**ORIGINAL ARTICLE**

# Assessing LNRF, FR, and AHP models in landslide susceptibility mapping index: a comparative study of Nojian watershed in Lorestan province, Iran

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## Abstract

Landslides and slope instabilities are major risks for human activities which often lead to economic losses and human fatalities all over the world. The main purpose of this study is to evaluate and compare the results of Landslide Nominal Risk Factor (LNRF), Frequency Ratio (FR), and Analytical Hierarchy Process (AHP) models in mapping Landslide Susceptibility Index (LSI). The study case, Nojian watershed with an area of 344.91 km$^2$, is located in Lorestan province of Iran. The procedure was as follows: first, the effective factors of the landslide basin were prepared for each layer in the GIS software. Then, the layers and the landslides of the basin were also prepared using aerial photographs, satellite images, and fieldwork. Next, the effective factors of the layers were overlapped with the map of landslide distribution to specify the role of units in such distribution. Finally, nine factors including lithology, slope, aspect, altitude, distance from the fault, distance from river, fault land use, rainfall, and altitude were found to be effective elements in landslide occurrence of the basin. The final maps of LSI were prepared based on seven factors using LNRF, FR, and AHP models in GIS. The index of the quality sum (Qs) was also used to assess the accuracy of the LSI maps. The results of the three models with LNRF (40%), FR (39%), and AHP (44%) indicated that the whole study area was located in the classes of high to very high hazard. The Qs values for the three models above were also found to be 0.51, 0.70 and 0.70, respectively. In comparison, according to the amount of Qs, the results of AHP and FR models have slightly better performed than the LNRF model in determining the LSI maps in the study area. Finally, the study watershed was classified into five classes based on LSI as very low, low, moderate, high, and very high. The landslide susceptibility maps can be helpful to select sites and mitigate landslide hazards in the study area and the regions with similar conditions.

**Keywords** Landslide susceptibility index · Nojian watershed · AHP model · FR model · LNRF model · GIS

## Introduction

Landslides cause great damages in residential areas, roads, facilities, agricultural fields, gardens, grasslands, etc. Recognizing the mechanism and zoning of prone areas to landslide occurrence play a crucial role in disaster management. It can be employed as a standard tool to support decision-making in different areas (Bui et al. 2016). According to its definition by engineering geology, landslide is the downward movement of a mass of material on a slope.

Nojian watershed in Lorestan province of Iran is located in Zagros tectonically active folded mountains across the Zagros Big Fault and the earthquake-prone belt of Alpine–Himalayan zone. Therefore, potentially there are suitable conditions for slope instability related to the alternating layers of limestone and thin layers of the marl and deeply weathered formation on the slopes. Due to geomorphological properties such as lithology, tectonics activity, altitude, seismicity, slope, climatic conditions, deeply weathered formation and human impact, the study watershed was potentially highly prone to landslide occurrence. Furthermore, conditions of topography and geomorphology, climatology and human impact of the study area have provided the best position for sliding small or large masses of materials of the slopes.

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According to the reports of the global organization of natural dangers in 2012, landslide was among the seven most dangerous natural disasters. Landslides, due to their nature and diversity and because of their potential hazards and the catastrophic effects for human's life and property, have always been examined by scholars of various disciplines of earth sciences including engineering geology, geomorphology, and watershed management. Therefore, planning to control and mitigate its damages seems important and necessary. Using different models of LSI mapping is one of the methods to identify the prone areas for future landslides and preventive activities should be taken to prevent or decrease their damages in those areas.

The United Nations proclaimed the 1990s as the International Decade for Natural Disaster Reduction (IDNDR); UNESCO named 1990s as the decade of dealing with natural disasters (Erich and Wolfgang 1994; Geeraay and Kariemi 2010). Therefore, these days in different centers of academia, extensive research is being carried out on landslides as an instance of natural disaster by many scholars worldwide. As the aim of this research is an evaluation of LNRF, FR and AHP models in mapping (LSI) in Nojian watershed; therefore, we will focus on the related literature having the purpose of the current study in mind. Although the mechanism of landslide occurrence has been studied by many geologists and geomorphologists at a large scale through quantitative methods (statistical), multi-criteria decision-making (MCDM), support vector machine, logistic regression, artificial neural network (ANN), frequency ratio (FR), including:

GIS-based landslide susceptibility mapping using analytical hierarchy process (AHP) and bivariate statistics (Zhu and Huang 2006; Fanyu Liu 2007; Yalcin 2008; Gupta and Joshi 1990; Akgun and Turk 2010; Bhatt et al. 2013; Kayastha et al. 2013; Dai and Lee 2002; Abedini et al. 2017; Gravina et al. 2017), Landslide Susceptibility Index (LSI), Logistic Regression (LR), and Artificial Neural Network (ANN), Frequency Ratio (FR) (Romer and Ferentinou 2016), landslide susceptibility mapping based on Frequency Ratio and Logistic Regression models (Ayalew and Yamagishi 2005; Lee and Sambath 2006; Lee and Pradhan 2007; Solaimani et al. 2013; Umar et al. 2014; Shahabi et al. 2014; Pham et al. 2015; Shirzadi et al. 2017b; Costanzo et al. 2014), comparison of logistic regression and Naive Bayes classifier (Tsangaratos and Ilia 2016), landslides susceptibility by dynamic landslide run-out model (Byron et al. 2016), multivariate and bivariate (Kavzoglu et al. 2015), auto logistic molding (Atkinson and Massari 2011; Costanzo et al. 2014), artificial neural network and comparison with frequency ratio and bivariate logistic regression (Pradhan and Lee 2010), static methods (Shirani and Seif 2012), analytical hierarchy process and multivariate statistics (Komac 2006; Pourghasemi et al. 2013; Amir Yazdadi and Ghanavati

2016), comparison between bivariate statistical and multivariate adaptive regression (Wang et al. 2015), two-class kernel logistic regression (Hong et al. 2015), support vector machine, artificial neural network kernel, logistic regression and logistic tree, Bui et al. (2016), frequency ratio, statistical index and certainty factor (CF):Wu et al. (2016a, b), landslide susceptibility mapping by support vector machine methods (Ballabio and Sterlacchini 2012; Gravina et al. 2016; Shirzadi et al. 2017a, b), random forest decision tree methods (Zhang et al. 2017), shallow landslide susceptibility assessment using a novel hybrid model (Shirzadi et al. 2017a, b), frequency ratio, statistical index, and weights (Razavizadeh et al. 2017), etc., has been done.

In addition, review of the literature indicated some researches results such as Gupta and Joshi (1990); Shadfar et al. (2011); Mohammadi et al. (2014) and Malik et al. (2016) indicated LNRF method has suitable method in landslide susceptibility mapping.

Our review of the literature of landslide-related research revealed that no research has ever been done on the study watershed with comparative models. On the other hand, this area is highly prone to slope instability, therefore, this research the main purpose of comparison and performance of the three models based on GIS has been done. In addition, based on the results of some studies in Iran, these methods are almost slightly better in providing and forecasting the landslide susceptibility maps. Therefore, to comparatively assess landslide susceptibility, three models of LNRF, FR, and AHP were selected for study area.

It is noted that data preparation and processing were carried out using ArcGIS Ver. 10.3. Although nowadays many methods have been employed for landslide susceptibility mapping around the world, the results of this study can practically be used in land use planning and identifying areas prone to landslide. However, there is an essential need to using methods and techniques to improve the accuracy of landslide prediction on a regional scale. Therefore, the major aims of this study are to select the most important and effective factors in landslide susceptibility and assess them with LNRF, FR, and AHP models by Mapping Landslide Susceptibility Index in the Nojian watershed in the Zagros Mountains of Iran. In addition, comparison of the results of LNRF, FR, and AHP models is made for study area. It should be mentioned that data preparation and processing wee done using Arc GIS 10.3, SPSS and Expert Choice (EC) software.

## The study area

Nojian watershed, with an area of about 344.91 km$^2$, is located in the 30 km Southeast of Khorramabad city, Lorestan province, Iran. This basin is located between 48°23′E and 48°40′E longitude and 33°06′N and 33°17′N
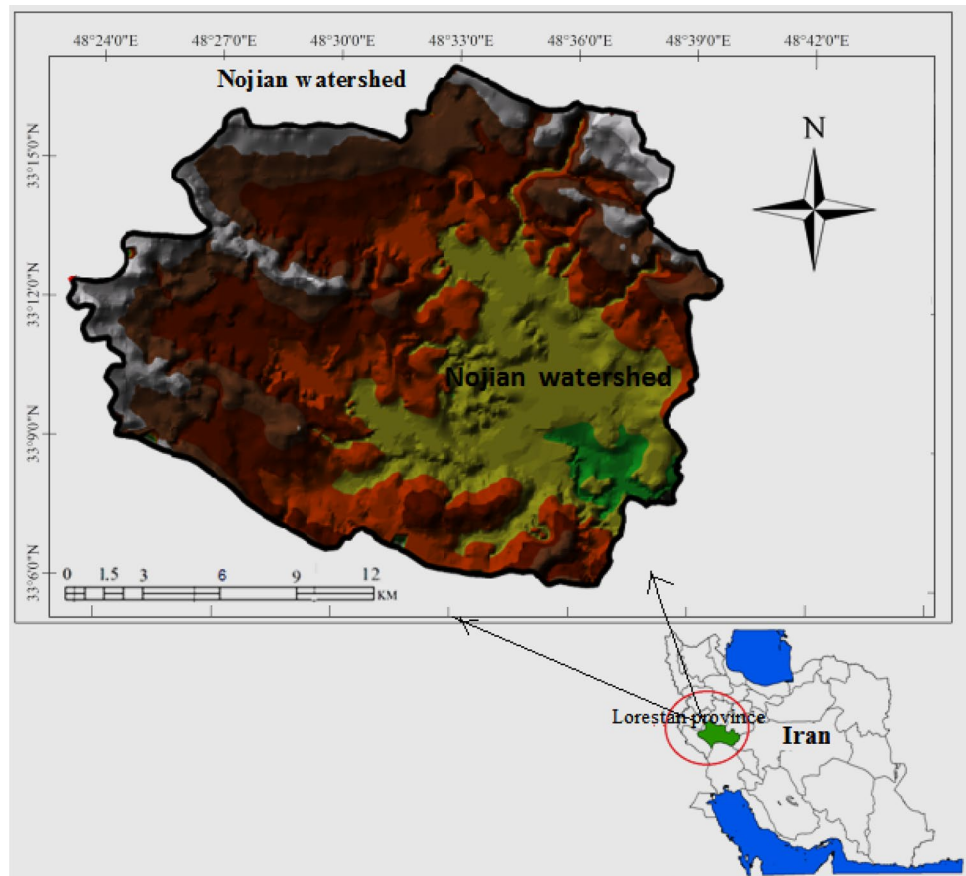
latitude (Fig. 1). Its average annual rainfall is 686 mm, and its climate is semi-moist with very cold winters. The average altitude is 1635 meters above the sea level. Due to geological properties such as lithology, tectonics, seismicity, and specific climatic conditions, Iran has areas of potential landslide. Located on the earthquake-prone belt of Alpine–Himalayan passing Zagros Big Fault, Lorestan province has plausible conditions for instability in large sections of the mountains slopes due to the alternating layers of massive limestone and thin embedded layers of the marl, shale, gypsum and conglomerate formation.

According to field and geology maps, the lithology of this basin is more diverse: massive limestone, shale and sandstone, dolomite, marly limestone, gypsum and sandstone, conglomerate with sand stone and red marl, quaternary alluvial and sediment.

## Methodology

### Landslide inventory map

In all versions of susceptibility mapping models, preparing landslide inventory map is the first step of data production.

According to the basic assumption, future landslides will occur under the same conditions (Lee and Talib 2005).

In this research, to identify the relationship between the landslide distribution and the relevant conditioning factors, the existing landslide inventory map is necessary. Therefore, to come up with a detailed and reliable inventory map for the study area, two processes were utilized including field surveys and laboratory interpretations. Therefore, the distribution location of landslides was collected from the Forests, Rangelands and Watershed Management Organization of Iran. Then, using field surveys, this location was checked and some characteristics of each landslide were recorded including length, width, and surface area of landslides using aerial photographs (1:40,000 scale), GPS and TM satellite images interpretation. In addition, we utilized SPSS to perform the statistical calculations in the models, Expert Choice (EC) software to determine the relative weighting of the effective factors, aerial photographs with the scales of 1:50,000, also topographic map with the scale of 1:50,000 and geological map with the scale of 1:100,000 and Isohyet is a line on map connecting which are the regions having same amount of rainfall. Landslide zoning includes dividing the land into separate regions and ranking them according to real degree or sensibility potential caused by landslide on hillside slopes. Due to the fact that the main purpose of this

study is the evaluation of LNRF, FR and AHP models in mapping LSI, the research method involved attritional form, morphometry, field work and experimental manipulation. In doing so, we pursued the following four steps:

1. Collecting and reviewing the relevant books, theses, articles, and any source related to the topic of the study,
2. observing the field,
3. doing the calculations and processing the data,
4. presenting the final report of the research.

Using aerial photographs, satellite imagery, and extensive fieldwork, landslide areas were identified. Then, the collected data were digitized using GIS to produce the landslide distribution map of the basin. Figure 2j shows the map of landslide distribution of the area.

1. *Elevation* Altitude change of each region is one of the very effective factors in the creation of soil erosion and slope mass movement. This factor intensively controls runoff direction and rate of drainage density (Hosseinzadeh et al. 2009: 29). The maximum altitude of the region is 2848 m and the minimum altitude is 762 m. In addition, the general altitude variance will be 2086 m. For this reason, the map of height was assorted in seven classes (Fig. 2a).
2. *Slope* In most studies related to landslide sensibility zoning, slope percentage is one of the most important factors (Abedini et al. 2017). Theoretically, with increasing the slope, shear stress is augmented and consequently increasing slope instability potential is expected. Slope map of the study region is prepared in six classes (Fig. 2b).
3. *Aspect* This factor has an important role in utilizing the amount of rainfall, sun energy and kind wind blowing in the any area and reflecting the influence of soil thickness, vegetation, moisture, etc. The study area is located in the middle attitude, therefore, in whole direction of slopes of landslide susceptibility is different. The aspect map of the study area is prepared in eight classes (Fig. 2c).
4. *Lithology* Lithological conditions of the basin are very effective in slope instability and landslide occurrence. On other hand, the stronger rocks give more resistance to the driving forces in compared to the weaker rocks, and hence are less prone to landslides and vice versa (Yalcin 2008). In determining the lithological resistance of the study area, the type of rocks, the tectonic condition, and their resistance to weathering factors were considered as the most important factors. From lithological perspective, the most susceptible area to landslide occurrence in the study watershed is where the formations contain marl and limestone, shale, gypsum and marly conglom-

erate are dominant. Therefore, to clarify landslide tendency of the structures, the density of existing landslides in different structures must be assessed (Fig. 2d).

5. *Distance from fault* Especially active faults play an important role in landslides from two points of view. First, they are the origin of earthquake occurrence. Second, active faults have important roles in cracking stones and creating instability. This discontinuity of geology formation leads to decreases in shear resistance of the slide and preparation of landslide occurrence (Fig. 2e).
6. *Distance from road* Roads have the most effective role in the concentration of runoff, therefore experience and existing statistics about landslide during reconstruction and road widening shows the necessity of using this factor in landslide sensitivity zoning. So, this layer consists of five classes (Fig. 2f).
7. *Distance from drainage network* The drainage density is one of the factors that have a determining role in mass movements as in some hillsides with low slope, waterway, and landslide aggression are high. This shows the importance of waterway aggression in landslide occurrence. In this study, the map of distance from drainage system was drawn in five classes (Hosseinzadeh et al. 2009: 32) (Fig. 2j).
8. *Land use* The form of land use is an important index in inconstancy of the slopes that affects the earth's traits and results in changes in its action. This map was drawn in five classes (Fig. 2h).
9. *Rainfall* Climate of the basin and rainfall intensity and its durability play an important role in landslide creation which depends on climate factors, topography, geology, and slope (Lydia and Daniel 2002: 183). Campbell also believes that precipitation over 254 mm and rainfall intensity about 6.35 mm causes landslide. In this study, precipitation map of the study area was drawn in five classes (Fig. 2i).

# Description of methods

## Analytical hierarchy process (AHP) method

The model of analytical hierarchy process (AHP) was proposed by Saaty (1980) for the first time. This model measurement through pairwise comparisons of effective factors in study and relies on the judgments of experts to derive priority scales. In addition, pairwise comparisons can allow decision makers to weigh coefficients and compare alternatives with relative case or factors in obtaining the suitable results (Saaty 2008). It works first with being weighted to every effective factor considered for zoning, and alternatives to be selected (Abedini et al. 2017). In AHP model, GIS is used for zoning. This section includes
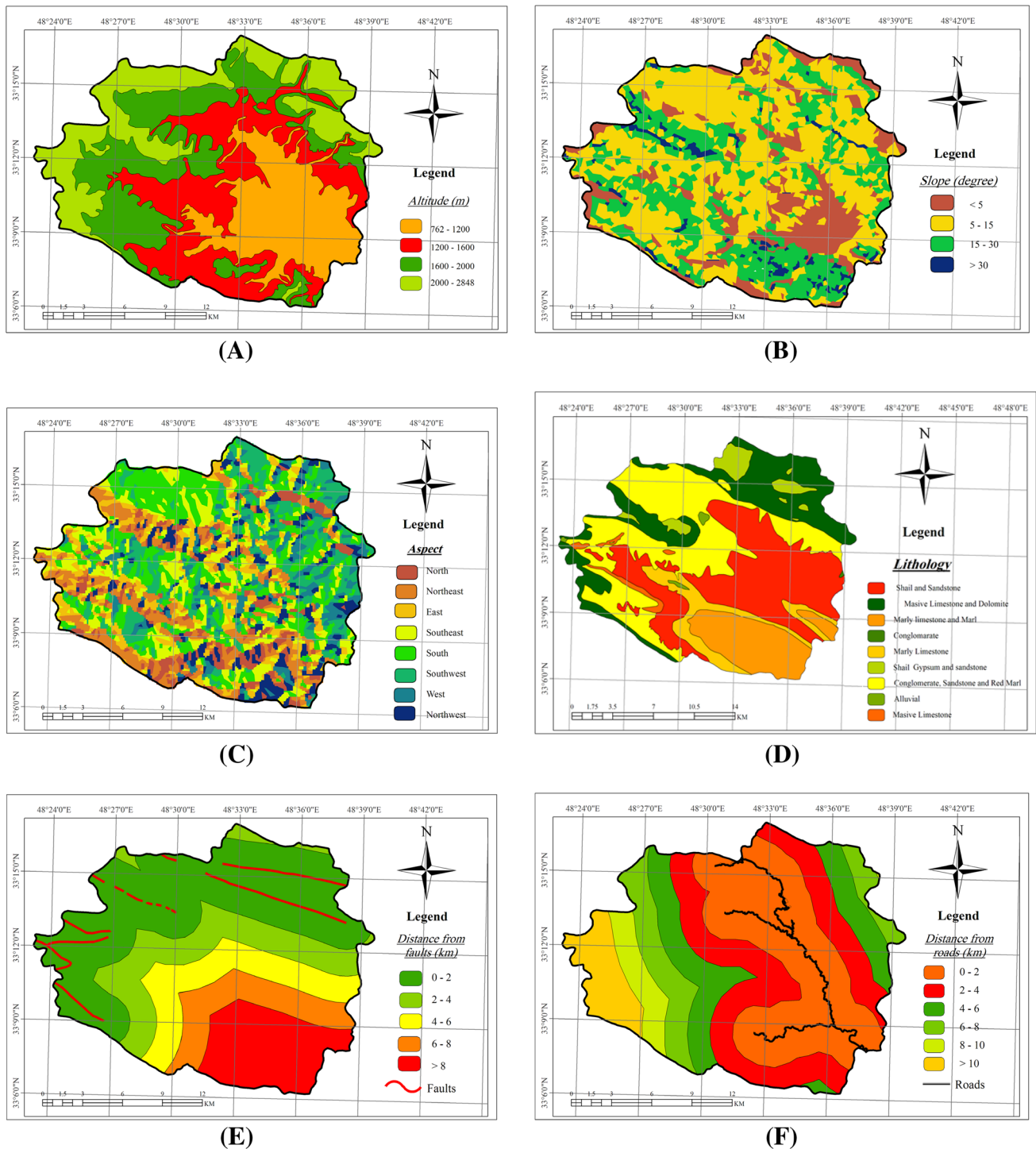
**Fig. 2** The contributing factor maps in landslides of the basin (**a**–**i**) and the landslide distribution map of the area (**j**)

entering the data into a GIS, then analyzing the production of the layers of information. The mapping of LSI using AHP model and EC and GIS was done as follows:

1. prioritization of the effective factors,

2. production of the pairwise comparison matrix based on expert opinion,

3. calculation of relative weight and the inconsistency rate determination using the EC software,
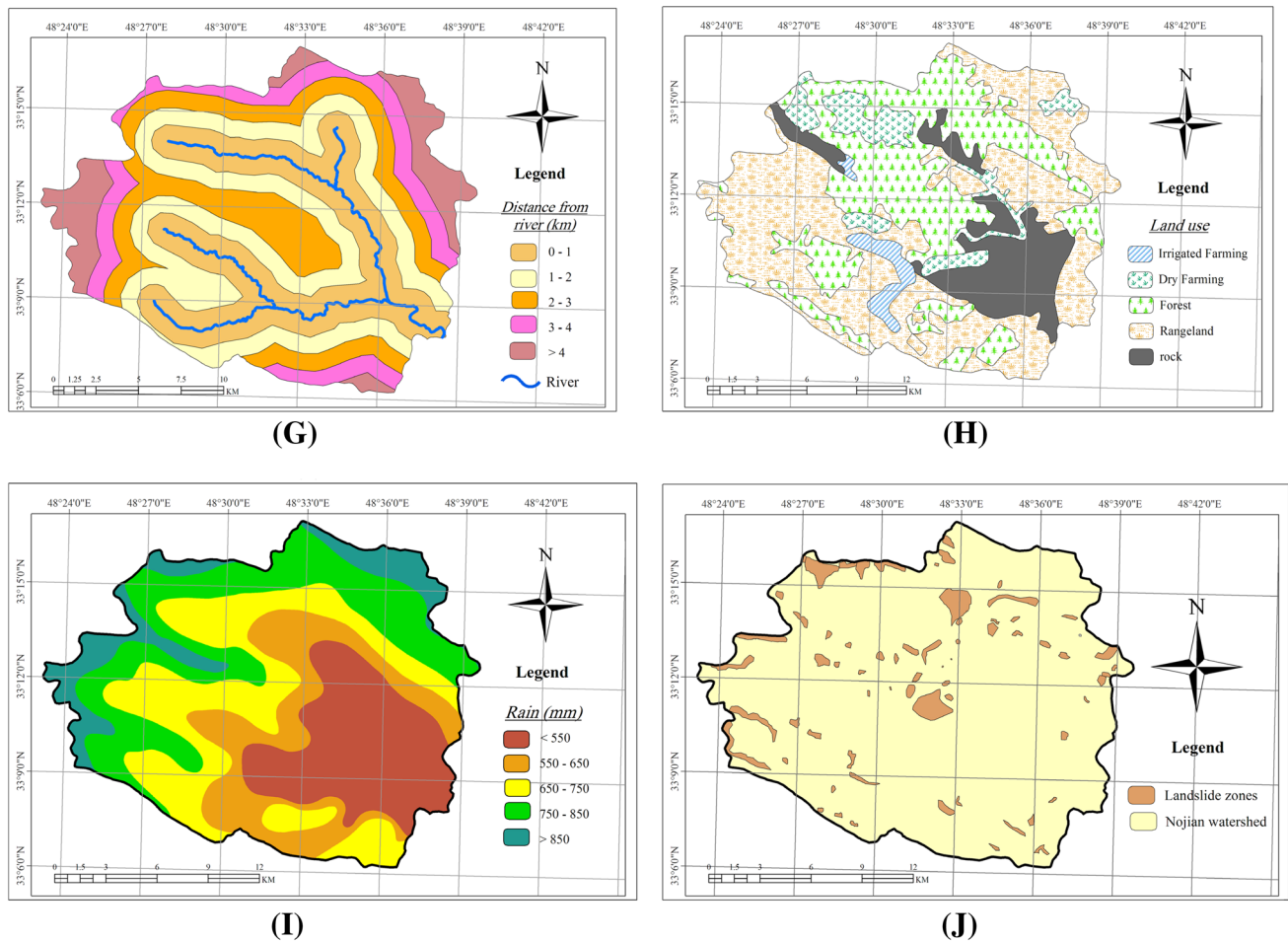
**(G)**



**(H)**



**(I)**



**(J)**

**Fig. 2** (continued)

and then points to any of classes corresponding to each of the factors, acquired coefficients based on them provide the final model. The main advantage of this method is that it helps the decisions to a complex problem be open to the hierarchical structure, and then solves it. Furthermore, AHP is a decision support system to seek optimum conditions for a complex circumstance through hierarchical structures, which comprised targets to be attained, various criteria for decision

4. calculation of the final weight of effective factors and prioritizing them,
5. preparation of the weighted maps based on the values of the final weight of units,
6. preparation of the zonation map through the sum of the weighted maps,
7. calculation of the area and the percentage of the area at risk zones.

## Numerical risk factor (LNRF) model

Landslide susceptibility map was integrated to compute the numeric value of each factor with the help of a Landslide Numerical Risk Factor (LNRF) model.

Landslide Numerical Risk Factor (LNRF) model that is a suitable model especially in the mountainous regions to landslide susceptibility mapping (Gupta and Joshi 1990). In this model, (LNRF > 1) indicates that the special category of that geo-environmental factor is more susceptible to landslides than the average. The lower value of (LNRF < 1) means that the particular geo-environmental category is associated with more stable slopes and less susceptible to landside occurrence (Gupta and Joshi 1990), (Mohammadi et al. 2014). This model is calculated from Eq. (1):

$$\text{LNRF} = A/B \text{ or LNRF} = \frac{N\text{pix (Si)}}{\left[\sum_{i=1}^{n} N\text{pix(Si)}\right]/n}, \tag{1}$$

where $A$ is the landslide area in every unit, and $E$ is the mean area of landslide in the whole unit.

**Table 1** The weight related to the amount of LNRF (Gupta and Joshi 1990)

| Number | Amounts LNRF | Weight |
|--------|--------------|--------|
| 1 | 0 | > 1 |
| 2 | 1 | 1–2 |
| 3 | 2 | < 2 |

In this method, which is called the credibility factor of landslide risk, using the occurred slip surface in a unit than mean occurred slip in the whole unit, the index is prepared (Mohammadi et al. 2014) (Table 1).

### Frequency ratio (FR) method

The Frequency Ratio (FR) model is one of the important probability methods in landslide susceptibility mapping based on the observed relationship between distribution of landslides and each landslide-related factor. Put simply, the frequency ratio (FR) is the ratio of the study area where landslides occurred in the whole study area. It is also the ratio of the probabilities of a landslide occurrence to a non-occurrence for a given attribute (Lee and Talib 2005). This model is a complete model including more independent variables that play an important role to determine the dependent variables (Abedini et al. 2017). As one of the serial generalized linear models, it is very useful for analyzing the existence of dependent variables and anticipating hillside instability (Dai and Lee 2002). The frequency ratio (FR) model is calculated through Eqs. (2–4). Every unit of each factor is the percentage of the landslide cells (A) divided by the percentage of no slip cells (B). The percentage of the landslide cells is the number of slide cells of each unit (A) divided by the total landslide cells of the basin (B) multiplied by 100. The percentage of the no-slide cells is the number of cells of each unit (C) divided by the total cells of the basin (D) multiplied by 100 (Solaimani et al. 2013; Razavizadeh et al. 2017).

$$FR = \frac{A(\%)}{B(\%)} \tag{2}$$

$$A(\%) = \frac{a}{b} \times 100 \tag{3}$$

$$B(\%) = \frac{c}{d} \times 100 \tag{4}$$

Mapping of LSI using FR model and GIS software was as follows:

1. preparation of the factor maps and their classification,
2. preparation of the landslides maps and the factor maps of the basin (cell size: 5 m × 5 m),
3. overlapping the raster layers of the factors with the raster layers of the basin landslides,
4. calculation of the landslide cells and the no-slip cells,
5. calculation of the FR values based on Eqs. (2–4),
6. preparation of the weighted maps based on the FR values obtained for the units,
7. preparation of the zonation map through the sum of the weighted maps,
8. calculation of the area and percentage of the area at risk zones.

### Landslide conditioning factors

The most common method of identifying effective factors is the use of questionnaire and morphometry of the landslides available inside the basin and using fieldwork which we did for Nojian watershed. The first important step in the zoning of landslide susceptibility is to identify locations of landslide occurrence in the past and present (Jiménez-Perálvarez et al. 2011). One of the basic steps in zoning landslide susceptibility is creating a dataset and collecting the required data (Kavzoglu et al. 2015). In fieldwork, cases such as the landslides location, structure lithology, soil type, land use in the area of landslides, vegetation, slope, aspect, linear elements (roads, drainages, and faults) are considered. The height was necessary and the relevant expert could study these to some extent to specify the effective factors in landslides (Abedini et al. 2017). Based on a review done on the basin, parameters such as land use, distance from faults, rainfall, lithology, slope, elevation, distance from the main drainage and the distance from the road, landslide zone were identified as effective factors in the occurrence of the landslide. The maps related to each factor were prepared by GIS. Using modulation of nine effective layers in landslide, drawing the final map of landslide sensibility zoning in the study area is the main objective of this study. Figure 2a–i shows the map of the factors influencing landslides in the study area.

## Discussion and results

### Weighting the effective factors

In AHP model, according to the different degrees of the effective factors in creating landslides, it is necessary to identify and prioritize the correct factors. Part of this is done by questionnaire and the other part by comparing each factor. To compare the paired items and determine the amount of the priority of the different factors relative to each other, a major scale was used with values from 1 to 9. In this matrix, two by two effective factors in landslide occurrence of the basin were compared and scored. In the combined weighting method, the effective factors were prioritized according to

**Table 2** The final weighting of the effective factors and their priority

| Priorities | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Effective factors | Lithology | Slope | Distance from the fault | Land use | Rainfall | Aspect | Altitude | Distance from the road | Distance from the main drainage |
| The final weight | 82.76 | 45.90 | 44.54 | 35.86 | 22.45 | 14.17 | 8.72 | 5.79 | 3.12 |

the judgment of experts and then each effective factor was classified in criteria's and weighted. The weights of criteria are calculated from the pairwise comparison matrix. To calculate the relative weight for effective factors, the values were entered into Expert Choice (EC) Ver. 10.3, and finally the relative weight of each factor was obtained. Therefore, based on the relative weight, the factor of lithology (0.242), slope (0.197), land use (0.183), distance from the fault (0.174), rainfall (0.103), altitude (0.043), aspect (0.026), distance from the road (0.018), and distance from the main drainage (0.014) in the order of priority were identified as the effective factors contributing to landslide occurrence in the Nojian watershed. The amount of the incompatibility rate[1] also was obtained to be 0.08, indicating the correctly paired comparisons of the effective factors.

To calculate the final weight, effective factors in landslide occurrence of the basin were divided by the units. We overlapped the landslide distribution map on each of the layers, and the percentage of the sliding surface was calculated for each unit. Finally, the percentage of the sliding surface of each unit was allocated a rate from zero to 100. This way, different values were given to each unit that had the maximum percentage of the sliding surface of the 100 value, and for other units also proportional to the amount of the percentage of the sliding surface. The scores obtained for every unit of each factor were multiplied by the relative weight of its factor to calculate the ultimate weight for each unit. By summing the final weights of the units together and the final weight for each factor was obtained (Table 2).

In FR model, first, the map of the effective factors was prepared and classified (cell size 5 m × 5 m). Then, the overlapped raster maps of factors with the raster map of landslides of the basin and the number of slide cells and the number of no-slide cells for every unit of each factor were obtained using GIS. Finally, using equations related to the model, the amount of the frequency ratio for every unit of each factor was calculated.

In LNRF model, first, the landslide area for every unit of each factor was calculated. Then, their average was

calculated. Finally, using the equation corresponding to the model, the amount of LNRF was obtained for every unit of each factor, and the values were standardized.

The values obtained for every unit of each factor showed that in all three models, two factors of the distance from the road and distance from the main drainage due to lack of logical relation with landslide distribution did not influence the landslide of the basin in the sense that with increasing distance from the road and distance from drainage, the percentage of landslides increased which was not logical. So these two factors were removed and were not considered in the preparation of the final maps of the zonation.

## Landslide susceptibility mapping

After calculating the final weight by the models, raster maps were obtained based on these weights. The maps of the weighted raster and the map of LSI were obtained for each model. Figure 3 shows these maps that have been classified into five susceptibility classes. Area and percentage of area for each of the classes of risk in the zonation maps are provided in Table 3.

As shown in Table 3, the results of assessment and classification of landslide susceptibly in the study area have been determined using the three models. The whole watershed area according to the landslide susceptibly hazard is classified into very low, low, high, medium, high and very high zones. Based on the landslide susceptibly hazard classification in the study watershed, AHP (44%), LNRF (40%), and FR (39%) form the total area located in the high and very high hazard zones. Therefore, the comparative results of the three models are very close together showing that the watershed is potentially very prone to landslide occurrence.

## Model validation and comparison

For the assessment accuracy and comparison of the zoning maps, quality sum (Qs) index was used. The amount of Qs index represents the desirability function of methods in predicting the landslide hazard in the study area. Therefore, in assessing the method, the greater the value of this index, the more desired utility and this method indicated accurate prediction. To determine this index, first the density ratio (DR) must be calculated. The amount of DR is obtained

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[1] If the obtained inconsistency rate is more than 0.1, this represents that the paired comparison and ratings were not done correctly, and this operation should be performed again with changes in the points.

**Fig. 3** The LSI maps of Nojian watershed
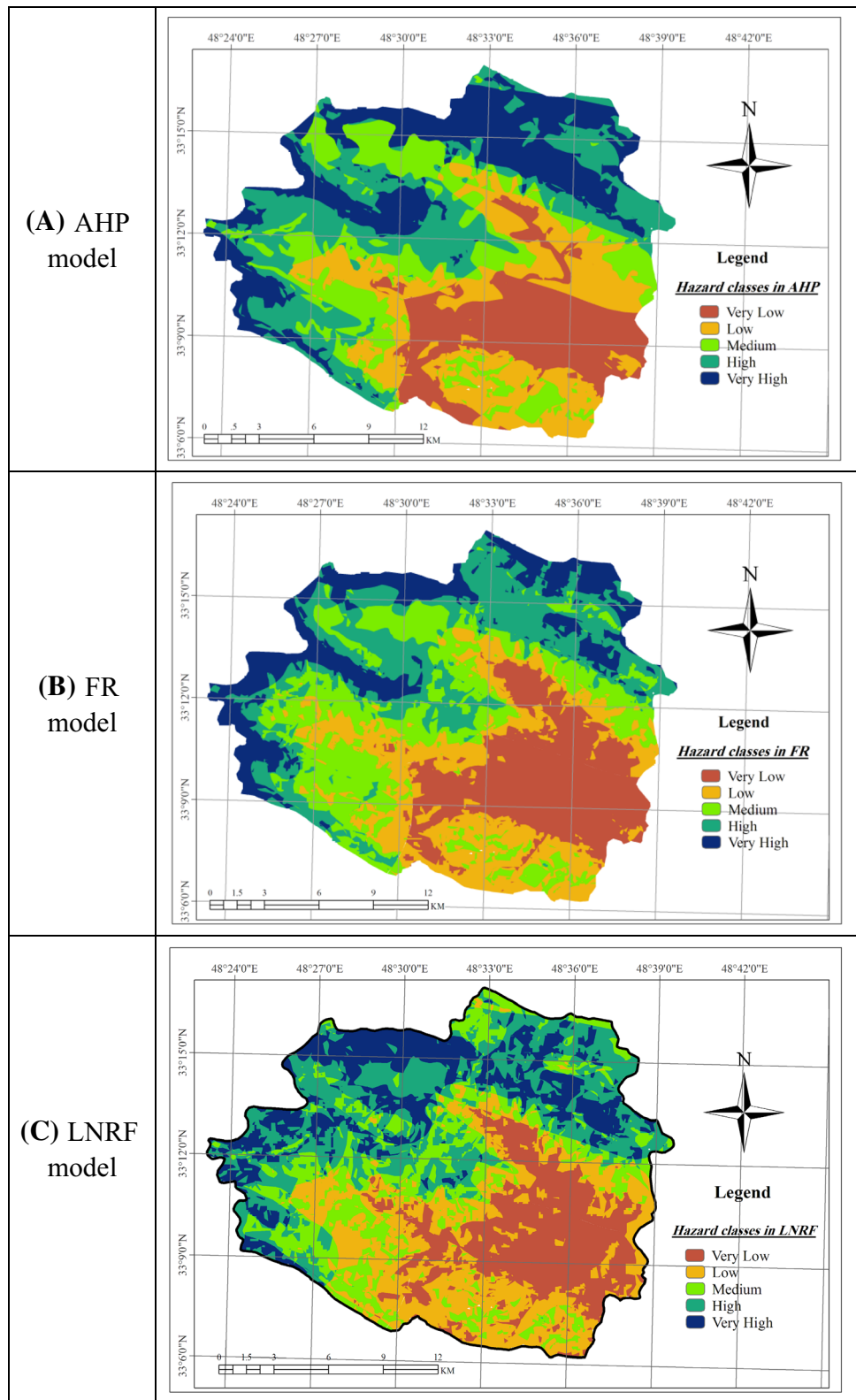


through Eq. (5). In this equation, Si is the sum of the area of the landslides in each class risk, Ai is the area in the class of risk and *n* is the number of risk classes in a zonation map.

The amount of Qs index also is obtained through Eq. (6) in which, Qs is the quality sum index, DR is the density ratio and *S* is the area ratio of each risk class to the total

**Table 3** The area and percentage of the area of the hazard zones in the zoning maps

| Models | Hazard zones | Si (km$^2$) | Ai (km$^2$) | DR | S | Qs |
|---|---|---|---|---|---|---|
| AHP model | Very high | 10.14 | 72.35 | 2.36 | 0.21 | 0.70 |
| | High | 6.6 | 79.47 | 1.4 | 0.23 | |
| | Medium | 1.97 | 63.29 | 0.52 | 0.18 | |
| | Low | 1.43 | 68.82 | 0.35 | 0.2 | |
| | Very low | 0.05 | 57.34 | 0.01 | 0.16 | |
| LNRF model | Very high | 6.71 | 54.23 | 2.16 | 0.15 | 0.51 |
| | High | 6.42 | 82.59 | 1.36 | 0.24 | |
| | Medium | 4.49 | 64.82 | 1.21 | 0.18 | |
| | Low | 1.7 | 76.57 | 0.38 | 0.22 | |
| | Very low | 0.15 | 63.05 | 0.04 | 0.18 | |
| FR model | Very high | 6.95 | 50.92 | 2.46 | 0.14 | 0.70 |
| | High | 7.06 | 75.54 | 1.68 | 0.22 | |
| | Medium | 3.53 | 80.62 | 0.78 | 0.23 | |
| | Low | 1.19 | 65.42 | 0.33 | 0.19 | |
| | Very low | 0.18 | 68.79 | 0.04 | 0.20 | |

**Table 4** The assessment results of the zoning maps of the basin, using the Qs method

| Parameters | The area of the hazard zones (km$^2$) | | | Percentage of the area of the hazard zones (%) | | |
|---|---|---|---|---|---|---|
| Models | LNRF | FR | AHP | LNRF | FR | AHP |
| Susceptibility zones | | | | | | |
| Very high | 54.32 | 50.92 | 72.35 | 16 | 16 | 21 |
| High | 82.59 | 75.54 | 79.47 | 24 | 23 | 23 |
| Medium | 64.82 | 65.42 | 63.29 | 19 | 20 | 19 |
| Low | 76.57 | 65.42 | 68.82 | 23 | 20 | 20 |
| Very low | 63.05 | 68.76 | 57.34 | 18 | 21 | 17 |

area (David 1992; Amir Yazdadi and; Ghanavati 2016). Table 4 shows the assessment results of the zonation maps of the basin using the Qs method.

$$Dr = \frac{\frac{Si}{Ai}}{\frac{\sum_i^n Si}{\sum_i^n Ai}}, \tag{5}$$

$$Qs = \sum_{i=1}^n \left( (Dr - 1)^2 \times S \right). \tag{6}$$

As shown in Table 4, in the hazard zones, the amount of density ratio (DR) has increased commensurate with the increased risk which represents a high level of the accuracy of the risk zone in the zoning maps. Moreover, the Qs values obtained for FR, AHP are 0.70, and 0.70 and 0.51 for LNRF models, respectively, representing the higher performance of these two models than the LNRF model in determining the zones susceptible to landslide occurrence in the study area.

Predicted accuracy values for FR (0.70), AHP (0.70) and LNRF (0.51) models showed that the map obtained from frequency ratio model and AHP is more accurate than the LNRF model. The results revealed the better performance of these two models (FR and AHP) than the LNRF model in determining the zones susceptible to landslide occurrence in the Nojian watershed.

# Discussion and conclusion

Landslide susceptibility mapping methods play an important role in providing a suitable approach to decision makers and authorities, particularly in landslide prone areas. Essentially, Landslide Susceptibility Mapping Index (LSMI) provides very fundamental knowledge of the effective factors and causes of landslide occurrence. In addition, it can be an effective method in hazard management and mitigation measures.

In the present study, we attempted to compare the results of landslide susceptibility mapping using three different models, namely Landslide Nominal Risk Factor (LNRF),

Frequency Ratio (FR), and Analytical Hierarchy Process (AHP).

The main objective of this study was to investigate potential application of LNRF, FR, and AHP models in mapping Landslide Susceptibility Index (LSI) especially compare each of them in the Nojian watershed in Lorestan province of Iran.

In the study area, landslides are mainly affected by altitude, faulting, slope, rainfall, various geological formations, road construction, and land use changes. For the preparation of the LSI map, there are numerous weight combining methods. In the present comparative study, FR, AHP, and LNRF models were employed for landslide susceptibility mapping in Nojian watershed located in the Lorestan province of Iran. The results revealed that density ratio (DR) and area ratio *S*, variant weights, and data value were the most accurate in dividing the classes of landslide. The preparation of the LSI map is important through which one can detect susceptible areas for the future landslides and use these maps for the future planning. The evaluation of the final weight of the effective factors and the resulting overlay of these layers with the landslides layer area revealed the highest landslide due to the kind of geological formation.

From lithological perspective, the most susceptible area to landslide occurrence in the study watershed is where the formations contain marl and limestone, shale, gypsum and marly conglomerate are dominant.

The majority of landslides were in the class of slope more than 30°, the class of altitude more than 2000 m, the distance less than 2 km from the faults, the forest land use (due to deforestation and conversion to agricultural land), and the class of rainfall more than 850 mm. Two factors of the distance from the road and distance from the main drainage were excluded due to the lack of reasonable relationship with the percentage of landslides, in the sense that, with an increase in distance from the road and distance from the main drainage, the percentage of landslides increased, which was not reasonable. So, based on the above models, seven factors of lithology, slope, distance from the fault, land use, rainfall, slope and elevation, respectively, were identified as the effective factors in the landslides of the basin.

Although the results of MCDM such as AHP, fuzzy logic, LNRF, FR, AHP, support vector machine (SVM), artificial neural network (ANN), and logistic regression (LR) models are slightly different from region to region, but the accuracy of the models is very close in providing the landslide susceptibility mapping. Meanwhile, many studies have found overall accuracy rate relatively similar in some models such as LNRF, FR, AHP, SVM, ANN and LR (Jin et al. 2010; Park et al. 2012), Conditional probability (CP), LR, ANN, and SVM (Yilmaz 2010; Gupta and Joshi 1990; Akbari and Mashayekhan 2012; Mohammadi

et al. 2014), MCDA, SVM, and LR (Kavzoglu et al. 2015; Abedini et al. 2017), heuristic and bivariate statistical models (Bijukchhen et al. 2012), probabilistic, bivariate and multivariate models (Pradhan and Youssef 2010; Kevin et al. 2011; Ozdemir and Altural 2013; Shahabi et al. 2014; Wu et al. (2016a, b).

On the other hand, a host of studies such as, Ayalew and Yamagishi (2005), Komac (2006), Yalcin (2008), Esmali Ouri and Amirian (2009), Jin et al. (2010), Dehban and Stakhri (2013), Bhatt et al. (2013), Pourghasemi et al. (2013), Kumar and Annadurai (2015), Amir Yazdadi and Ghanavati (2016), Romer and Ferentinou (2016), Wu et al. (2016a, b), Abedini et al. (2017), Shirzadi et al. (2017a, b), Razavizadeh et al. (2017) indicated that FR and AHP models were more often better than the logistic regression in Japan, Iran, China, respectively.

In addition, some research results such as Gupta and Joshi (1990); Shadfar et al. (2011); Mohammadi et al. (2014) and Malik et al. (2016) indicated LNRF method has suitable method in landslide susceptibility mapping.

The results based on LNRF, FR and AHP models in study watershed, respectively, accounted for 40, 39 and 44% of the area of the basin located in the classes of the high to very high hazard zones due to the landslides susceptibly. The prediction performance of the susceptibility map is checked by considering quality sum amount ($Q_s$). The quality sum ($Q_s$) values for the three models above also were obtained to be 0.51, 0.70 and 0.70, respectively. Therefore, according to the amount of Qs and comparison of the results, we conclude that the two models of AHP and FR have better performance than the LNRF model in determining the LSI maps in the Nojian watershed. In addition, comparison of the past landslide occurred map (Fig. 2j) with provided landslide susceptibility map by LNRF, FR, AHP models (Fig. 3a–c) was showed high conformity. In other words, this demonstrates the high capability of these models in the preparation and evaluation of landslide susceptibility maps in the studied watersheds.

Finally, the study watershed was classified into five sensitivity classes of very high, high, moderate, low and very low. Based on the results, landslide hazard zoning maps and information can be useful for general development planning, landslide risk management, selecting sites and mitigating landslide hazards for decision makers in the regions with similar conditions.

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