**Urban flood risk zoning using GARP and QUEST models: A comparative study of artificial intelligence approaches**

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**Abstract**

Flood risk mapping is important to prevent urban flood damage. In this study, a flood risk map was produced using limited hydrologic and hydraulic data using two state-of-the-art machine learning models: Genetic Algorithm Rule-Set Production (GARP) and Quick Unbiased Efficient Statistical Tree (QUEST). The flood conditioning factors used in modelling were precipitation, slope, curve number, distance to river, distance to channels, depth of groundwater, land use, and elevation. Based on the available reports and field surveys in Sari city (Iran), 113 points were identified as flooded areas (assigned the value 1 for each flooded zone). Different socio-economic condition related factors including urban density, quality of buildings, history of buildings, and population density were taken into account to analyze flood vulnerability. In addition, the weight of conditioning factors incorporated in the flood vulnerability were determined based on the exports’ knowledge and Fuzzy Analytical Network Process (FANP). Subsequently, the urban flood risk map was produced using the flood hazard and flood vulnerability maps. The area under receiver operator characteristic curve (AUC-ROC) and Kappa statistic were applied to evaluate the performance of models. Results demonstrated that GARP model (AUC-ROC=93.5%, kappa=0.86) had the higher performance accuracy than QUEST model (AUC-ROC=89.2%, kappa=0.79). Furthermore, results indicated that distance to channels, land use, and elevation play the main roles in flood hazard modeling, whereas population density, quality of buildings and urban density were the most important factors in terms of the vulnerability. The results of this study demonstrate that machine learning models are helpful for flood risk mapping, especially where detail hydraulic and hydrologic data are not available.

**Keywords**: Urban planning, Flood risk management, GIS, FANP, Data-mining

**1. Introduction**

Urban areas can be flooded due to intense precipitation, rapid snow melt, poor drainage systems, inadequate sewer systems, impervious materials, and also elevated sea or lake, river and ground water levels (Schmitt et al., 2004; Fernández and Lutz, 2010). Urban environments are vulnerable to flood damage due to the density of economic and social assets and lots of infrastructures, and there is an increasing attention to implement flood risk reduction measures. Flood impacts can be mitigated by improved prediction, awareness (early warning) and mapping. In flood studies, it has been widely accepted that absolute flood protection is impossible (Kreibich et al., 2005; Schanze, 2006; Kubal et al., 2009). Instead, growing attention has been given to the spatial prediction of flood risk (Büchele et al., 2006; Lee et al., 2017; Tehrany et al., 2017; Siahkamari et al., 2018). Future flood consequences can be limited through risk assessment and flood management measures such as changes in building codes and land uses, improved flood defenses, selective relocation of vulnerable assets, insurance policies, and emergency preparedness (Woodward et al., 2014; Koks et al., 2015; Otto et al., 2018). Importantly, flood inundation models play a central role in prediction planning, and the implementation of these measures in high-risk zones (Ernst et al., 2010). However, complexities in the urban areas and their drainage infrastructures have an inherent influence on surface runoff and flood inundation which poses challenges for modeling urban flood risk (Chen et al., 2009; Mansur et al., 2018).

Previous studies have used different types of models to assess ﬂoods in urban areas such as [Hydrological Simulation Program-FORTRAN](https://www.epa.gov/exposure-assessment-models/basins-framework-and-features) (HSPF) model (Bicknell et al., 1993), the Illinois Urban Drainage Area Simulator (ILLUDAS) model (Terstriep and Stall, 1974), Technical Release 55 (TR-55) model (USDA, 1986), Hydrologic Engineering Center-River Analysis System (HEC-RAS) model (Wiles and Levine, 2002), Storm Water Management Model (SWMM) (Cole and Shutt, 1976), and the Urban Flood Cell Model (MODCEL) (Gomes Miguez et al., 2017). In addition, geospatial information system (GIS)-based multi criteria decision analysis such as Analytic Hierarchy Process has been widely used (Fernández and Lutz, 2010; Stefanidis and Stathis, 2013; Tang et al., 2018).

With the recent advancements in artificial intelligence approaches, many researchers have paid attention to apply these predictive models in natural hazard assessment. According to the literature, various types of GIS-based machine learning and/or data-mining models including support vector machine (SVM) (Tehrany et al., 2015), artificial neural network (ANN) (Campolo et al., 2003; Kia et al., 2012), decision tree (DT) (Tehrany et al., 2013), maximum entropy (Siahkamari et al., 2018), random forest (RF) (Rahmati and Pourghasemi, 2017; Lee et al., 2017; Hong et al., 2018b), adaptive neuro fuzzy inference system (ANFIS) (Hong et al., 2018a; Termeh et al., 2018), boosted regression trees (BRT) (Rahmati and Pourghasemi, 2017), multivariate adaptive regression splines (MARS) (Shafizadeh-Moghadam et al., 2018), logistic model tree (LMT) (Chapi et al. 2017), naïve Bayes trees (NBT) (Khosravi et al., 2018), weights-of-evidence (Tehrany et al., 2014; Rahmati et al., 2016), logistic regression (LR) (Pradhan 2010), Shannon’s entropy (Haghizadeh et al. 2017) have been employed for flood hazard modelling. So far, however, a few studies have investigated the capability machine learning models for flood risk modeling (e.g., Wang et al., 2015).

The biggest challenge addressed in several urban flood models is that the mentioned hydraulic models rely on detailed hydrologic and hydraulic data. Therefore, these models cannot be directly used in data-scarce environments, especially in developing countries where data availability is still a big challenge. The current study was employed to develop new approaches including Genetic Algorithm Rule-Set Production (GARP) and Quick Unbiased Efficient Statistical Tree (QUEST), as two state-of-the-art machine learning algorithms, for modeling ﬂood inundation risk in an urban environment. These models are enable to analyze the relationship between topo-hydrological spatial data and flood inundation events. As their strong advantages, these models don't deﬁne strict assumptions prior to analysis and can also handle data from various measurement scales. In addition, they allow to accurately discover complex relationships between variables in a dataset (Gleason and Im, 2012).

The GARP model have been successfully applied for modeling the effects of climate change on distributions of triatomine species (Carmona‐castro et al., 2018), modeling species’ ecological niches (Townsend Peterson et al., 2007; De Meyer et al., 2008), modelling the occurrence of marine animals (MacLeod et al., 2008), predicting the spatial distribution of invasive plant species (Zhu et al., 2007; Qin et al., 2015), modeling the potential distribution of emerald ash borer (Sobek-Swant et al., 2012), and etc. The QUEST algorithm has many advantages over other models as it is a quick, impartial, and efficient statistical tree and employs a linear or unbiased variable selection model and uses imputation instead of substitute splits to deal with missing values (Sut and Simsek, 2011). Previous studies have applied the QUEST algorithm for modeling the ground subsidence (Lee and Park, 2013), groundwater potential mapping (Lee and Lee, 2015; Huajie et al., 2016), landslide susceptibility (Park and Lee, 2014), and predicting soil map (Behrens and Scholten, 2006). From the aforementioned literature review, it was revealed that applications of the GARP and QUEST models in urban flood risk assessment are not yet investigated. Therefore, this study aims to apply two state-of-the-art machine learning techniques for investigating flood risk in an urban area. The main objectives of the present work was to: i) assess the role of different factors resulting in ﬂooding in the urban area of Sari city (Iran), ii) predict and validate flood hazard map by GARP and QUEST models, iii) produce vulnerability map to flood using Fuzzy Analytical Network Process (FANP), and iv) create a flood risk map based on flood inundation hazard and vulnerability analysis. The results of this study are useful for modeling flood risk in urban environments, especially where a complete hydrologic and hydraulic dataset are not readily available.

**2. Material and methods**

**2.1. Description of study area**

Sari city is one of the largest cities of Northern Iran extending between latitudes 35°58′39′′ to 36°50′12′′ North and longitude of 52°56′42′′ to 53°59′32′′ East and the altitude is between 9 to 82 m. (Fig. 1). The city with 296,417 populations is the second largest city in the southern coast of Caspian Sea (Zali et al., 2016). The city covers an area about 42 km2 and is located at outlet of Tajan river watershed (with area about 4352 km2), Tajan River passes from the eastern part of Sari and then discharged to the Caspian Sea. The residential part of the city is surrounded mainly by agricultural land, orchards and high mountain (Alborz) covered by forest. The climate type in the region is dry semi-humid (aridity index: 0.73 based on Sahin, 2012; Choubin et al., 2018), with 734 mm annual precipitation and 1004 mm potential evapotranspiration. Rainfall data (for the years 1986-2016 for Sari weather station were obtained from the Iranian Meteorological Organization (IRIMO).

**Fig. 1.** SOMEWHERE HERE

**2.2. Data used**

**2.2.1. Conditioning factors of urban flood hazard**

There are no universal guidelines for selecting flood conditioning factors in urban areas. In the present study, eight different factors were selected based on the literature to evaluate flood inundation hazard including rainfall, land use / land cover (LULC), elevation, slope percent, curve number (CN), distance to river, distance to the channels, and depth to groundwater level (Thieken et al., 2005; Chen et al., 2009; Fernández et al., 2010; Ouma and Tateishi, 2014).

- **Rainfall:** daily rainfall data was obtained from the meteorological stations to prepare the rainfall amount map. It varies from 722 mm (in the east of study area) to 745 mm (in the west of study area) (Fig. 2a).

- **Land use / land cover:** runoff conditions vary considerably under different land use/ land cover patterns. LULC map was obtained from the municipality of Sari for 2015. According to the LULC map (Fig. 2b), the study area was subdivided into three main group types: open spaces (include orchard, parks and agriculture area), urban districts (residential buildings, commercial, business and industrial buildings) and water body (river).

- **Elevation:** a Digital Elevation Model (DEM) with a resolution of 5m was obtained from municipality of Sari (Fig. 2c). Elevation of the study area ranges from 9 to 82 m.

- **Slope percent:** the slope percent factor plays a main role in flooding as it affects the water velocity. In addition, flatlands or lowlands have gentle slopes that reflect a constant threat of flooding (Wang et al., 2015). The slope map was extracted from the DEM of the study area in ArcGIS 10.3 to quantify topographic controls on hydrological processes. The slope varies from more than 6% along the south of area to less than 1% in the center and north of study area. (Fig. 2d).

- **Curve Number (CN):** the curve number (CN), which has been developed by USCS (United State Soil Conservation Service), is a function of land use treatments and hydrologic condition, antecedent soil moisture, and soil type. Land use and Hydrologic Soil Group (HSG) maps were used to estimate the contribution of rainfall in runoff. In this study the CN map (Fig. 2e) was extracted based on the land use map and the HSG map and lumped CN value using ArcCN-runoff tool in ArcGIS software (Zhan & Huang 2004; Darabi et al 2014). As shown in Fig. 2e, different CN class are given corresponding codes, where larger code value indicates stronger runoff generation capability.

- **Distance to river:** the banks of Tajan Riverare considered as major flood-prone areas during floods. Hence, the map of distance to the river plays an important role in urban flood mapping in Sari city. The Euclidean distance to the river was calculated using Euclidian Distance module in ArcGIS 10.3 (Fig. 2f).

- **Distance to channels:** Channels or drainage systems over the urban environments collect surface water and the map of ‘distance to channels’ was prepared using Euclidian distance module (Fig. 2).

- **Depth to groundwater level:** infiltration capacity generally depends on the soil moisture and depth to groundwater, which directly affects the surface runoff volume during high-intensity precipitation (Fernández and Lutz, 2010). Some studies have documented that depth to groundwater level has effective factor for the initial storage capacity over the basin (Yin and Li, 2001; Fernández and Lutz, 2010). The groundwater level data used in this study were obtained from Iranian Water Resources Management Company (IWRMC). As can be seen in Fig. 2h, the depth of groundwater level ranges from 1.9 (in the northern parts of study area) to 20.8 (in the sought of study area).

Among of the eight conditioning factors on urban flood inundation hazard, the continuous factors include elevation, slope, depth to groundwater, distance to channel, distance to river and rainfall, whereas the categorical factor include the land use and curve number.

**Fig. 2.** SOMEWHERE HERE

**2.2.2. Flood inventory map**

Mapping the ﬂood locations in the study area is vital to explain the correlation among the ﬂooding and the conditioning factors.

In this study, a flood inventory map was prepared based on both multiple field surveys and documents available (flood historical database) of municipality of Sari during 2015 to 2017. The location of the flooded sites was recorded using a Global Positioning System (GPS) device. In this area, floods have been occurred in the wet periods (December-May). Fig. 1 shows the severity of the ﬂood that occurred in 2015–2017. In order to develop urban flood hazard map, the flooded and non-flooded (absence of flooding) areas were assigned codes of 1 and 0, respectively. In this step, the historical records of flood occurrence and inspection provide essential information (Fig. 1). Based on the field surveys in urban area of Sari, a total of 113 points were identified as flooded area, whereas 76 non-flooded points were randomly chosen in non-flooded zones. For flood hazard analysis, the flood inventory locations were randomly divided into two groups 70% (79 flood locations) and 30% (34 flood locations) for the purpose of training and validation, respectively. In addition, non-flood dataset also was randomly split into two groups of training (70% of non-flood locations) and validation (30% of non-flood locations).

**2.2.3. Vulnerability factors**

Vulnerability has been defined as *“the conditions determined by physical, social, economic and environmental factors or processes, which increase susceptibility to the impact of hazards”* (UNDP, 2004). Ouma and Tateishi (2014) explained that flood vulnerability is the process of determining the susceptibility degree of a given place to flooding if information on its exposure to floods is known. There are various socio-environmental factors that inﬂuence vulnerability in urban areas and their inclusion may depend on available data (Dayal et al., 2018). In the present study, several different factors including urban density, quality of buildings, history of buildings, population density, and socio-economic conditions were taken into account.

In the case of building density condition, the urban density of the municipality of Sari was divided into four classes, including high, medium, low and very low according to suggestion of Güneralp et al. (2017) (Fig. 3a). Quality and the age of buildings have significant impacts on damages caused by urban floods. Quality of buildings are divided into five classes, including very high, high, medium, low and very low which reflect quality of buildings condition. Also in the quality of building map, there are areas namely no building which represents areas without buildings (Fig. 3b). Low quality building is unsafe for their inhabitants and their properties, and have more vulnerable to natural hazards, especially earthquakes and floods (Schubert and Sanders, 2012, Gerl et al., 2014). The current architectural structure of Sari city shows its historical development. The densely built-up by historical and modern buildings with administrative and commercial functions is located in the Sari city center. In neighboring districts, settlement areas with multi-history residential buildings and open space areas are abundant. Buildings are divided into five classes such as very old, old, medium, new and newest which reflects the historical condition and also no buildings area (Fig. 3c). To prepare the urban flooding and vulnerability map, the age and quality of buildings have to be considered. For studied area, the quality and history of buildings map were obtained from the municipality of Sari for 2015. Population density and socio-economic information from inhabitants are two last but not at least key issues, which have to be considered to prepare flood vulnerability map. Population density refer to the number of people inhabiting a given urbanized area and higher levels of population density and associated with economic conditions, higher productivity and also higher susceptibility to natural hazards such as earthquake and floods (Güneralp et al., 2017). In this study, population density map is divided into four classes, high, medium, low and very low which reflect population density condition (Fig. 3d). Socioeconomic data, contain in-depth information on the inherent properties and behavior of humans and society within a specific geographical region. These types of information are valuable in taking account of the otherwise indirect and intangible impacts of natural hazards such as flooding (Kaspersen and Halsnæs, 2017). In the current research, socio-economic condition map is divided into five classes, including A, B, C, D and E which reflect very good, good, moderate, weak and very weak socio-economic condition respectively (Fig. 3e). There are also natural areas surrounding the Sari city, which was not considered as residential area. The population density and socio-economic condition map for this study were obtained from the municipality of Sari for 2015. The classification of all the aforementioned variables was carried out by the municipality of Sari.

**Fig. 3.** SOMEWHERE HERE

**2.3. Risk prediction**

Risk is a function of hazard and vulnerability. Therefore, the urban flood risk map is produced through flood hazard and vulnerability maps using equation 1 (Dewan, 2013).

(1)

Description of the models used for prediction of the flood hazard, assessing models performance, preparing the vulnerability map based on the Fuzzy Analytical Network Process (FANP), and extraction of the flood risk map mention are presented in the next section.

**2.3.1. Flood hazard prediction**

In this study, two state-of-the-art machine learning models namely Genetic Algorithm for Rule-set Prediction (GARP) and Quick, unbiased, and efficient statistical tree (QUEST) were applied to produce flood hazard map.

**2.3.1.1. Genetic Algorithm for Rule-set Prediction (GARP)**

GARP is a machine-learning algorithm that has shown excellent predictive capability in different fields such ecological modeling (Stockwell, 1999; Peterson et al., 2002a). The GARP algorithm was selected to predict flood inundation hazard in the study area. It is inspired by models of genetic evolution as a presence-only modeling tool that analyzes the relationship between flood inundation dataset and topo-hydrological variables through an iterative process and conditional rules for model building (Zhu et al., 2007; Sánchez-Flores, 2007; Boeckmann and Joyner, 2014; Qin et al., 2015). The GARP algorithm (Boeckmann and Joyner, 2014) produces several flood inundation in urban areas through iteration process to improve the stability of model output. In the other words, multiple runs for producing the different outputs of model, and also utilize the best-subset method are an important to select the best output with optimum parameters. Set of models that find a harmony between omission (sensitivity) and commission (specificity) errors thresholds are defined by the user (Anderson et al., 2003; Boeckmann and Joyner, 2014). The GARP output is a collection of grids over the study area which these grids can be used in a GIS environment to find flood-prone areas (Boeckmann and Joyner, 2014). In this study, the GARP model was performed using DesktopGARP software. Based on optimum combinations of error components the 10 best-subset models were chosen out of the 100 repeats (Anderson et al., 2003; Sobek-Swant et al., 2012). In addition, the importance of conditioning factors (ICF) (precipitation, slope, curve number, distance to river, distance to channels, and depth of groundwater, land use, and elevation) in the urban flood hazard was analyzed using GARP model. A complete mathematical and technical description of GARP model can be found in Peterson et al. (2002b) and Fitzpatrick et al. (2007).

**2.3.1.2. Quick, unbiased, and efficient statistical tree (QUEST)**

The QUEST (Loh and Shih, 1997) is a popular data-mining model which produces subsets of the data which are as homogeneous as possible with respect to the response variable (Rattray et al., 2009; Ture et al., 2009). The QUEST as a quick, unbiased, efficient and statistical tree-structured classification algorithm that yields a growing binary-split decision tree (Lee and Park, 2013). It is a sequential tree growing method which utilizes a linear discriminate analysis method in splitting of tree nodes and have many advantages over recursive tree construction methods such as classification and regression tree (CART) (Ierodiaconou et al., 2011). In addition, it is unbiased in choosing splitting rules and does not use an exhaustive variable search routine (Sut and Simsek, 2011).

The QUEST algorithm was selected as the second model to predict flood inundation. Moreover, the QUEST algorithm and applies imputation instead of surrogate splitting to deal with missing values. According to Ture et al. (2005) QUEST has a negligible bias because it uses an unbiased variable-selection technique in modeling. Therefore, QUEST can easily handle categorical and continues factors (Chou, 2012; Lee and Park, 2013; Lee and Lee, 2015).

**2.3.2. Evaluating the predictive performance of models**

The receiver–operator characteristic (ROC) was used to evaluate of the performance of models (Gorsevski, 2006; Jiménez‐Valverde et al., 2012). The area under the curve (AUC-ROC) has been widely used for evaluating the model accuracy (Frattini et al., 2010). The AUC-ROC value is the probability that a test record is accurately differentiated from a random point in the predetermined context the area of study (Phillips and Dudík, 2008). Area under the curve values range from 0 to 1, and models will be classified when AUC-ROC varies between 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9 and 0.9–1 as weak, average, good, very well and excellent, respectively (Yesilnacar, 2005). The AUC-ROC is considered as one of the most popular evaluation criterion to assess the performance of the different models which produce both success and prediction rates (Tehrany et al., 2014). In addition, the Kappa statistic uses the model classiﬁcation probabilities to calculate the likelihood of agreement by chance based on null hypothesis investigation (Monserud and Leemans, 1992). According to the Monserud and Leemans (1992), Kappa statistic can be classified into five classes of performance: k < 0.4, 0.4 < k < 0.55, 0.55 < k < 0.85, 0.85 < k < 0.99, 0.99 < k < 1.00 poor, moderate, good, excellent and perfect, respectively. All performance analyses were carried out in R software.

**2.3.3. Urban flood vulnerability map**

Urban density, quality and historical background of buildings, population density, and socio-economic conditions (Figure 4) were used to determine vulnerable areas to flood inundation events. The relative weights of these factors were determined using Fuzzy Analytical Network Process (FANP). FANP is one of the multiple decision making techniques which incorporate the Analytical Network Process (ANP) with Fuzzy set theory. FANP is conducted in five steps: (Buyukozkan and Cifci, 2012; Sajedi-Hosseini et al., 2018): i) Transformation of problem to a network structure. The first step was done by Fuzzy Decision Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) to design a network structure from effecting factors on vulnerability to flood. Fuzzy DEMATEL has been widely used to solve structure of complex problems through visual structural model and assess the causal relationship between factors (Wu and Lee, 2007). In Fuzzy DEMATEL, the directed influential degrees between pair-wise criteria are expressed as fuzzy interval numbers (Table 1). To find more details of Fuzzy DEMATEL see Chang et al. (2011), Dalalah et al. (2011), and, Sajedi-Hosseini et al. (2018); ii) Pairwise comparisons of criteria based on their importance using fuzzy extent analysis. Details of fuzzy extent analysis are described in Chang et al. (2011). Triangular fuzzy numbers to pairwise comparisons are represented in Table 1; iii) Calculation of the initial super-matrix based on the weights obtained from the previous step; iv) Computation of the weighted super-matrix through multiplying the initial super-matrix by cluster weights; v) Eventually, convert weighted super-matrix into limit super-matrix and determining the priorities and importance of factors. The FANP and Fuzzy DEMATEL methods were used in the super decision and MATLAB software respectively, and then output layers were overlaid in the GIS environment.

**Table 1:** SOMEWHERE HERE

**3. Results and discussion**

**3.1. Performance of models**

The efficiency and precision of the GARP and QUEST models were assessed using AUC-ROC and Kappa evaluation criteria (Fig. 4 and Table 2). According to validation results (Fig. 4 and Table 2), GARP and QUEST models achieved 93.50% and 89.20% prediction rates, respectively. Therefore, the efficiency of the GARP model was somewhat better than the QUEST model. In addition, the Kappa value was 0.86 and 0.79, for GARP and QUEST models, respectively. The performance of GARP and QUEST models was classified as excellent and good according to Kappa statistic classification (Table 2). Machine learning and data mining techniques have been become more popular in the field of spatial modeling of natural hazards, especially in flood hazard/risk mapping (Tehrany et al., 2014; Rahmati and Pourghasemi, 2017; Lee et al., 2017; Hong et al., 2018b). It is not possible to have a direct comparison between obtained results in this study and previous studies, because the efficiency of GARP and QUEST models has not been explored in the literature of urban flood risk. According to the literature, the use of hydraulic models for flood inundation mapping in urban areas is the time-consuming in inputs process, calibration, and outputs and also they need detail hydraulic and hydrologic data, while the machine learning algorithms have the advantage of automatically discovering interactions between a natural hazard such as flood (i.e., dependent variable) and geo-environmental and topo-hydrological characteristics (i.e., independent variables) (Bates, 2004; Tehrany et al., 2013). In addition, machine learning models do not deﬁne strict assumptions prior to flood analysis and can also handle data from various measurement scales (Wang et al., 2015). Some researchers have used multi-criteria decision analysis (MCDA) methods for flood hazard zoning in an urban area, although these kind of subjective methods are based on expert’s opinions which it will result in higher uncertainty (Fernández and Lutz, 2010).

**Fig. 4** SOMEWHERE HERE

**Table 2** SOMEWHERE HERE

**3.3. Urban flood hazard mapping**

The urban flood maps produced by GARP and QUEST models (Fig. 5a and 5b) describe flood inundation probability over study area. Both models demonstrated that zones with high hazard probability are mostly located in the north, center of study area (along the Tajan river). Also, Fig. 5 shows that both modeling approaches are similar to each other in terms of flood inundation prediction. Both models provided valuable information to map flood hazard, although there were no detailed hydrological and hydraulic data.

**Fig. 5.** SOMEWHERE HERE

**3.4. Contribution analysis of predictive factors**

The results of GARP model indicated that distance to channel (ICF=1.00), land use (ICF=0.96) and elevation (ICF=0.89) were the most important factors. This was followed by curve number (ICF=0.83), distance to river (ICF=0.74), depth to groundwater (ICF=0.57), rainfall (ICF=0.38) and slope (ICF=0.22) (Fig. 6). Therefore, all thematic layers had a significant contribution in flood inundation modeling, hence, all of them were used as independent variables in GARP and QUEST models to generate the urban flood hazard map. In this context, Fernández and Lutz (2010) demonstrated that the distance to channels is most important factor in urban flood hazard zoning, which confirmed our finding in this study.

**Fig. 6** SOMEWHERE HERE

Probability curves of GARP model for each of the continuous factors are presented in Fig. 7. Fig. 7a shows that increasing the altitudes up to 30 meters, the probability of flood inundation hazard also increases, and after altitude value of 30 m, flood inundation probability decreases. This can be due to the fact that rising altitude has a significant role in reducing the occurrence of flood inundation hazard (Wang et al., 2015). Heights above 50m were assigned as the most favorable class from a flood hazard point of view. Also with respect to Fig. 7b, with increasing slope up to 1.4%, flood inundation hazard will increase, and later, with the slope > 1.4%, the probability of flood inundation hazard will decrease.. In fact, on very flat zones where ponding areas occur, a considerable amount of the surface runoff may be retained, resulting a flood inundation.

Fig. 7c shows that when groundwater depth increases, the flood inundation hazard significantly decreases. It is due to this fact that infiltration capacity and saturation process are significantly affected by groundwater–surface water interactions, hence, sites with high water-table levels have flood inundation problems (Westbrook et al., 2006; Fernández et al., 2010). This result is in agreement well with findings reported by Bryant and Rainey (2002) and Nosetto et al. (2015).

In Fig. 7d and 7e, flooding inundation hazard increases with decreasing ‘distance from the river’ as well as ‘distance from the channel’, and these two variables showed similar response to the probability of the flood inundation occurrence. Increasing the distance from the river and channels for every 200 meters, the average probability of flood inundation hazard decreases by 0.08 and 0.1, respectively. Surveying of the study area and the records from the local authorities demonstrated that the most affected areas during flood inundation events are those near channels and Tajan river, as a consequence of overflow. The actual capacity of the urban drainage system in some parts of the city is not enough to discharge the upstream, resulting in flood inundation problems. In this regard, Meierdiercks et al. (2010) highlighted that drainage density and presence of stormwater ponds significantly impact flood inundation and peak discharge. Furthermore, according to Fig. 7f, the probability of the flood inundation occurrence increases as rainfall increases. Fu et al. (2011) and Qin et al. (2013) demonstrated that rainfall characteristics have significant effects on flood inundation hazard in urban areas.

**Fig. 7.** SOMEWHERE HERE

**3.5. Vulnerability map**

Regarding FANP results to evaluate the relative importance analysis of urban flood vulnerability factors, population density (0.370), quality of buildings (0.185) and urban density (0.148) were the most important factors and followed by the history of buildings (0.148) and socio-economic (0.147). Also the weight assigned to each class of the urban density, quality of buildings, history of buildings, population density, and socio-economic factors (based on the exports’ knowledge and FANP method) are summarized in the Table 3.

**Table 3:** SOMEWHERE HERE

The urban flood vulnerability value of each part of the city which created based on FANP method is shown in Fig. 8a. The most vulnerable flooding zones are located in the center part of the Sari city. For better visual interpretation of urban flood vulnerability, the vulnerability map was classified into five classes of flood vulnerability (Fig. 8b): very low, low, moderate, high and very high with 35.49%, 15.25%, 13.52%, 22.61% and 13.10% of study area, respectively.

**Fig. 8.** SOMEWHERE HERE

**3.6. Risk map**

Figure 9a indicates flood risk index map which risk value ranges from 0.05 to 0.76. The flood risk map was classified into five classes using the natural break method,: very low, low, moderate, high and very high which cover 32.90%, 21.71%, 21.98%, 7.70% and 15.69% of study area, respectively (Fig. 9b). The flood risk map indicates that the central and northern sites of Sari city were increasingly exposed to the flood risk. Since risk is a function of hazard and vulnerability, distance to channel, land use, population density, quality of buildings and urban density were found to be the most important factors in flood risk analysis

The main limitation of the study is that some of the predictive factors vary over time, which result in uncertainty of the outcomes. For example, rainfall is a dynamic process, which changes over time and space (Shahid, 2010). However, in this study, we have considered some heavy rainfall events (resulting sever flood inundation) to produce the rainfall map. These models also can’t consider the rainfall return periods to flood hazard prediction. In addition, curve number varies over the time by increasing the impervious areas (such as buildings and streets) which substantially reduce infiltration capacity (Mishra and Singh, 2004).

**Fig. 9.** SOMEWHERE HERE

**5. Conclusion**

Flood risk assessment is vital for urban management and sustainable urban development. Urban floods are influenced by different factors, which in developing countries are often related to unplanned urban development along lowlands and riversides (e.g. river floods), poor maintenance and clogging of urban drainage. In the current research, two state-of-the-art machine learning models namely GARP and QUEST were applied for the first time to produce an urban flood risk map. The results obtained show how machine learning techniques can be applied to urban flood risk zoning, when there are no detail hydrologic and hydraulic datasets. In a policy term, the results highlighted that the distance to channels and population density are important factor in flood risk mapping. Furthermore, the validation results demonstrated that both GARP and QUEST models represented reliable results without complex hydrodynamic information, although GARP model had a higher accuracy. The approach presented is particularly useful in other regions to quickly define and expose floods hazards. The mapping also serves as a first step to developing flood risk reduction strategies and to allocate resources for developing some efficient flood risk managements and flood warning systems. In addition, the scientific achievements of this research could help decision makers and planners to proper design and maintenance of drainage systems for sustainable urban management flood risk reduction.

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