geoinformation 80, 26–37.

Norouzi, G., Taslimi, M., 2012. The impact of flood damages on production of Iran's Agricultural Sector. Middle-East Journal of Scientific Research 12 (7), 921-926.

Saaty, T. L., and L. G. Vargas. 2013. Decision Making with the Analytic Network Process: Economic, Political, Social and Technological Applications with Benefits, Opportunities, Costs and Risks. Vol. 195. Dordrecht: Springer Science and Business Media.

Shafapour Tehrani, M., Pradhan, B., Jebur, M.N., 2013. Spatial prediction of flood susceptible areas using rule-based decision tree (DT) and a novel ensemble bivariate and multivariate statistical models in GIS. Journal of Hydrology 504, 69–79.

Tang, Z., Zhang, H., Yi, S., Xiao, Y., 2018. Assessment of flood susceptible areas using spatially explicit, probabilistic multi-criteria decision analysis. Journal of Hydrology 558, 144-158.

Yahaya, S., Ahmad, N., Abdalla, R.F., 2010. Multicriteria analysis for flood vulnerable areas in Hadejia-Jama'are River basin, Nigeria. European Journal of Scientific Research. 42(1), 71-83.