

A hybrid model using data mining and multi-criteria decision-making methods for landslide risk mapping at Golestan Province, Iran

Elham Rafiei Sardooi

University of Jiroft

Ali Azareh (✉ aliazareh@ujiroft.ac.ir)

University of Jiroft

Tayyebeh Mesbahzadeh

University of Tehran

Farshad Soleimani Sardoo

University of Jiroft

Eric J. R. Parteli

University of Duisburg Essen - Campus Duisburg: Universitat Duisburg-Essen

Biswajeet Pradhan

University of Technology Sydney

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1 A hybrid model using data mining and multi-criteria decision-making

2 methods for landslide risk mapping at Golestan Province, Iran

3 Elham Rafiei Sardoo^{1*}, Ali Azareh^{2*}, Tayyebeh Mesbahzadeh³, Farshad Soleimani Sardoo⁴, Eric J. R. Parteli⁵,
4 Biswajeet Pradhan^{6,7}

6 1. *Department of Ecological Engineering, Faculty of Natural Recourses, University of Jiroft, Kerman, Iran, Corresponding
7 author: ellrafiee@ujiroft.ac.ir

⁸ 2. * Department of Geography, University of Jiroft, Kerman, Iran, Corresponding author: alizareh@ujiroft.ac.ir

9 3. Department of Reclamation of Arid and Mountain Regions, Faculty of Natural Resources, University of Tehran, Tehran,
10 Iran, tmesbah@ut.ac.ir

11 4. Department of Ecological Engineering, Faculty of Natural Recourses, University of Jiroft, Kerman, Iran,
12 f.soleimani@ujiroft.ac.ir

¹³ 5. Faculty of Physics, University of Duisburg-Essen, 47057 Duisburg, Germany, eric.parteli@uni-due.de.

14 6. The Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), Faculty of Engineering & IT,
15 University of Technology Sydney, Ultimo 2007, New South Wales, Australia, Biswajeet.Pradhan@uts.edu.au

16 7. Department of Energy and Mineral Resources Engineering, Sejong University, Choongmu-gwan, 209, Neungdong-ro,
17 Gwangjin-gu, Seoul 05006, Korea; biswajeet24@gmail.com

18 Abstract

The accurate modelling of landslide risk is essential pre-requisite for the development of reliable landslide control and mitigation strategies. However, landslide risk depends on the poorly known environmental and socio-economic factors for regional patterns of landslide occurrence probability and vulnerability, which constitute still a matter of research. Here, a hybrid model is described that couples data mining and multi-criteria decision-making methods for hazard and vulnerability mapping and presents its application to landslide risk assessment in Golestan Province, Northeastern Iran. To this end, landslide probability is mapped using three state-of-the-art machine learning (ML) algorithms – Maximum Entropy, Support Vector Machine and Genetic Algorithm for Rule Set Production – and combine the results with Fuzzy Analytical Hierarchy Process computations of vulnerability to obtain the landslide risk map. Based on obtained results, a discussion is presented on landslide probability as a function of the main relevant human-environmental conditioning factors in Golestan Province. In particular, from the response curves of the machine learning algorithms, it can be found that the probability p of landslide occurrence decreases nearly exponentially with the distance x to the next road, fault or river. Specifically, the results indicated that $p \approx \exp(-\lambda x)$, where the length-scale λ is about 0.0797 km^{-1} for road, 0.108 km^{-1} for fault and 0.734 km^{-1} for river. Furthermore, according to the results, p follows, approximately, a lognormal function of elevation, while the equation $p = p_0 - K \cdot (\theta - \theta_0)^2$ fits well the dependence of landslide modeling on the

34 slope-angle θ , with $p_0 \approx 0.64$, $\theta_0 \approx 25.6^\circ$ and $|K| \approx 6.6 \times 10^{-4}$. However, the highest predicted landslide risk
35 levels in Golestan Province are located in the south and southwest areas surrounding Gorgan City, owing to the
36 combined effect of dense local human occupation and strongly landslide-prone environmental conditions.
37 Obtained results provide insights for quantitative modelling of landslide risk, as well as for priority planning in
38 landslide risk management.

39 **Keywords:** landslide; hazard; vulnerability; risk; GIS

40 1 Introduction

41 Landslides constitute one of the most hazardous natural phenomena, causing live losses and devastating impact
42 on local infrastructure every year around the globe (e.g., Radbruch-Hall & Varnes 1976; Suzen and Doyuran,
43 2004a; Suzen and Doyuran, 2004b; van Westen et al. 2005; Guzzetti et al. 2012; Wang et al. 2019; Lato et al.
44 2019). The development of improved measures for landslide damage control and mitigation relies on the
45 quantitative assessment of local landslide risk, i.e., the potential degree of personal and material loss due to the
46 occurrence of damaging landslide events (Chacon et al. 2006; Glade and Crozier, 2005a; Glade and Crozier, 2005b;
47 Glade et al. 2005; Guzzetti, 2005; Guzzetti et al. 2012; Varnes, 1984). However, this assessment is challenging
48 due to the broad range of environmental and anthropogenic factors involved, and because the processes underlying
49 landslide initiation and dynamics are still poorly understood (de Blasio, 2011; Shanmugam & Wang, 2015;
50 Achour & Pourghasemi, 2020).

51 The first step toward a modeling framework for landslide risk assessment consists in estimating landslide-prone
52 zones based on the landslide occurrence in the area. Therefore, a *landslide hazard map*, which characterizes the
53 probability of landslide occurrence in a certain area under consideration of the main local and regional factors that
54 potentially trigger landslides, is required. To this end, the various potential causative factors must be statistically
55 evaluated against the background of a local inventory map, which encodes information on the areas affected by
56 damaging landslides (Brabb, 1985).

57

58 The last decade has witnessed much progress in the modelling of landslide hazard maps, in particular owing to
59 recent advances in artificial intelligence and its application to remote sensing and geoscientific research
60 (Yesilnacar & Topal 2005; Pradhan et al. 2010; Erener & Düzgün 2012; Kornejady et al. 2017; Mirzaei et al.
61 2018; Chen et al. 2017a; Pandey et al. 2020; Vakhshoori et al. 2019). For instance, GIS-based multi-criteria
62 decision-making approaches, such as Fuzzy Analytic Hierarchy Process (FAHP), have been applied to
63 identifying areas susceptible to damaging landslides (Ercanoglu & Gokceoglu 2002; Gorsevski et al. 2006;
64 Gorsevski & Jankowski 2010; Vahidnia et al. 2010; Pourghasemi et al. 2012; Feizizadeh et al. 2013; Tazik et al.

65 2014; Roodposhti et al. 2014; Feizizadeh et al. 2014; Zhao et al. 2017; El Bcharia et al. 2019; Roy & Saha,
66 2019). Moreover, various machine learning algorithms, including support vector machine (SVM) (Pourghasemi
67 & Kerle 2016; Youssef et al. 2016; Pandy et al. 2018), Maximum Entropy (MaxEnt) (Park, 2015; Kornejady et
68 al. 2017; Pandy et al. 2018; Mokhtari & Abedian, 2019), Genetic Algorithm Rule-Set Production (GARP)
69 2015; (Stockwell, 1999; Rahmati et al. 2019; Adineh et al. 2018) and Random forest (RF) (Goetz et al.
70 Pourghasemi & Kerle 2016; Sevgen et al. 2019; Pourghasemi et al. 2020), and also, deep learning techniques
71 including recurrent neural network (RNN) and Convolution Neural Networks (CNN) (Xiao et al. 2018;
72 Ghorbanzadeh et al. 2019; Mohan et al. 2020; Bui et al. 2020; Ngo et al. 2021) have been applied to assessing
73 landslide hazard within a broad range of geographical locations and conditions of soil type, topography, land
74 use/land cover, climate and anthropogenic influences (for a recent discussion, see Achour and Pourghasemi,
75 2020). However, the performance of the different algorithms in the computation of spatial landslide probability
76 distribution is still poorly known. More precisely, as shown in previous studies, the GARP algorithm has good
77 performance in spatial modeling (Stockman et al. 2006; Sánchez-Flores, 2007; Wang et al. 2010; Adineh et al.
78 2018). However, this model has been rarely used in landslide studies. Furthermore, the SVM and MAXENT
79 models have performed very well in spatial prediction of landslides (Park, 2015; Kornejady et al. 2017; Chen et
80 al. 2017a; Kalantar et al. 2018). Therefore, it is pertinent to evaluate the applicability of these models in the
81 context of hazard and vulnerability maps.

82

83

84 Furthermore, the landslide hazard map must be combined with information on the level of damage associated with
85 a landslide of a certain type. Specifically, an additional map – the *landslide vulnerability map* – which describes
86 the potential landslide damage on local population, property, infrastructure, and public services, is required. This
87 vulnerability map constitutes the second step toward landslide risk assessment (Guillard-Gonçalves & Zêzere
88 2018). By suitably combining the vulnerability map with the hazard map, a *landslide risk map* can be obtained,
89 which provides a joint probabilistic assessment of damaging landslide occurrence and the concatenated socio-
90 economic impacts (Frigerio & Amicis, 2016; Murillo-García et al. 2017; Guillard-Gonçalves & Zêzere, 2018).

91

92 However, landslide vulnerability mapping constitutes a challenging field of work given its intrinsic social,
93 environmental, and economical facets. Specifically, both physical vulnerability (i.e., the potential degree of

94 damage caused to physical components such as buildings, infrastructure, etc.) and social vulnerability must be
95 modeled. Indeed, the concept of social vulnerability refers, in a broad sense, to personal injuries and impact of a
96 damaging landslide on different socio-economical groups, but still lacks common definition (Guillard-Gonçalves
97 & Zêzere, 2018). Furthermore, various aspects of social vulnerability relate to potential material losses in the
98 private and public sectors as well, and it is, thus, difficult to mathematically treating social vulnerability by
99 excluding the physical aspect of vulnerability.

100

101 In the present work, a new method is presented for landslide risk assessment and its application to Golestan
102 Province in Iran (Fig. 1). This method integrates data mining and decision-making methods, which have received
103 less attention in previous studies of landslide, to estimate the regional hazard and vulnerability maps, under
104 consideration of the local landslide inventory, as well as all main relevant human-environmental factors, as
105 described next. Subsequently, the landslide risk map is obtained by combining the hazard and vulnerability maps,
106 which allows us to identify and characterize high-risk landslide areas in Golestan Province. Specifically,

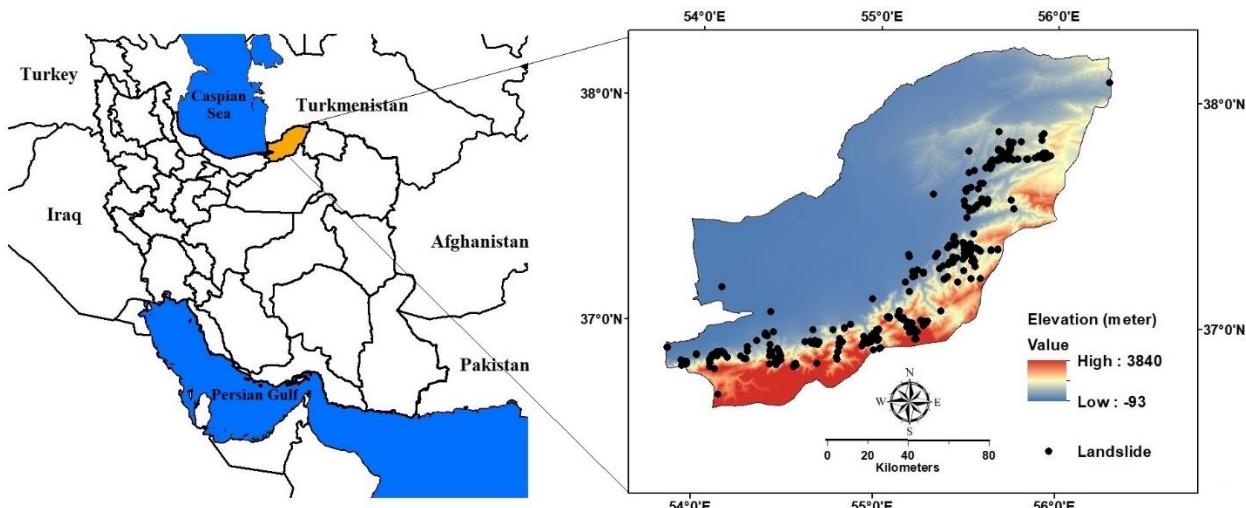
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108 **2 Factors for landslide hazard and vulnerability in the study area**

109 Golestan Province lies in Northeastern Iran, within latitude ranges from $36^{\circ}27'48''$ N to $38^{\circ}14'56''$ N, and
110 longitude ranges from $53^{\circ}40'29''$ E to $56^{\circ}30'44''$ E (Fig. 1). It has an area of 20347 km^2 , which comprises 1.3%
111 of Iran's territory. Data on landslide positions (440 points) within Golestan Province are available from the
112 Geological Survey and Mineral Explorations of Iran (GSI). These data were processed using Google Earth images
113 and field surveys, which led to the spatial distribution of landslide events is shown in Fig. 1. Moreover, images of
114 landslides within the study area have indicated in Fig. 2.

115 We remark that one constraint in the type of spatial analysis performed in our work is that the maps associated
116 with the different input factors are available at distinct scales. This constraint is indeed common to the type of
117 study considered here, i.e., it is an inevitable constraint in environmental research and is related to *limitations* on
118 *data availability* (Mosavi et al. 2020), as discussed thoroughly in preceding work (Pourghasemi et al. 2013; Hong
119 et al. 2016; Mokhtari and Abedian, 2019; Mosavi et al. 2020). However, the solution to this constraint consists in
120 resampling the input variables to the same spatial resolution, which is what we have done in the present work. By
121 suitably rescaling the input data sets, the computation of the landslide hazard maps in developing countries can
122 provide a helpful tool in land degradation research.

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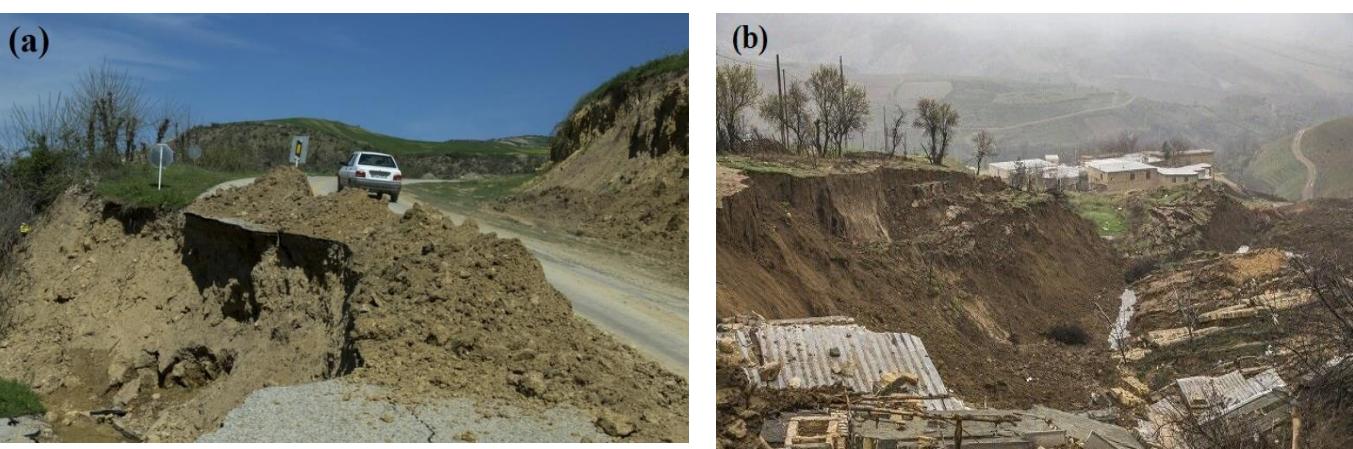


Fig. 2. Images of landslides within the study area (retrieved from Mehrnews, 2020).

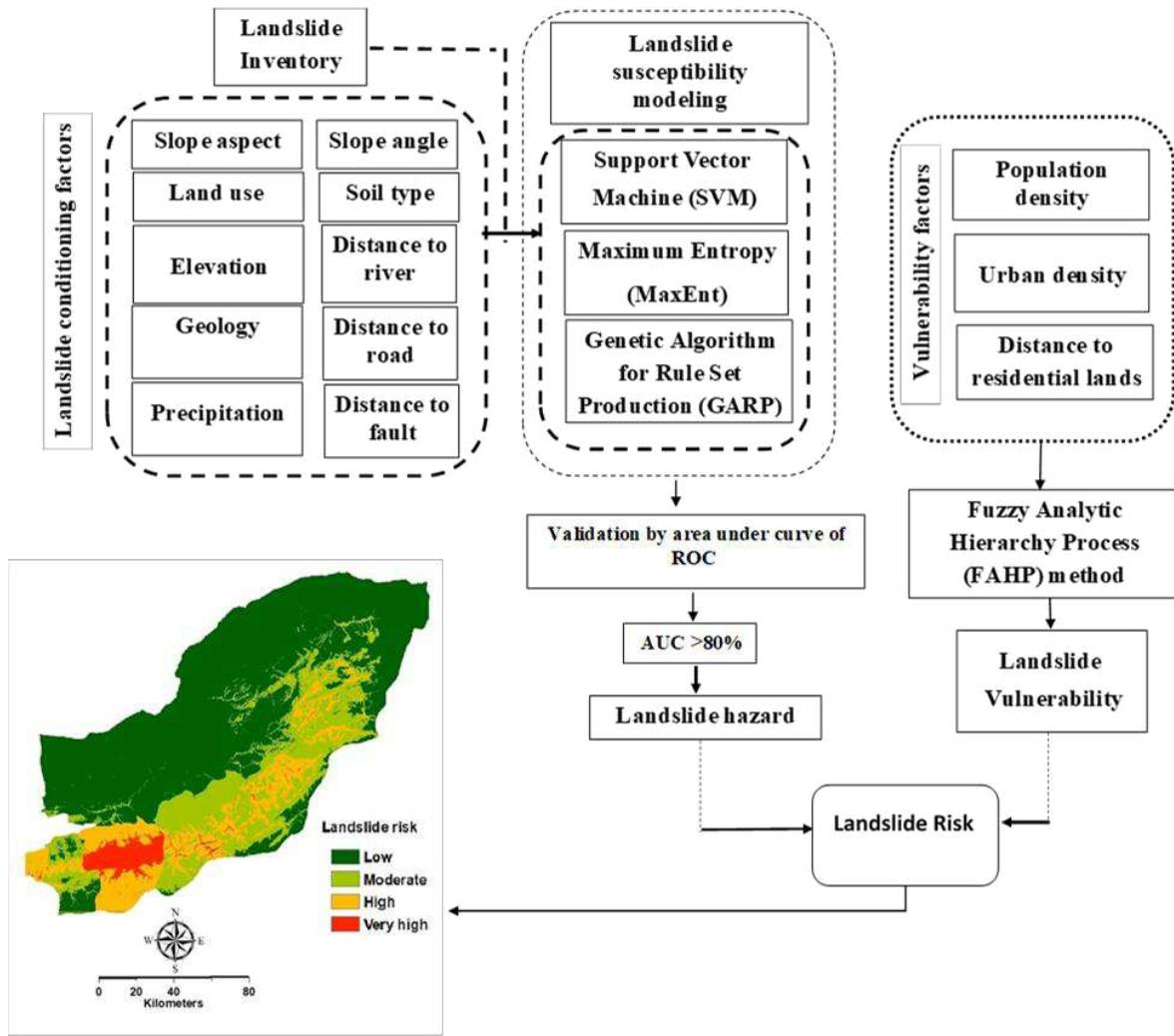
132 Various factors compete to rendering the study area of the present work potentially prone to damaging landslide
133 events. The average annual rainfall of Golestan Province ranges from 200 mm to 1000 mm. There is a significant
134 relationship between elevation and rainfall (Dhurmea et al. 2009). Since the elevation of the study area ranges
135 from -93 meters (below the average sea level) in coastal regions to 3840 meters asl (above the average sea level)
136 in southern regions, as a result, rainfall changes in the study area are high. The local geology of the study area

137 consists of limestones of the Lar and Mozdoran Formation (upper Jurassic age), Quaternary sediment types (Qm
138 and Qsw), shales of the Sanganeh Formation (Early Cretaceous) and shale and sandstone of the Shemshak
139 Formation (Triassic-Jurassic). Furthermore, nonprincipled criteria for road construction and land use/land cover
140 adopted in Golestan Province are some of the human influences affecting landslide hazard in the area.

141 In particular, forest prevails in the southern and eastern regions, while agriculture and pasture represent the main
142 types of land use/land cover elsewhere. However, the relevance of the various factors for the spatial distribution
143 of landslides is poorly known. In the following subsection, the various landslide hazard factors are described based
144 on GIS and statistical data sets available for Golestan Province. Subsequently, the social-economic factors
145 controlling landslide vulnerability are specified and discussed. Figure. 3. indicates the methodological flowchart
146 of this study.

147 According to flowchart, the major steps of this study are: (1) comparing the machine learning methods of Genetic
148 Algorithm for Rule Set Production (GARP), Support Vector Machine (SVM) and Maximum Entropy (MaxEnt)
149 to predict landslide hazard maps, (2) assessing the landslide conditioning factors and the determination of the
150 most important factors, (3) creating landslide vulnerability map based on the analytic hierarchy process (AHP)
151 approach, (4) integrating the best machine learning method with MCDM approaches to create landslide risk map
152 and to characterize the high landslide risk regions.

153



154

155 **Fig. 3. The methodological flowchart of the present study**

156 **2.1 Landslide hazard factors**

157 To calculate the landslide hazard map for Golestan Province, we follow Ashournejad et al. (2019) and consider
 158 the following main two-dimensional fields: Digital Elevation Model (DEM), soil type, slope-aspect, slope-angle,
 159 geology, distance to fault, land use/land cover (LULC), distance to road, distance to the river and precipitation.
 160 The characteristics of these factors in Golestan Province are described below.

161

162 We note that the maps associated with the factors considered in the study area are not available all at the same
 163 scale. However, we have resampled all maps using the same cell size (30 meter) in ArcGIS, thus allowing us to
 164 overlay the various maps. This scenario resembles, indeed, the situation encountered in previous work, in which
 165 data sets associated with different spatial scales were considered for the computation of hazard maps associated
 166 with landslide and other environmental studies (Adineh et al. 2018; Pourghahsemi & Kerle, 2016).

167

168 *2.1.1 Slope-aspect*

169 Slope-aspect affects local solar radiation and vegetation growth, and has been thus pointed out as important and
170 effective factor for landslides (Sidle & Ochiai, 2006; Kumar & Anbalagan, 2015). Golestan Province hosts a
171 mountainous terrain which leads to potentially relevant spatial variability in slope-aspect. Thus, slope-aspect
172 was considered as potential factor for landslide hazard in Golestan Province. Figure. 4a displays the
173 corresponding slope-aspect map, prepared and classified on DEM with a cell size of 30 m × 30 m in ArcGIS
174 10.2.2.

175

176 *2.1.2 Slope-angle*

177 Moreover, the angle between the sloping side of a granular soil and the horizontal – i.e., the slope-angle – is one
178 of the most important parameters for landslide initiation. Wherever this angle exceeds the soil's angle of maximal
179 stability against gravitational stresses, the surface relaxes through avalanches in the direction of steepest descent,
180 thus triggering a landslide (see, e.g., Beakawi Al-Hashemi and Baghabra Al-Amoudi, 2018). However, this angle
181 of maximal stability, also called angle of repose, depends on frictional and cohesive inter-particle forces that
182 follow a still poorly known function of various factors, such as particle size distribution, degree of consolidation,
183 moisture content, particle shape and material (Parteli et al., 2014; Schmidt et al., 2020). Moreover, the modeling
184 of landslide initiation processes and the role of slope-angle must consider whether the soil is cohesive or not, and
185 whether the soil is constituted of consolidated materials or rocks. The relationship between the probability of
186 landslide occurrence and slope-angle is still uncertain (Neuhäuser & Terhorst, 2007; Dymond et al. 2006; Demir
187 et al., 2013). In the present work, the slope-angle map was generated for Golestan Province based on the DEM in
188 ArcGIS 10.2.2. Figure. 4b shows that the slope-angle ranges from about 0° degrees in the north to approximately
189 71° degrees within the south and east areas of Golestan Province.

190

191 *2.1.3 Precipitation*

192 As shown in previous work, the local landslide occurrence probability is strongly correlated with rainfall
193 (Kawagoe et al. 2010; Althuwainee et al. 2015). Infiltration and runoff enhance soil instability and saturation
194 levels, raindrop impacts on sloping granular surfaces constitute an important mechanism of downhill sediment
195 transport, and rainfall-induced processes may increase landslide hazard over multiple time-scales, for instance by

196 affecting moisture content and increasing local slope instability (Hong et al. 2006). In the present work, the
197 precipitation map of Golestan Province (Fig. 4c) has been calculated based on annual average precipitation data
198 of 33 rain gauge stations from the Iran Meteorological Organization. According to Fig. 4c, the amount of
199 precipitation ranges from 200 mm near the borders of coastal regions to 1000 mm near the central region of
200 Golestan Province (Fig. 4c).

201 It should be noted that the intensity and variation of rainfall are important aspects in the statistics, in addition to
202 the mean rainfall. However, recording rain gauge stations and hourly rainfall data would be needed to estimate
203 the intensity of rainfall. In the study area, the number of recording rain gauge stations (with hourly data) was
204 limited, so that the analysis of the present work relies on the average rainfall data based on the statistics of rain
205 gauge stations. Therefore, the present study can be compared to previous work, in which the conditioning factor
206 associated with rainfall was based on average precipitation data (Aghdam et al., 2017).

207

208 *2.1.4 Distance to river*

209 There are three main and consistent rivers in Golestan Province, namely Gorgan River, Qarasu and Atrak rivers
210 (they are not valleys or streams). Distance to the river may affect landslide hazard, as groundwater flow toward
211 rivers and water rivers provides an effective mechanism for soil undercutting (Korup et al. 2007; Tang et al. 2011;
212 Zaruba and Mencl 2014). Previous work has shown that landslides occur often along river sides, and that the
213 proximity to rivers underwashes hillside slope foot by flood, thus further enhancing landslide hazard (Dai et al.,
214 2001). Figure 4d shows the spatial distribution of distance to the river for Golestan Province, obtained with
215 ArcGIS 10.2.2.

216

217 *2.1.5 Land use/Land cover*

218 Land use/land cover has an impact on soil properties, geology and land cover dynamics, and represents one major
219 factor for enhancing rainfall-driven landslide occurrence. Human activities of various types are well-known cause
220 of vegetation cover reduction and increased soil instability, and favor gully and runoff erosion (Fell et al. 2008;
221 Karsli et al. 2009). Moreover, forest, orchard, rangeland and agricultural lands stand for the land use/land cover
222 practices with highest impact on landslide occurrence (Ercanoglu & Gokceoglu, 2004). For instance, agricultural
223 and orchard land use/land cover affect soil mechanics through irrigation processes and alterations in natural
224 vegetation cover, while forest practices further increase landslide hazard wherever land use/land cover is

225 inappropriate, especially near roads (see below). Landsat Operational Land Imager (OLI) images (Landsat 8) was
226 used to extract the 2019 land use/land cover map for Golestan Province. The supervised classification method of
227 Maximum Likelihood (ML) was used in ENVI 5.1 software to provide the land use/land cover maps. Finally, land
228 use/land cover map of the study area was classified into six classes including: urban, bare land, rangeland, forest,
229 orchard and agriculture (Fig. 4e).

230 *2.1.6 Elevation*

231 Elevation is another important factor for landslide occurrence, since at higher altitudes various phenomena
232 compete to favor soil instability processes, such as snowmelt, sparse vegetation, enhanced rock weathering and
233 rainfall (Pachauri, 1998; Dai & Lee, 2002; Catani et al., 2013). Figure. 4f shows the Digital Elevation Model
234 (DEM 30 meter) of Golestan Province, which has been obtained from topographic maps in 1:25000 scale prepared
235 by Department of Water Resources Management of Iran (DWRMI). The preparation of DEM map based on topography
236 map was done in ArcGIS 10.2.2 using "Topo to raster" command. According to Fig. 4f, the elevation of the study
237 area ranges from -93 meters (below the average sea level) in coastal regions to 3840 meters asl (above the average
238 sea level) in southern regions. Specifically, negative values of elevation (Z) mean that the Z is below a reference
239 value (Z= 0) associated with sea level. Persian Gulf is the base level for measuring elevation in Iran. Elevation in
240 coastal region was -93 meters below the average sea level.

241 *2.1.7 Distance to fault*

242 Fault dynamics cause rock displacement, avalanches, seams and cracks on the soil, thus constituting one major
243 cause for slope instability (Pham et al. 2018). Landslide occurrence in areas affected by tectonic processes and
244 seismic activity tends, thus, to increase with proximity to fault. By means of field investigation and remote sensing,
245 a negative exponential scaling was proposed to quantitatively predict the number of earthquake-triggered
246 landslides per unit area as a function of the distance to the causative fault (Zhuang et al., 2010). However, this
247 quantification is difficult because landslide hazard depends on the interplay between prevailing seismic modes,
248 perturbation magnitude, fore- and aftershock dynamics and the other local environmental factors causative of
249 landslides.

250 The study area is placed in Northeast Iran, north of the Eastern Alborz Mountains and east of the South Caspian
251 block and its lithology consists of limestone, Quaternary sediment types, shales and sandstones. The Khazar and
252 North Alborz fault zones are the most important faults of the study area. One of the important active fault zones
253 located in the Golestan province is the Khazar fault zone, including Minoodasht, Behshahr, Sari, and Amol faults

254 (Tourani et al. 2021). According to previous studies, the thrusting of the Alborz Mountains towards the south of
255 the Southern Caspian block occurs along the Khazar fault zone (Axen et al. 2001 and Allen et al. 2003). The active
256 Khazar fault zone indicates reverse/thrust fault properties and has created many significant earthquakes during
257 the instrumental period (Tourani et al. 2021).

258 Figure. 4g shows the two-dimensional field associated with local distance to the next fault within Golestan
259 Province, which it has been obtained using ArcGIS 10.2.2.

260 *2.1.8 Lithology*

261 Lithology, i.e., the type of rock constituting the soil, affects landslide hazard because some types of rock are more
262 affected by degradation resulting from water infiltration than others. However, the relationship between lithology,
263 rock degradation and soil instability is poorly understood. Different geological formations in the Golestan
264 Province, such as limestone, gypsum, shale and sandstone, which are particularly prone to infiltration-induced
265 degradation, occur in areas of high density of landslides (Fig. 4h). Furthermore, there are Quaternary sediments
266 including Qm and Qsw, along the margins of the Caspian Sea. Swamp deposits (Qsw) include gray to brown,
267 silty, clayey, gravelly sand covered by organic rich, fine to coarse sand and silt. Swamp deposits are found in the
268 upper reaches of the modern stream valleys, along the margins of the Caspian Sea, and in poorly-drained areas on
269 the uplands. Along the margins of the Caspian Sea, swamp deposits are up to 15 ft thick and have several feet of
270 organic silt near the land surface. Marsh deposits (Qm) include light-gray to brown, organic-rich, clayey silt.
271 These deposits are located along the margins of the Caspian Sea. In general, the thickness of marsh deposits is
272 less than 10 ft. Table 1 lists the main classes of lithology in Golestan Province.

273
274
275

Table 1. Lithology classes in the study area.

Code	Lithology	Formation	Geological age
Qm	Marsh deposits	-	Quaternary
Ksn	Grey to block shale and thin layers of siltstone and sandstone	Sanganeh	Early Cretaceous
Qsw	Swamp deposits	-	Quaternary
DCkh	Limestone, locally including gypsum	Lar & Mozdoran	Jurassic
TRJs	Dark grey shale and sandstone	Shemshak	Triassic-Jurassic

276
277

2.1.9 Soil type

278 Soil type constitutes one main property for hillslope instability. Fine-grained soils, in particular, are less permeable
279 and more prone to landslides than coarse-grain soils (Lepore et al. 2012; Alkhasawneh et al. 2014), while material
280 properties and particle chemistry further affect inter-particle frictional forces and soil flowability. Following
281 USDA soil taxonomy, soil types in Golestan Province can be classified into the following categories:

- 282 ▪ alfisol – rich in iron, aluminum, moisture and clay
- 283 ▪ aridisol – dry, poor in organic matter, characterized by slow formation rates
- 284 ▪ entisol – unconsolidated sediments, in particular sand, clay or volcanic ash
- 285 ▪ inceptisol – young soils with poorly developed vertical profile
- 286 ▪ mollisol – deep, fertile soils of soft texture characterizing grasslands

287 The spatial distribution of the prevailing soil type in Golestan Province is shown in Fig. 4i. It should be noted that
288 soil type and lithology constitute distinct environmental factors, and there is a significant relationship between
289 these factors with landslide hazard based on Jackknif test, as shown later in this manuscript. There, it is necessary
290 to use both factors. We refer to previous work (Van Den Eeckhaut et al. 2012 and Mohammady et al. 2012) which
291 has used both factors for modeling landslide hazard, such as in the present study.

292

293 *2.1.10 Distance to road*

294 Regions within higher proximity to roads are more prone to landslide occurrence due to undercutting- and
295 overloading-driven processes of mechanical hillslope destabilization (Duman et al. 2006, Lee, 2007, Yalcin,
296 2008). The effect of roads on landslide hazard is tendentially stronger in developing countries owing to inadequate
297 drainage system, which further contributes to enhance soil instability. As shown in previous work (Brenning et
298 al., 2015), landslide hazard near highways may be increased by one order of magnitude, both owing to mechanical
299 stresses on the base of hillslopes and to the contribution of further types of human interference in nearby areas,
300 such as grazing. Moreover, roads cause vertical cuts that increase the pressure on their lower part, thus further
301 enhancing landslide hazard. Figure. 4j shows the spatial distribution of distance to the road in Golestan Province.

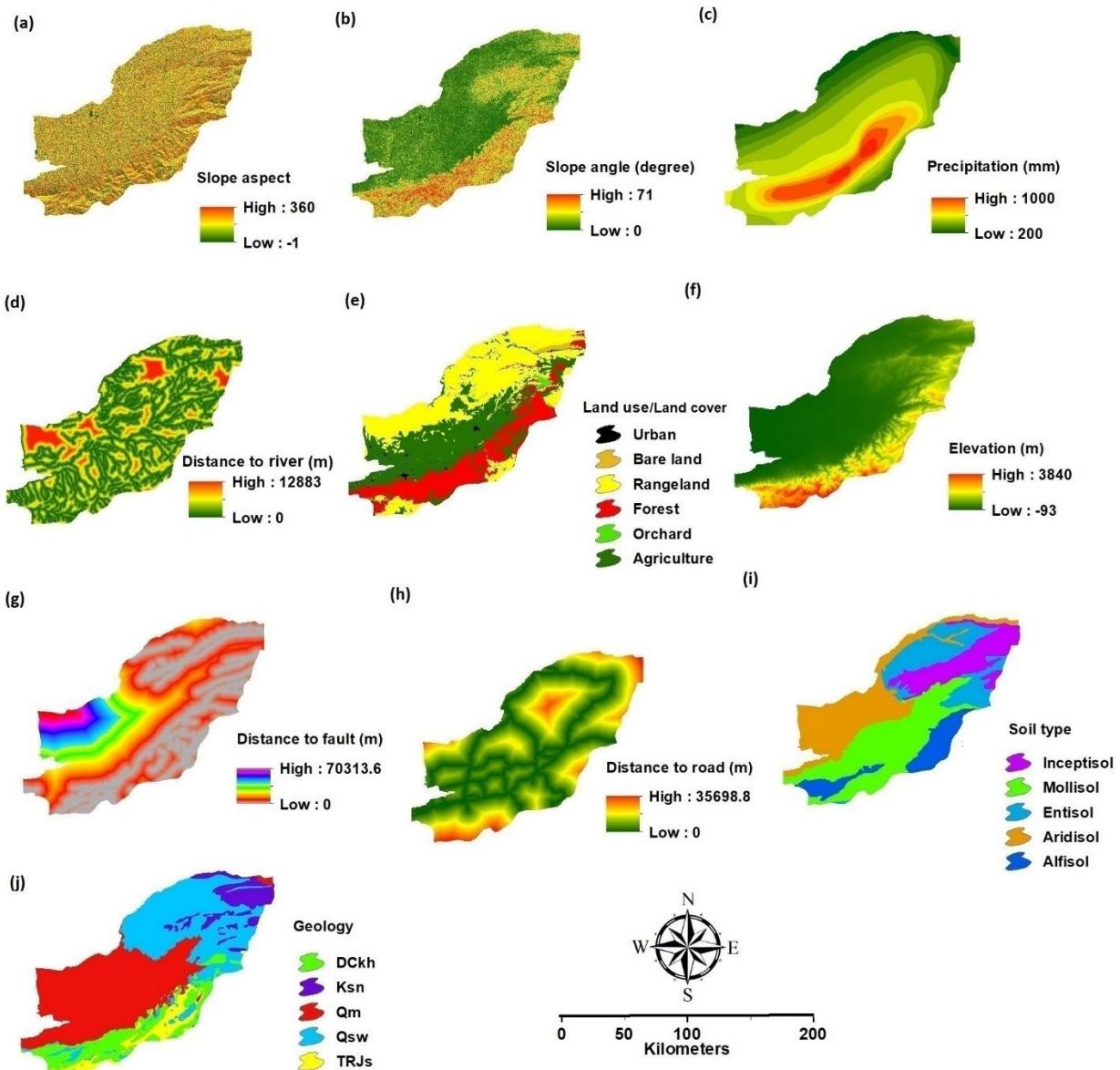


Fig. 4. Spatial distribution of the main landslide hazard factors in Golestan Province: a) slope-aspect, b) slope-angle, c) precipitation, d) distance to river, e) land use/ land cover, f) elevation g) distance to fault, h) distance to road, i) soil type, and j) lithology.

2.2 Landslide vulnerability factors

Vulnerability refers to the potential level of devastation caused by a natural hazard of a certain type to society, infrastructure and properties (Tobin & Montz, 1997). However, vulnerability has no standard definition and must be characterized under consideration of the type of natural hazard and the various aspects associated with the human-environmental setting that are relevant for damage characterization. Following considerations of previous

313 work (Murillo-García et al. 2017; Guillard-Gonçalves & Zêzere, 2018), finally, the following landslide
314 vulnerability factors within Golestan Province were identified: urban population density, urban building density
315 and distance from urban areas to landslide locations (discussed below).

316 Indeed, the maps associated with the landslide vulnerability factors in the study region are not available all at the
317 same scale. We share, thus, the challenge met by different authors in previous work dealing with diverse maps,
318 each with a distinct spatial resolution (Adineh et al. 2018; Pourghahsemi & Kerle, 2016). In the present work, we
319 have resampled all maps based on the same cell size (30 meter) in ArcGIS, so that the analysis has been performed
320 using this spatial resolution.

321 *2.2.1 Urban population density*

322 Urban population density is defined as the number of individuals per unit area residing in an urban region. The
323 larger the population density, the larger the number of individuals subjected to a local damaging landslide, and
324 the higher, thus, the social vulnerability (Cutter et al. 2003; Uzielli et al. 2008; Kjekstad & Highland; 2009,
325 Murillo-García et al. 2015). We noted that additional social aspects, such as population distribution and social-
326 economic development, may further affect, to some extent, local landslide vulnerability. However, given that
327 political and cultural influences do not vary much within Golestan Province, it is reasonable to regard population
328 density as the main causative factor for social vulnerability in the study area. Population density in Golestan
329 Province was classified as specified in Fig. 5a and table 2 (data from Iran Statistical Center Organization, 2016).

330 Table2. Population density in different cities of Golestan Province

City	Population	Area(km ²)	Urban population density (person/km ²)
Gorgan	480541	1578	305
Gonbad-e Qavus	348744	4996	70
Aliabad-e Katul	140709	1100	128
Aqqala	132733	1842	72
Kalaleh	117319	1863	63
Azadshahr	96803	848	114
Ramian	86210	827	104
Bandar-e Torkaman	79978	283	283
Minudasht	75483	663	114
Kordkuy	71270	856	83
Gomishan	68773	1281	54
Galikash	63173	868	73
Maraveh Tappeh	60953	3097	20
Bandar-e Gaz	46130	246	187
Total	1868819	20347	92

331

332 2.2.2 *Urban building density*

333 Urban building density – the number of buildings per unit area within an urban region – is one major factor for
334 physical vulnerability. We noted that this vulnerability incorporates potential damage to any physical component
335 of the private and public sectors, including building distribution. However, if we assume that public-infra structure
336 and private property represent potential development indicators in Golestan Province, and that these indicators
337 are correlated with each other to some extent, then it is plausible to adopt urban building density as one quantitative
338 measure for socio-economic development – and vulnerability. Figure. 5b shows the building density map for the
339 study area (data available from Iran Statistical Center Organization, 2016).

340

341 2.2.3 *Distance from urban area to next landslide location*

342 Because frictional forces cause energy dissipation thus counteracting the sediment transport processes, landslide
343 vulnerability tends to decrease with distance to landslide areas. By contrast, the closer an urban area is to a
344 landslide location, the higher the potential level of damage associated with an event of a certain type. Figure. 5c
345 shows the two-dimensional field corresponding to the distance between the urban regions and landslide locations,
346 obtained from the Digital Elevation Model of Golestan Province. We noted interurban infra-structure such as
347 roads and railway could be also incorporated into Fig. 5c, but have not been included in this map given that they
348 depend on the spatial distribution of urban areas and further reflect regional levels of socio-economic development
349 that have been already considered in Sections 2.2.1. Therefore, vulnerability factors considered above incorporate
350 all main aspects controlling potential socio-economic damage of landslides and are, thus, applied for landslide
351 risk mapping as described next.

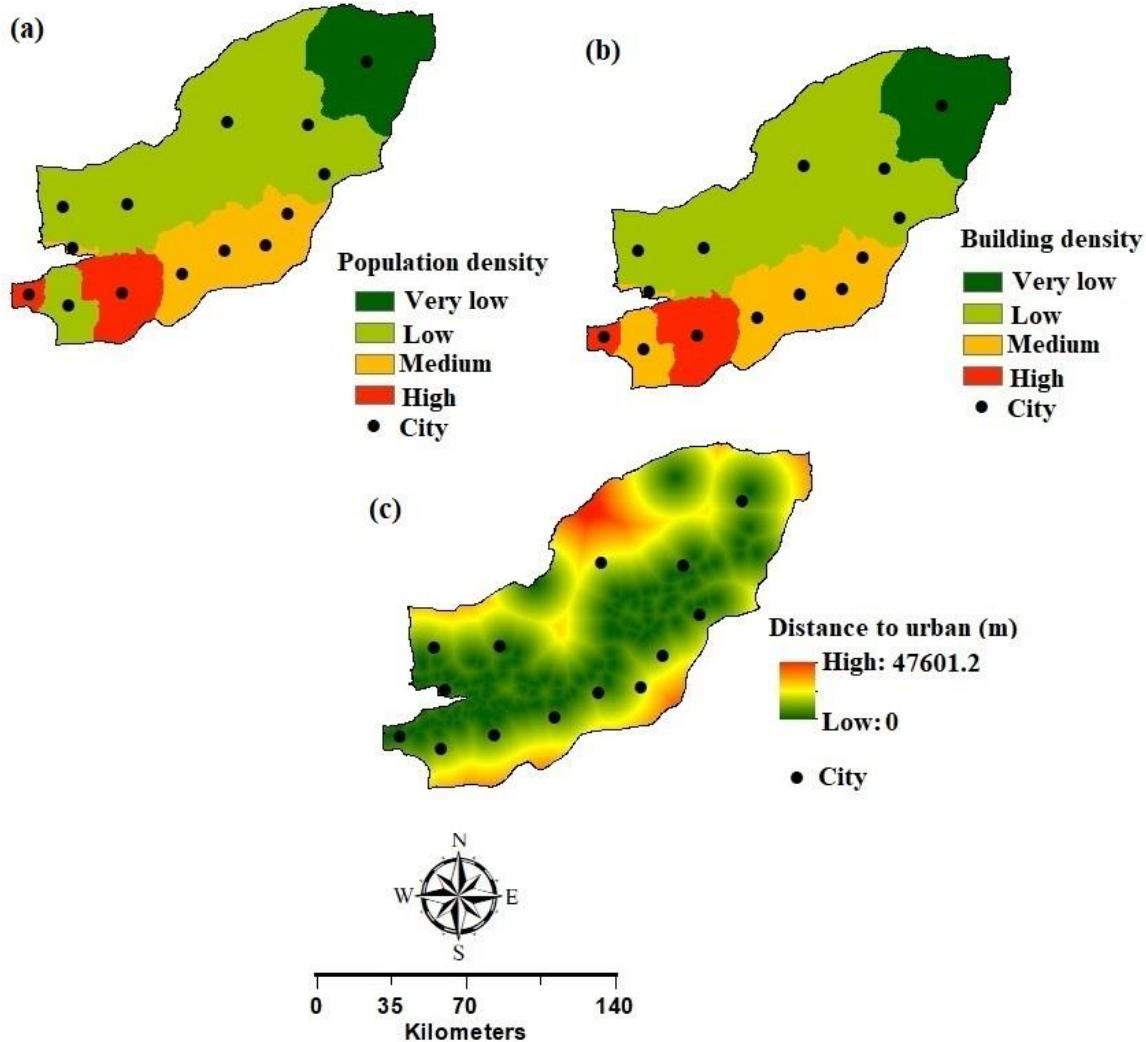


Fig. 5. Spatial distribution of the main landslide vulnerability factors: a) urban population density, b) urban landslide density, and c) distance from urban area to landslide location.

3 Calculation of the landslide hazard, vulnerability and risk maps

Machine learning algorithms were applied to calculate hazard, vulnerability and risk maps based on the data sets described in the previous section, as well as the landslide inventory map shown in Fig. 1. To this end, the positions in the inventory map associated with the 440 landslide events were divided into two groups: Training data, corresponding to randomly chosen 70% of the landslide positions, and test data, comprising 30% of the corresponding data set (Pourghasemi et al. 2013; Adineh et al. 2018). Specifically, the first group was employed in the search for correlation patterns between spatial distributions of landslide events, hazard factors and vulnerability factors, while the second group was used for testing the obtained relationships in the framework of

365 machine learning (Hastie et al., 2017). Based on these relationships, the maps for landslide hazard and
366 vulnerability were computed, whereupon a landslide risk map for Golestan Province was obtained as described in
367 the following subsections.

368

369

370 **3.1 Landslide hazard map using Support Vector Machine, Maximum Entropy and Genetic
371 Algorithm for Rule Set Production**

372 To obtain the hazard map, we employed and compared the performance of three different machine learning
373 algorithms for modelling landslide occurrence probability as a function of the conditioning factors specified in
374 Section 2.1. These methods are described in Sections 3.1.1 – 3.1.3.

375

376 *3.1.1 Support Vector Machine (SVM)*

377 Support Vector Machine (SVM) stands for a learning-based data classification method (Vapnik, 1999; Yao et al.,
378 2008; Peng et al., 2014). In the present work, SVM was applied for the first time to compute the hazard map for
379 the entire Golestan province area. The goal is to divide the study area in classes of landslide hazard (from low to
380 very high) based on the landslide inventory map and conditioning variables. More precisely, SVM assigns to each
381 observed landslide location within the training data set one vector in the two-dimensional space, which is then
382 classified according to a *local hazard level*, which is determined by the values of all hazard factors at the
383 corresponding landslide location. Subsequently, the hazard map is computed by subdividing the study area into
384 classes (clusters) of landslide hazard, each indicating a specific hazard level on the map. The border lines that
385 separate neighboring classes on the map, which are called hyperplanes. The optimal hyper-plane maximizes the
386 margin to divide the two categories, e.g., landslide and non-landslide. SVM has this name because each hyperplane
387 is modeled using linear fitting functions determined from the vectors that lie nearest to it – these vectors are known
388 as support vectors in the algorithm (e.g., Vapnik, 1999). The optimal hyper-plane can be determined based on the
389 solution of optimization problem as follows (Samui, 2008):

390

391
$$\begin{aligned} & \text{Minimize} \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\ & \text{if } \sum_{i=1}^n \alpha_i y_i = 0 \text{ and } 0 \leq \alpha_i \leq C \end{aligned} \tag{1}$$

392 where x is a vector of input space which includes selected conditioning factors, y is a training vector, C and α_i
393 are the penalty factor and lagrange multipliers, respectively.

394 The training vectors consist of two categories (landslide and non-landslide pixels) are specified by two classes -1
395 and +1, respectively. The SVM method searches for an optimal hyper-plane which can recognize these two
396 categories from these training vectors (Samui, 2008).

397 However, due to non-linearity effects inherent to natural systems, prior to applying classification the domain is
398 often linearized by means of (kernel) functions. Specifically, the training vectors are mapped into a higher-
399 dimensional space, in which computations can be performed using linear hyperplanes (Kecman, 2005; Hofmann
400 et al. 2008; Marjanović et al. 2011; Ballabio & Sterlacchini, 2012; Chen et al. 2017a).

401 In this case, to classify the new dataset based on the SVM approach, the following decision function can be applied
402 (Samui, 2008):

403
$$g(x) = \text{sign}(\sum_{i=1}^n y_i \alpha_i K(x_i x_j) + b) \quad (2)$$

404 where $g(x)$ is decision function, b is a scalar base, $K(x_i x_j)$ is the kernel function,

405 Following previous work (Pourghasemi et al., 2013; Lee et al. 2017), we chose a Gaussian (bell-shaped) kernel
406 function, which is also called Radial basis function (RBF) and has proven to deliver the best classification results
407 in landslide hazard problems. This kernel function was determined using following equation (Vapnik, 1995):

408
$$K(x_i x_j) = e^{-\gamma(x_i - x_j)^2}, \gamma > 0 \quad (3)$$

409 where γ is kernel width. The SVM model with RBF kernel available was run in openModeller Desktop 1.3.0 (de
410 Souza Muñoz et al. 2011).

411

412 3.1.2 MaxEnt (Maximum Entropy)

413 MaxEnt is a data mining method to predict the occurrence of one event based on maximum entropy (Elith et al,
414 2011) that approximates the probability distribution of presence data based on environmental limitations (Phillips
415 et al., 2006). In this model, the occurrence points (X_1 to X_m) are used to obtain an unknown probability distribution
416 (Π) (Phillips et al. 2004; Phillips and Dudík, 2008; Kumar & Stohlgren, 2009) and the suitability of each pixel
417 in the environment is expressed as a function of environmental variables. The maximum entropy model chooses
418 a probability distribution that is near to reality and has entropy maximization (Phillips et al. 2006; Phillips et al.
419 2009; Felicísimo et al. 2013).

420 In this study, ME model was selected to predict landslide hazard. This model determines landslide occurrence
421 probability distribution (π) in the set of positions X. The MaxEnt method has shown acceptable accuracy in the
422 spatial modeling (Convertino et al. 2013; Chen et al. 2017b; Azareh et al. 2019). The objective occurrence
423 probability at position x is expressed as (Phillips, 2008):

$$424 P(y=1/x) = \frac{P(y=1)P(x/y=1)}{P(x)} = \frac{P(y=1)\Pi(x)}{\sum_{x'}\Pi(x')} \quad (4)$$

425 where the probability of landslide occurrence is $P(y = 1)$, while $|x|$ is the number of pixels over the study area.
426 Implementation was accomplished using the software MaxEnt 3.3.3 (Phillips et al., 2006).

427

428 3.1.3 Genetic Algorithm for Rule Set Production (GARP)

429 GARP is a data mining method based on a genetic algorithm designed to perform ecological modeling (Stockwell
430 & Noble, 1992; Stockwell, 1999; Townsend Peterson et al. 2007; Adineh et al. 2018; Darabi et al. 2019). The
431 algorithm was employed in previous spatial modelling (Stockman et al. 2006; Sánchez-Flores, 2007; Wang et al.
432 2010; Adineh et al. 2018), but its performance in regional landslide probability modelling is still uncertain.

433

434 A genetic algorithm starts with a large set of randomly generated competing solutions to a certain problem, which
435 are refined over time to converge toward an optimal solution. Indeed, each solution can be regarded as a set
436 (“chromosome”) of models or parameter values (“genes”), which are iteratively refined by producing new sets of
437 solutions. Moreover, in the framework of GARP, the solutions represent sets of environmental conditions, such
438 as rainfall, elevation, climatic conditions, etc., which must be iteratively improved with regard to habitability by
439 a given species on the basis of an inventory map for species occurrence (Stockwell, 1999; Townsend Peterson et
440 al. 2007; Zhu et al. 2007; Wang et al. 2010; Boeckmann and Joyner, 2014; Adineh et al. 2018; Darabi et al. 2019).

441

442 In the problem of landslides investigated here, the landslide events stand for the species of the GARP algorithm,
443 while the landslide inventory map constitutes the set of local observations that are needed to initialize the
444 computations. The GARP model was run in openModeller Desktop 1.3.0 (de Souza Muñoz et al. 2011) to estimate
445 the relationship (optimal solution) between spatial distribution of landslide occurrence and hazard factors, thus
446 leading to the landslide hazard map.

447

448 **3.2 Landslide vulnerability map using Fuzzy Analytical Hierarchical Process**

449 A multi-criteria decision analysis technique was applied to evaluating local potential damage in Golestan
450 Province, based on the landslide vulnerability factors identified in Section 2.2, i.e., urban population density,
451 urban building density and distance to landslide location. Since the relative weights of these factors for the
452 vulnerability map must be known, the method of Fuzzy Analytical Hierarchical Process (FAHP) was applied to
453 estimate the combined effect of the respective spatial distributions.

454

455 Specifically, the FAHP method, has been described in detail in the literature (Saaty 1977; Carver 1991;
456 Malczewski 1999; Ohta et al. 2007; Chen et al. 2016; Abay et al. 2019), discretizes the normalized values of each
457 vulnerability factor to generate fuzzy variables, each allowing for 3 possible “membership” values: 0 (the
458 minimum), 1 (the maximum) and an intermediate value reflecting the shape of the distribution. Each fuzzified
459 vulnerability factor can take, thus, one of these membership values at a given location. Thereafter, the fuzzified
460 factors are combined according to a weight vector, which encodes the relative influences (weights) of the different
461 factors on the potential level of damage. Thus, a survey of local experts in the geology of Golestan Province was
462 conducted to estimate the relative influences of the vulnerability factors of Section 2.2. Based on this information,
463 in the framework of GARP, a comparison matrix encoding the weight ratio of all vulnerability factors is obtained
464 and combined with the aforementioned fuzzy maps, thus leading weighted fuzzy maps (also called layers)
465 associated with the different environmental and socio-economical variables. The final vulnerability map is
466 obtained by overlaying the weighted fuzzy layers, which was accomplished here in the ARCGIS 10.2.2
467 environment.

468 It should be emphasized that the AHP-FUZZY method is used in our study, and not the pure AHP method. The
469 AHP method determines the importance of variables only. However, in our work, each pixel was weighed and
470 valued based on the fuzzy method, which was applied to the purpose of our work as described in Section 3.
471 Furthermore, the importance of variables is determined entirely by decision-making methods and experts, and
472 does not rely on any other method.

473

474 **3.3 Landslide risk map**

475 Interpretation of risk in the present work follows Schneiderbauer & Ehrlich (2004). Risk is a function of
476 vulnerability and hazard (Glade and Crozier, 2005a; Glade and Crozier, 2005b; Dewan, 2013). Therefore, local

477 landslide risk is obtained here by combining the probability that a landslide occurs at a given location, under
478 consideration of the conditioning factors (hazard), with the probability associated with a certain level of
479 devastation caused by a damaging landslide (vulnerability). The landslide risk probability map for Golestan
480 Province is obtained from the product of the landslide hazard and vulnerability maps, i.e., for every location, the
481 local hazard is multiplied by the local vulnerability, which gives the local risk (Eq. 5) (Zezere et al. 2008;
482 Remondo et al. 2008; Dewan, 2013).

483 $Risk = Hazard \times Vulnerability$ (5)

484 The obtained landslide risk map is a quantitative and probability map (Hervas & Bobrowsky, 2009 and Corominas
485 et al., 2014).

486 Therefore, the purpose of this study is to model landslide risk in Golestan Province. Risk encodes the
487 information on both hazard and vulnerability. Hazard is more related to environmental factors (slope, aspect,
488 elevation, etc.), while vulnerability is related to socio-economic factors, such as building density and population
489 density. A region may have high landslide hazard while being not socio-economically vulnerable, or vice versa.
490 Therefore, both vulnerability and hazard should be considered together for risk analysis. Therefore, the machine
491 learning tools and environmental factors are used to prepare the landslide hazard map, but socio-economic
492 factors and the decision-making method (FAHP) were applied to prepare a vulnerability map. Finally, our
493 analysis leads to a hazard and vulnerability map, as discussed next. After predicting the Hazard map and
494 preparing the Vulnerability map, the Risk map is calculated through the raster calculator tools in the ArcGIS
495 environment based on Eq. (5)

496 **3.4 Model performance evaluation**

497 In this study three metrics, comprising: threshold-independent area under curve (AUC) of the receiver-operator
498 characteristic curve (ROC), True Skill Statistic (TSS), and Accuracy (or efficiency), were used to evaluate the
499 performance of landslide hazard models (Pontius & Schneider, 2001; Lee and Park, 2013; Shabani et al. 2018;
500 Rahmati et al. 2019; Dodangeh et al. 2020). These metrics have been broadly applied for the evaluation of machine
501 learning models (Allouche et al., 2006; Wang, 2007; Rahmati et al. 2019).

502

503 Accuracy shows how well a test accurately identifies or excludes a condition and it is obtained by Eq. (6), where,
504 FP is false positive, FN is false negative, TP is true positive, and TN is true negative. TP and TN are the number
505 of pixels that are accurately classified while FP and FN are the numbers of pixels incorrectly classified (Beguería,
506 2006; Manfreda et al., 2014; Bui et al., 2016).

507 The True Skill Statistic (TSS) was calculated by Eq. (7) based on the sum of sensitivity (Eq. 8) and specificity
508 minus 1 (Eq. 9). (Allouche et al., 2006 Shabani et al. 2018; Dodangeh et al. 2020). TSS value varies from -1 to
509 +1, where -1 demonstrates predictive capabilities of not better than a random model, 0 demonstrates an
510 indiscriminate model and +1 a perfect model (Allouche et al., 2006).

511 The area under the receiver-operator characteristic curve (AUROC) provides a measure of model accuracy in
512 predicting landslide occurrence (Gorsevski, 2006). The range of possible AUC values lies in the interval [0, 1],
513 where values of AUC close to 1 indicate high model performance (Yesilnacar, 2005; Pearce & Ferrier, 2000;
514 Fielding & Bell, 1997; Philips, 2004; Wang, 2007; Frattini et al. 2010).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$517 \quad TSS = Sensitivity + Specificity - 1 \quad (7)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (8)$$

$$519 \quad 1 - Specificity = \frac{FP}{TN + FP} \quad (9)$$

520 **4 Results**

521 4.1 Landslide hazard map

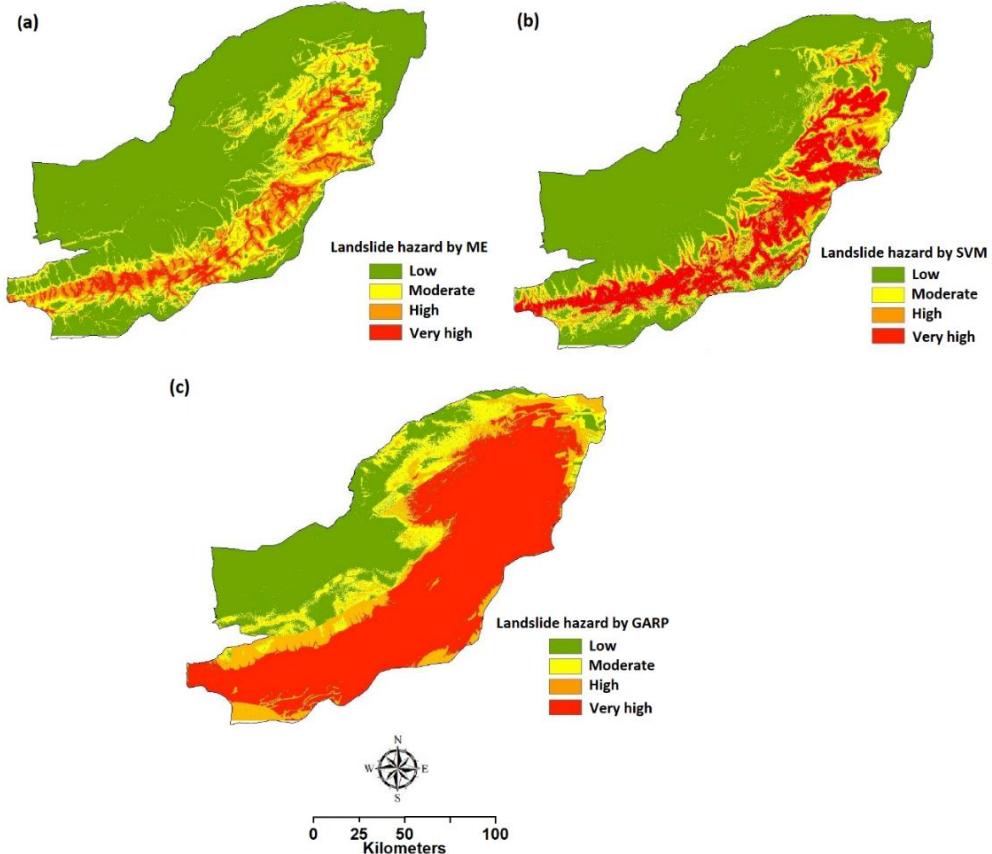
Figure. 6 shows the landslide hazard maps obtained with the algorithms discussed in Section 3.1, i.e, MaxEnt, SVM and GARP, by classifying hazard levels as low, moderate, high and very high. Moreover, Figure. 7 displays the results from AUC ROC statistics (see Section 3.4) on the accuracy of the different algorithms. As can be seen from Fig. 7 and table 3, the MaxEnt model delivered the best performance (AUC = 92%, TSS=82.3%, Accuracy=87.5%), followed by SVM (AUC = 81%, TSS=73.6%, Accuracy=78.3%) and GARP (AUC = 74%, TSS=66.8%, Accuracy=71.6%). Therefore, the results of MaxEnt were used to prepare landslide risk.

Table 3. Predictive performance of models using three evaluation statistics

Statistics	MaxEnt	SVM	GARP
AUCROC (%)	92	81	74
Accuracy (%)	87.5	78.3	71.6
TSS (%)	82.3	73.6	66.8

531 It is interesting to note that previous work also revealed slightly superior performance of MaxEnt for different
532 applications, compared to other models (Phillips et al., 2006; Hong et al., 2016; Park, 2015; Kornejady et al.,
533 2017). Various reasons for this behavior have been suggested, in particular the fact that MaxEnt incorporates an
534 explicit regularization mechanism to avoid overfitting while modeling the spatial distribution of event occurrence
535 directly, without relying on assumption of absence locations (Phillips and Dudík, 2008). However, as can be seen
536

537 from the hazard maps in Fig. 6, despite the differences in model accuracy, all 3 algorithms (MaxEnt, SVM and
 538 GARP) associate the mountainous east, south and southwest areas of Golestan Province with the highest levels of
 539 landslide probability. This result is interesting, considering that these areas are characterized by complex
 540 topography, steep slopes and relatively high rainfall, and given the potential impact of local human interferences
 541 in the area (see Section 5.1).



542
 543 **Fig. 6.** Landslide hazard maps obtained for Golestan Province with the different machine learning algorithms
 544 considered in the present study: (a) Maximum Entropy (MaxEnt), (b) Support Vector Machine (SVM) and
 545 Genetic Algorithm for Rule Set Production (GARP).
 546

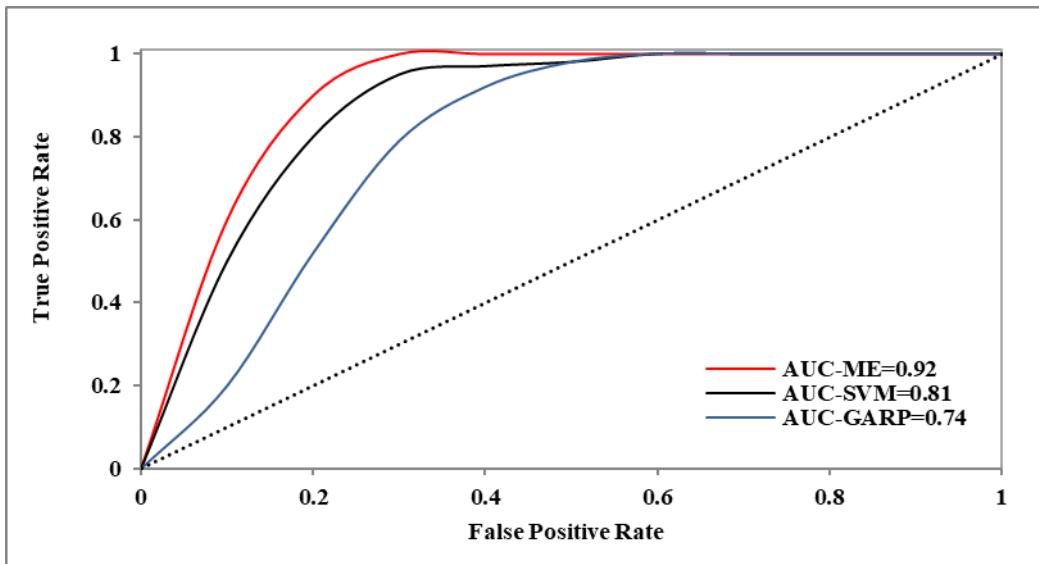


Fig. 7. Receiver operating characteristic (ROC) curves of MaxEnt, SVM and GARP algorithms in the landslide hazard mapping for Golestan Province.

4.2 Landslide vulnerability map

The results showed that the factor urban population density is the most significant vulnerability factor for Golestan Province, followed by urban building density and distance to landslide location. The normalized weights of the different factors in the framework of FAHP are shown in Fig. 8. Moreover, the consistency of the comparison matrix associated with these weights is assessed by a FAHP index called consistency ratio (CR). The smallest the value of CR, the higher the consistency of the comparison matrix (Leung and Cao, 2000). As can be seen in Fig. 8, the value of CR obtained here is significantly smaller than 10%, thus indicating acceptable consistency of the decision-making process applied.

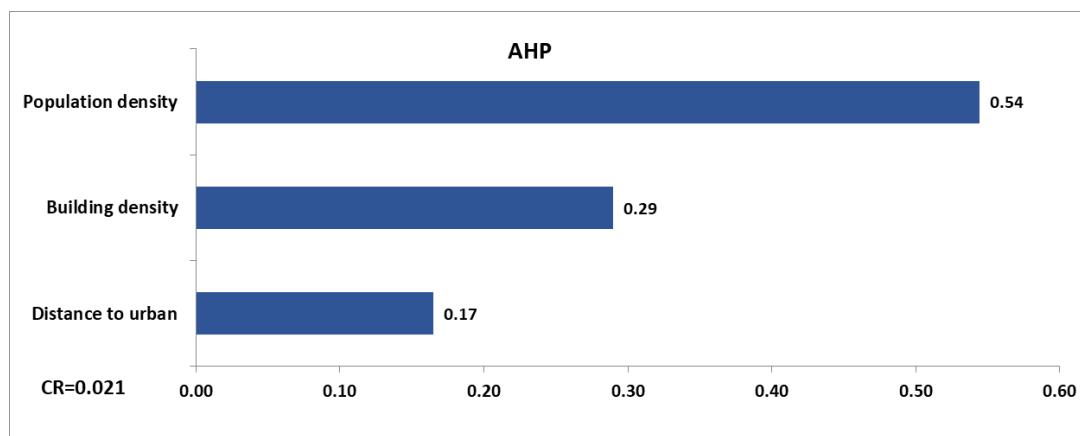
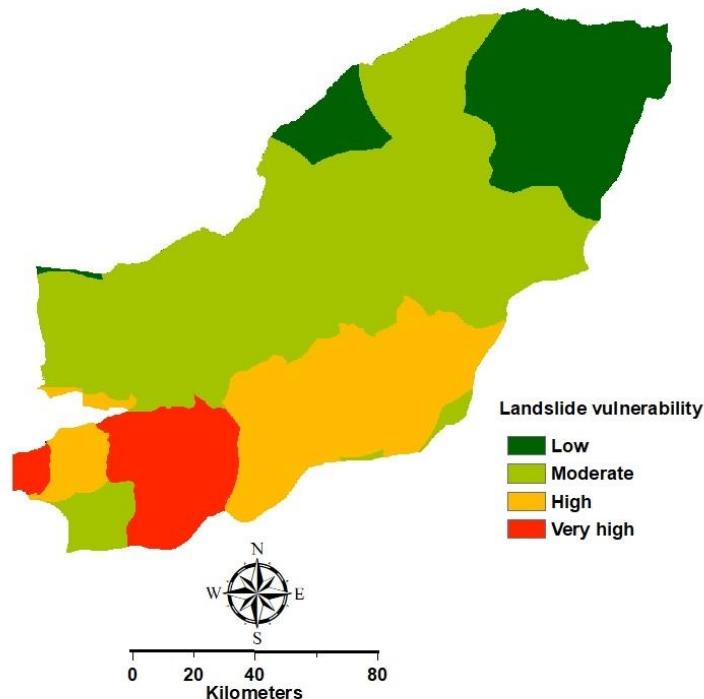


Fig. 8. Normalized weights of the vulnerability factors obtained in the framework of the FAHP computations.

563
 564
 565 Based on the results of Fig. 8 and the spatial distributions of the vulnerability factors (Fig. 5), the landslide
 566 vulnerability map was obtained. Finally, this map was categorized into four classes (Fig. 9), i.e., low, moderate,
 567 high, and very high vulnerability, which encompass 25.43%, 49.56%, 15.93%, 9.07% of the study area,
 568 respectively. According to Fig. 9, the areas of highest landslide vulnerability are located in the south and southwest
 569 of Golestan Province.



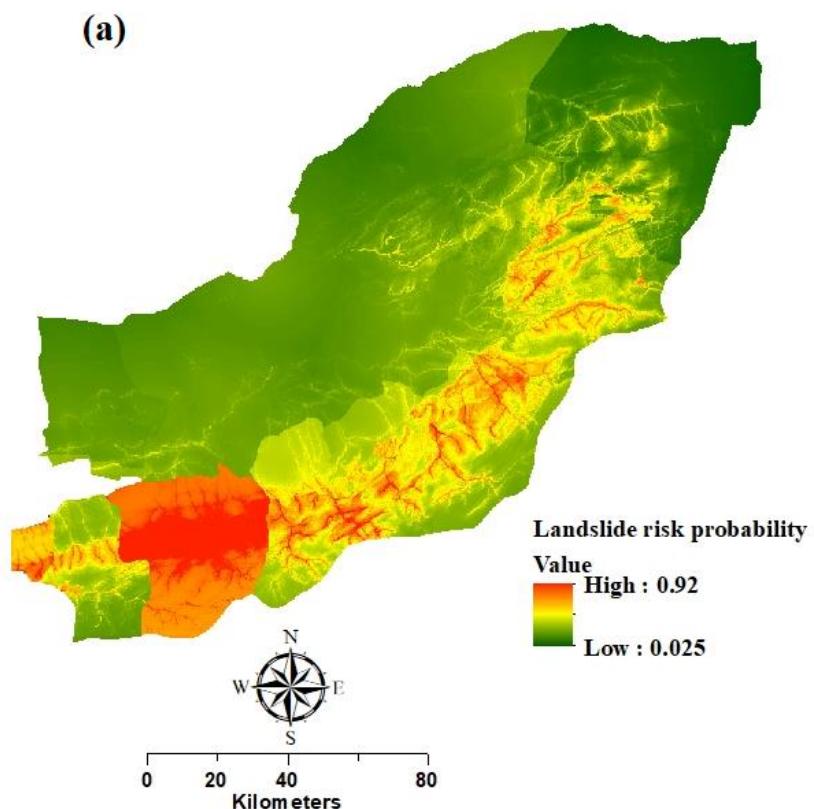
570
 571 **Fig. 9.** Landslide vulnerability map obtained with FAHP for Golestan Province.
 572
 573

574 **4.3 Landslide risk map**

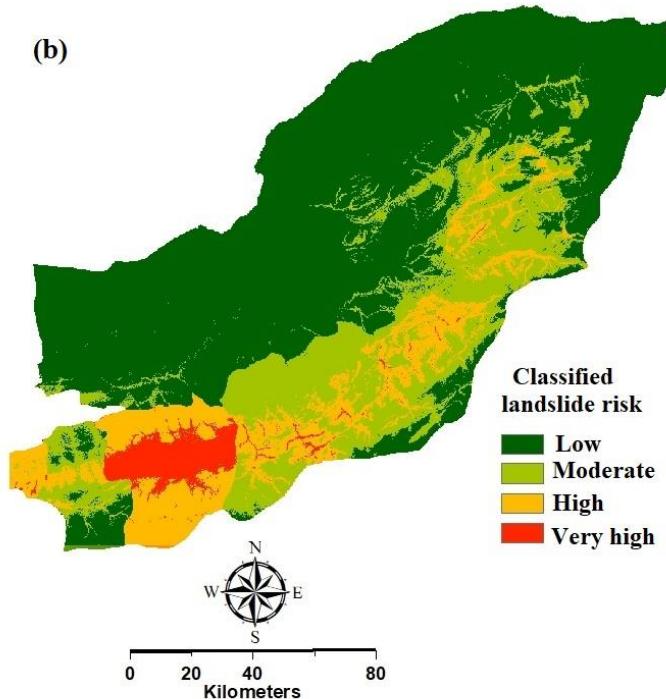
575 The landslide risk probability map (Fig. 10a) obtained from the product of the vulnerability and hazard maps and
 576 then was classified into four classes: low, moderate, high, very-high risk, corresponding to 72.47%, 17.37%,
 577 7.85%, and 2.29% of the study area, respectively (Fig. 10b). According to this figure, the regions of highest
 578 landslide risk are the south and southwest regions of Golestan Province. We remark that our results are based on
 579 the landslide risk probability map (between 0 and 1), i.e., a quantitative map. Subsequently, we applied a
 580 classification to the results of this quantitative map to produce a new qualitative map. The landslide risk

581 probability map is shown in Fig 10a. We further note that the output of GARP model had the highest correlation
582 with soil map compared to other two models. Based on GARP model, the most hazardous areas in terms of
583 landslide were located in all soil types except aridisols. Therefore, the output of GARP model is more accordance
584 with soil map. Moreover, the MaxEnt model had the best performance and therefore the results of ME were used
585 to prepare landslide risk (risk=hazard *vulnerability). The respective roles of the various environmental factors
586 are discussed in the next section in the light of our results.

587



588



589
590
591

Fig. 10. Predicted landslide risk map of Golestan Province.

5 Discussion

593 The goal of this study is to construct a landslide risk map for Golestan Province, which can be used by the local
594 government to identify the regions of highest landslide risk. Since a region may have high landslide hazard but
595 little vulnerability to landslide damage (and vice-versa), the risk map produced here incorporates both hazard and
596 vulnerability maps (Schneiderbauer & Ehrlich, 2004; Dewan, 2013; Zezere et al. 2008; Remondo et al. 2008). In
597 the following paragraphs Fig. 10 was analyzed by discussing the role of the various human-environmental factors
598 on landslide hazard and vulnerability in Golestan Province.

5.1 Relative influences of the landslide hazard factors in Golestan Province

600 To shed light into the relative influences of the different hazard factors, it can be referred to the Jackknife test
601 results from the MaxEnt model, which are displayed in Fig. 11. In the framework of this test, the model is run
602 with only one hazard factor at a time (under exclusion of all other factors), thus leading to the ROC AUC values
603 denoted by the blue bars in Fig. 11. Moreover, the green bars in Fig. 11 correspond to the ROC AUC values from
604 the complementary model, i.e., in which one of the factors at a time has been excluded from the model.

605

606 According to Fig. 11, MaxEnt identified the factors elevation, precipitation, soil type, lithology, land use/land
607 cover and distance to river as the most relevant ones for landslide hazard in Golestan Province – all these factors
608 have been associated with $AUC > 0.7$, close to the total $AUC = 0.89$ (red bar in Fig. 11). Moreover, according to
609 Fig. 11, the factor slope-aspect is closest to the worst possible $AUC (0.52)$ and has, thus, the lowest relevance,
610 while the factors slope-angle, distance to road and distance to fault have comparable, intermediate impact on
611 landslide hazard in the study area.

612

613 Furthermore, to better understand the functional dependence of landslide hazard on the conditional variables, it
614 can be referred to the respective response curves displayed in Fig. 12. Each subplot in Fig. 12 shows the variations
615 in the logistic prediction of landslide hazard as a function of the selected variable, under the constraint that the
616 values of all other factors are considered constant and equal to their average. The response curves are briefly
617 discussed in the next subsections.

618

619 *5.1.1 Elevation*

620 As shown in Fig. 12a, the response of landslide modeling to elevation displays two regimes, which are separated
621 by an intermediate range of relatively constant susceptibility between 200 m and 1000 m. In regime I ($H \lesssim 200$
622 m), predicted landslide occurrence probability p increases with elevation H , but in regime II ($H \gtrsim 1000$ m), a
623 negative correlation is observed.

624

625 We propose that decreased human presence and interferences at high altitudes contribute to the behavior observed
626 in Fig. 12a. In particular, the sparse vegetation cover and the concatenated changes in land use/ land cover practice
627 may contribute to reducing landslide probability at high altitudes. Furthermore, the lower infiltration rates
628 associated with high elevation levels are associated with lower soil saturation (Salarian et al. 2014), thus
629 contributing to decreasing landslide hazard. Moreover, snow precipitation may provide one further slope
630 stabilizing agent at high elevations, although this process is still poorly understood.

631

632 We find that a logarithmic function, i.e.,

$$633 p = \frac{a}{H} \cdot \exp \left\{ -\frac{1}{2} \cdot \left[\frac{\ln(H) - b}{c} \right]^2 \right\}, \quad (10)$$

describes reasonably well the response curve of landslide occurrence probability p as a function of elevation H Golestan Province (see Fig. 13a). The best fit to the data using Eq. (10), with H in km, yields $a \approx 0.58$ km, $b \approx 0.18$ and $c \approx 0.83$, with correlation coefficient $R^2 \approx 0.96$. We note that this logarithmic function describes well the rapid increase of the susceptibility p with elevation in regime I, and the much slower decrease in regime II. Moreover, the value of $a \approx 0.58$ km is well within the intermediate range ($200 \lesssim x \lesssim 1000$) separating both regimes as estimated above. Future research is thus necessary to shed light on the values of a , b and c as a function of regional conditions.

5.1.2 Precipitation

Figure. 12b shows that landslide probability increases with increasing precipitation up to 850 mm, which suggests prevailing influence of streamflow-induced, downhill sediment transport processes in this regime. However, according to Fig. 12b that landslide probability decreases for precipitation levels higher than 850 mm. We interpret this behavior as result of increased saturation associated with such high precipitation levels, thus enhancing resistance of local lithology to water erosion and increasing soil stability in the corresponding areas.

5.1.3 Slope

Moreover, our results indicate the existence of an optimal slope of about 25° for landslide occurrence (Fig. 12c). Under high enough levels of gravitational stresses, the soil surface relaxes through landslides in the direction of steepest descent (Neuhäuser & Terhorst, 2007; Dymond et al. 2006). As shown in Fig. 12c, this behavior dictates landslide probability trend in the regime of small slopes below the threshold of approximately 25° (denoted here regime I). However, the opposite trend is observed for larger slopes (regime II). We find that the dependence of response curve on slope-angle can be approximately described by the following equation:

654

$$655 \quad p = p_0 - K \cdot (\theta - \theta_0)^2, \quad (11)$$

656

where p denotes the predicted probability of landslide occurrence, θ is the slope-angle in degrees, p_0 is the value of p at $\theta = \theta_0$, which separates regimes I and II above, and K is constant that has units of degrees $^{-2}$. The best fit to the data using Eq. (10) gives $p_0 \approx 0.64$, $\theta_0 \approx 25.6^\circ$ and $|K| \approx 6.6 \times 10^{-4}$, with correlation coefficient $R^2 \approx 0.96$ (see Fig. 13b).

661

662 It is interesting to note that Demir et al. (2013) also found a peak in the landslide hazard for a slope-angle θ_0 of
663 approximately 25° at North Anatolian Fault Zone at Kelkit Valley, Turkey. As discussed by Abedini et al. (2014),
664 geological formations on higher slopes are often associated with harder materials, which are less permeable and
665 more resistant to gravitational stresses. Moreover, we note that, since various types of loose sediment have angle
666 of repose in range $20^\circ - 35^\circ$, terrain slopes exceeding this range provide rather unfavorable conditions for long-
667 term deposition of deep granular layers, thus potentially contributing to decreasing levels of gravitational stress
668 accumulation and landslide probability on slopes much steeper than 25° .

669

670 *5.1.4 Aspect*

671 The relationship between the slope-aspect and predicted landslide occurrence probability is shown in Fig. 12d. As
672 can be seen from this figure, landslide hazard is highest in the north aspect (350°), which can be understood by
673 increased heat absorption and higher humidity levels associated with this aspect (Fig. 12d). Enhanced landslide
674 hazard for slopes facing north and northeast was also found by Demir et al (2013) in the North Anatolian Fault
675 Zone at Kelkit Valley, Turkey. Indeed, soil response to atmospheric events depends on slope facing direction,
676 which influences local precipitation, solar radiation and freeze-thaw processes and is thus an important component
677 in the landslide hazard map (Demir et al. 2013). However, our results indicate that aspect has the smallest influence
678 on landslide hazard in Golestan Province (see Fig. 11).

679

680 *5.1.5 Lithology*

681 As shown in Fig. 12e, the lowest values of landslide hazard as a function of lithology are associated with Qm
682 (swamp and marsh) and Qsw (swamp) types, i.e., wetlands corresponding to saturated areas and relatively stable
683 soil conditions with respect to landslide. Moreover, our results are consistent with previous observations that
684 DCkh (limestone, locally including gypsum) and TRJs (dark grey shale and sandstone) formations are more prone
685 to landslide occurrence (Ohlmacher, 2000), which is reflected in the high values of landslide hazard obtained from
686 the model (Fig 12e).

687

688 *5.1.6 Land use/Land cover*

689 The results from the MaxEnt Jackknife test (Fig. 11) suggest land use/land cover as the main anthropogenic factor
690 for landslide hazard in Golestan Province. Moreover, Fig. 12f shows that orchard and forest are the types of land

691 with highest influence on landslide hazard. We expect orchard to substantially affect soil conditions and stability
692 through multiple human interferences, such as irrigation. Furthermore, from Fig. 4e and Fig. 6, we see that forest
693 areas occur within the regions associated with the highest landslide hazard levels. Indeed, forest areas are
694 associated with high infiltration levels and have been largely affected by unprincipled road construction, which
695 further contributes to increasing soil instability (Reichenbach et al. 2014; Leventhal & Kotze, 2008). Figure. 12f
696 shows that land use/land cover types agriculture, urban and rangeland lead to similar values of landslide
697 probability, which are nearly twice as large as on rock areas. These results clearly indicate the substantial effect
698 of land use/land cover on landslide hazard and provide a basis for future considerations on land use/land cover
699 practices in Golestan Province with regard to landslide control and mitigation.

700

701 *5.1.7 Soil type*

702 As expected, Fig. 12g shows that aridisols, consisting of stony clays and silts of slow formation rates and low
703 degree of erodibility, lead to the lowest values of landslide hazard. By contrast, alfisols, mollisols and inceptisols
704 are associated with higher landslide hazard (Fig. 12g), owing to their fine texture and high permeability levels,
705 and given their suitability for land use/land cover.

706

707 *5.1.8 Distance to the fault, distance to the river, distance to the road*

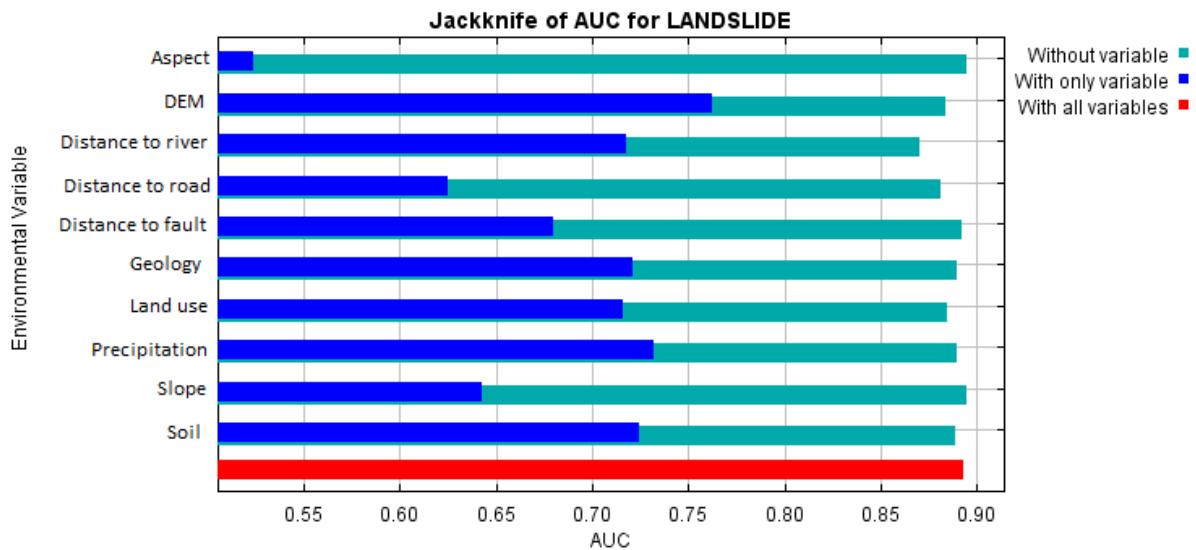
708 As can be seen from Figs. 12h, 12i and 12j, landslide hazard tends to be consistently smaller the larger the distance
709 to the next fault, river or road. Indeed, it is well known that the amplitude of a given seismic event decreases non-
710 linearly with distance from the origin – this behavior is reflected by the dependence of landslide modeling on
711 distance to fault in Golestan Province (Fig. 12h). Zhuang et al. (2010) found that the occurrence rate of earthquake-
712 triggered landslides in Beichuan County, China, decreases exponentially with distance to fault. From the data of
713 Fig. 12h, we find that the exponential decay describes approximately the response curve of landslide modeling
714 with distance to fault, as shown in Fig. 13c. Moreover, this figure further shows that the exponential law adjusts
715 reasonably well predicted hazard as a function of distance to river and distance to road. Specifically, the equation
716 used to fit the data in Fig. 13c reads,

717

$$718 \quad p = \exp(-\lambda x), \quad (12)$$

719

720 where $1/\lambda$ denotes a characteristic length that dictates how fast the hazard decreases with distance x from the
 721 road, river or fault. The best fits to the data in Fig. 13c using Eq. (12) yield $\lambda_{\text{road}} \approx 0.0797 \text{ km}^{-1}$ for road ($R^2 \approx$
 722 0.83), $\lambda_{\text{fault}} \approx 0.108 \text{ km}^{-1}$ for fault ($R^2 \approx 0.94$) and $\lambda_{\text{river}} \approx 0.734 \text{ km}^{-1}$ for river ($R^2 \approx 0.95$). The
 723 characteristic decay lengths read, thus, $1/\lambda_{\text{road}} \approx 12.5 \text{ km}$, $1/\lambda_{\text{fault}} \approx 9.3 \text{ km}$ and $1/\lambda_{\text{river}} \approx 1.4 \text{ km}$,
 724 respectively. Therefore, our results suggest that landslide hazard decreases the slowest with distance to the next
 725 road, compared to distance to the next river or fault.
 726



727
 728 **Fig. 11.** Results of Jackknife test to estimate the relative influence of the various hazard factors in MaxEnt. Blue
 729 bars denote the AUC-ROC obtained with only one factor at a time (under exclusion of all other factors), the
 730 green bars give the complementary information and the red bars indicate the total AUC-ROC for MaxEnt.
 731
 732
 733
 734

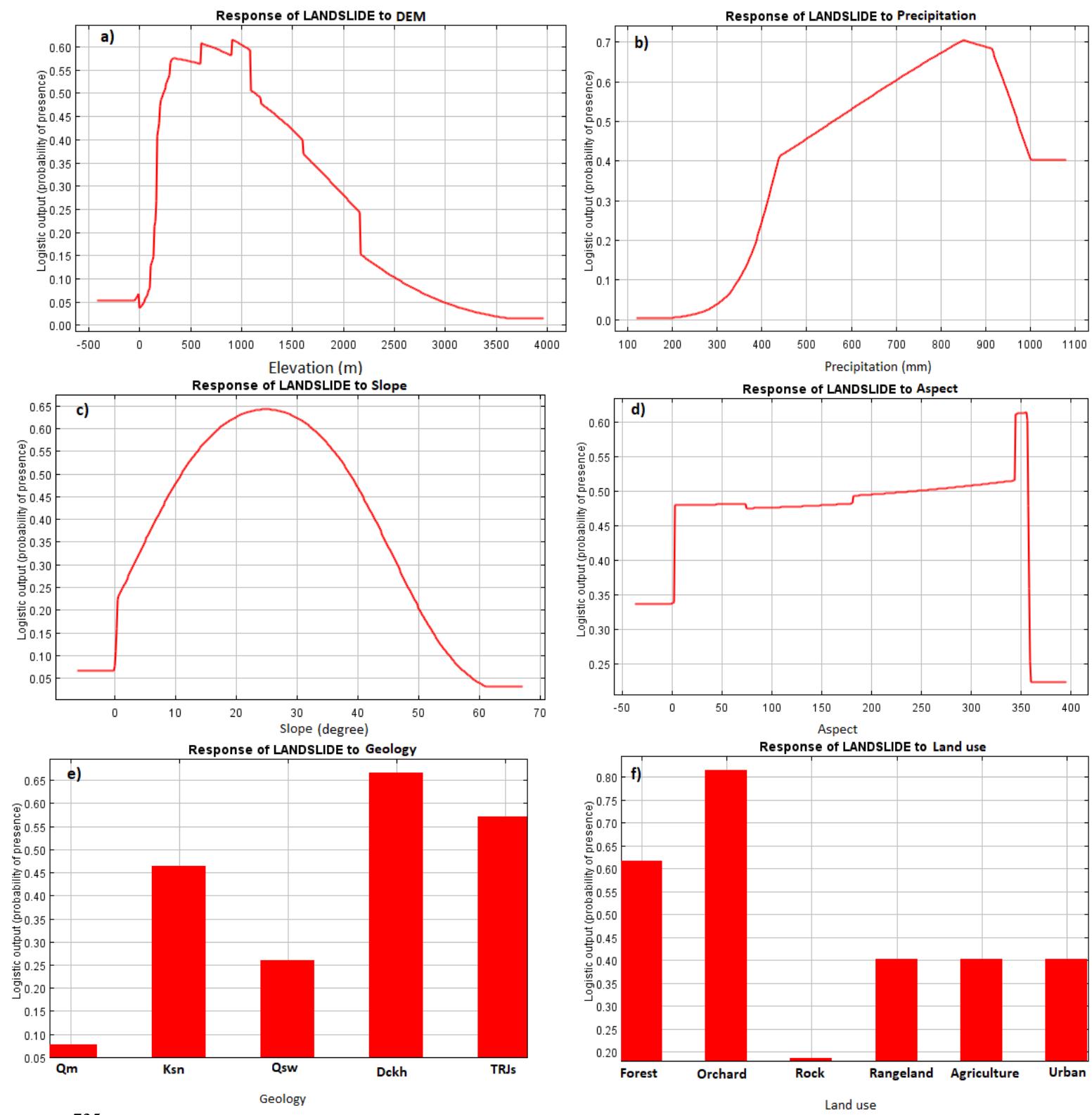
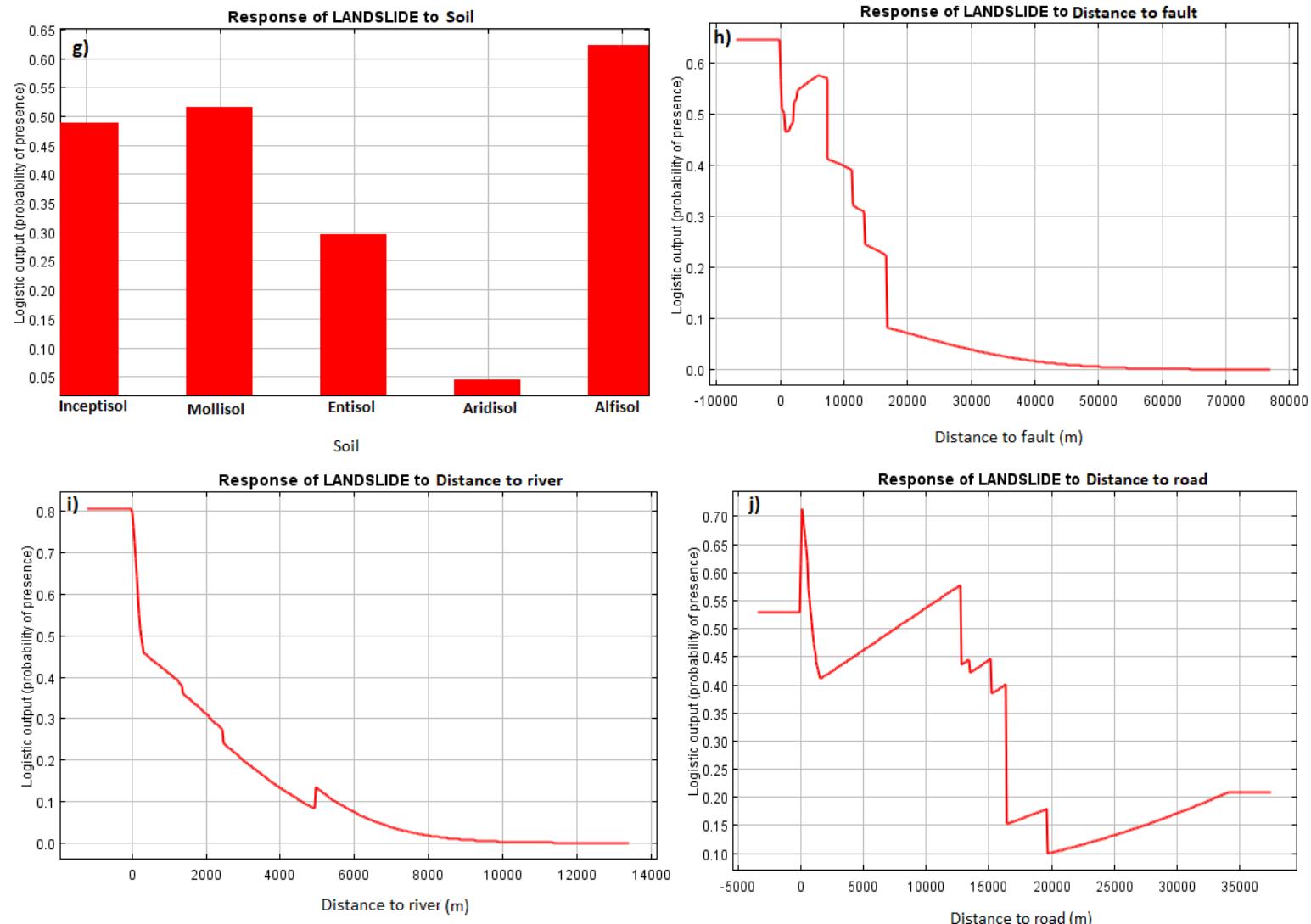
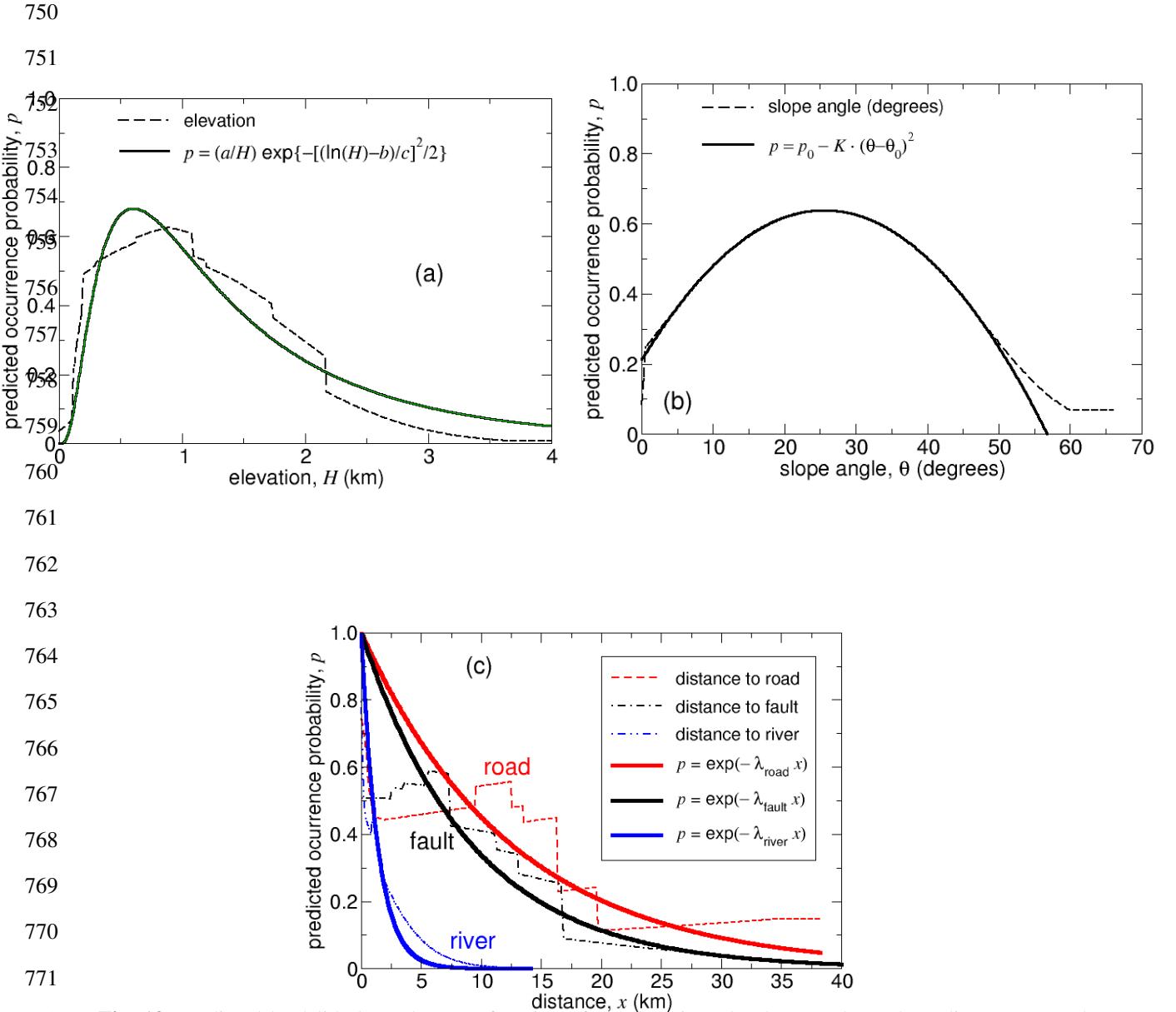


Fig. 12. Response curves of landslide modeling to the conditioning variables as predicted with MaxEnt

**Fig. 12. continued**



784 **5.2 Vulnerability and risk: implications for landslide control and mitigation strategies**

785 The results discussed in the previous section yield new insights about landslide hazard as a function of the
786 anthropogenic and environmental conditioning variables. For instance, from the considerations above,
787 recommendations can be derived for road construction with regard of the distance to populated areas, while
788 optimization strategies for land use/land cover changes can be developed to decreasing the impact of
789 anthropogenic influences on landslide initiation.

790

791 However, because risk encodes both landslide probability and the associated level of damage, knowledge of the
792 spatial distribution of vulnerability is required to improving risk management. By combining the hazard map (Fig.
793 6) with the vulnerability map (Fig. 9), as described in Section 3.3, it is found that the south and southwest areas
794 of Golestan Province are associated with the highest landslide risk levels. These regions encompass Gorgan city,
795 the center of Golestan Province, and have, correspondingly, particularly high urban population and building
796 density. Risk in Golestan Province has been assessed high throughout the entire region of very high landslide
797 hazard, i.e., from southwest to the east (compare Figs. 6 and 10), but the area of highest risk level is located in the
798 southwest – the location of Gorgan city. The risk level distribution in Fig. 10 provides governmental agencies and
799 stakeholders, thus, with more appropriate information to guide priority plans for landslide mitigation in Golestan
800 Province.

801 **5.3 Final remarks and outlook**

802 Summarizing, risk is function of vulnerability and hazard. Vulnerability is related to socio-economic factors, while
803 hazard is related to environmental factors. In previous work (Mokhtari et al. 2020), risk was modeled by
804 considering hazard only, thereby incorporating environmental factors, but ignoring vulnerability factors. By
805 contrast, here we considered *both* vulnerability *and* hazard to compute the landslide risk map for Golestan
806 Province. Firstly, we obtained the landslide hazard map based on the environmental factors (slope, elevation, etc.)
807 and landslide occurrence observation points. Subsequently, we calculated the landslide vulnerability map based
808 on socio-economic factors (population density, etc.), and obtained the landslide risk map from the combination of
809 *both* landslide hazard *and* landslide vulnerability maps.

810

811 It should be noted that including landslide size and duration in our statistics would greatly improve the assessment
812 of landslide distribution. However, unfortunately, in the study area considered in our work, the statistics of the

813 extent of sliding and the time of the occurrence of the landslides is not available. Furthermore, our goal in this
814 manuscript is to provide an estimate of landslide occurrence distribution without regard of the time of the duration
815 and size of the individual landslide events. Therefore, the methods employed in our work employ the information
816 on landslide locations to produce the landslide hazard maps. We further refer to previous work in which landslide
817 hazard has been evaluated based solely on landslide occurrence points (Pourghasemi et al., 2013; Aghdam et al.,
818 2017; Adineh et al., 2018).

819

820 We further note that we could not monitor the whole area of Golestan Province because it was not possible to
821 access all parts of the map. In the machine learning modeling employed, the distribution of the samples does not
822 affect the modeling process because the geographic locations are not used as input. Rather, the similarity of
823 characteristics in each pixel with trained pixels affects the model output. We nevertheless believe that our analysis
824 is providing a valuable contribution as it is paving the way toward a future quantitative modeling of hazard and
825 vulnerability in Golestan Province, and because our discussion section is including yet unreported mathematical
826 expressions relating landslide hazard and causative factors. These mathematical expressions are physically based
827 and grounded on the dynamics of landslide occurrence that have been discussed extensively in previous work.
828 Therefore, it is noticeable that our statistics, which unfortunately misses the information of duration and
829 magnitude of the individual landslides (not available for Golestan Province), allows us to develop a mathematical
830 model based on the machine learning computations and the observation map. We believe that this first step will
831 motivate future modelers to go beyond the mere computation of a risk map, i.e., that future modelers will follow
832 our work to elaborating mathematical expressions thus increasing both the predictive power and the physical
833 understanding of their Machine Learning results – however by including event duration and magnitude.

834

835 **6 Conclusion**

836 In conclusion, the landslide risk map was computed for Golestan Province, Iran, from an explicit consideration of
837 all main relevant local human-environmental landslide hazard and vulnerability factors. To this end, the spatial
838 distributions of landslide location occurrences and conditioning variables have been combined using machine
839 learning algorithms – specifically, GARP, SVM and MaxEnt – to obtain a regional landslide hazard model for
840 Golestan Province. This model was then coupled with the information of local landslide vulnerability, by taking
841 the local urban population and building densities, as well as the distance to landslide locations into account.

842 Moreover, to generate the landslide vulnerability map, the Fuzzy Analytical Hierarchical Process (FAHP) method
843 was applied. FAHP has been developed for multi-criteria decision-making problems involving many variables
844 and has proven here potentially useful to improving priority landslide control plans.

845

846 Based on our results, empirical expressions were obtained for predicting landslide occurrence probability as a
847 function of elevation, slope-angle, and distance to roads, faults and rivers. It would be interesting to verify the
848 applicability of these equations to other regional settings, based on observations of landslide hazard, to shed light
849 on the physical mechanisms underlying the values of the parameters associated.

850

851 Our results show that, to accurately assessing landslide risk, event occurrence probability must be considered
852 against the background of its potential damage level. Although a strongly landslide-prone region extending from
853 southwest to east of Golestan Province is clearly visible in the hazard map, a subset of this area, which surrounds
854 Gorgan City, is associated with the highest landslide risk level in the risk map. This result is explained by
855 integration of the vulnerability map into the hazard evaluation. More precisely, Gorgan City represents the area
856 of highest urban population density *and* is located within the regions associated with very high hazard. Moreover,
857 we have found that landslide hazard decreases approximately exponentially with distance to faults, roads and
858 rivers, and that there is an optimal slope for landslide hazard.

859

860 We emphasize that the computation of risk performed here relies on knowledge about the distribution of the main
861 conditioning variables, and that changes in the specific choice and relative weights of the vulnerability factors
862 may lead to slight differences in the final risk map. Therefore, these weights must be estimated *a priori*, from
863 reliable and comprehensive data on local socio-economic and environmental conditions. As shown here, FAHP
864 indicated consistent estimates of the different vulnerability factor weights. Moreover, we have found similar
865 results for landside hazard distribution without regard of the machine learning method considered –
866 notwithstanding the observed differences in model accuracy – thus allowing us to discuss on the functional
867 relationship between hazard and the different conditioning variables. Our findings provide insights for the
868 assessment of landslide hazard, anthropogenic influences and risk, and are relevant to local governmental agencies
869 and stakeholders with regard to optimizing regional landslide control, mitigation and management.

870

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875 **Compliance with ethical standards**

876 **Conflicts of interest** Authors declare they have no conflict of interest

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