

# Towards a Flood Vulnerability Assessment of Watershed Using Integration of Decision Making Trial and Evaluation Laboratory, Analytical Network Process, and Fuzzy Theories

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## Research Article

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1 **Towards a flood vulnerability assessment of watershed using integration of decision making**  
2 **trial and evaluation laboratory, analytical network process, and fuzzy theories**

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14

15 **Abstract**

16 Among natural disasters, flood is increasingly recognized as a serious worldwide concern that  
17 causes the most damages in parts of agriculture, fishery, housing, and infrastructure, and strongly  
18 affects economic and social activities. Universally, there is a requirement to increase our  
19 conception of flood vulnerability and to outstretch methods and tools to assess it. Spatial analysis  
20 of flood vulnerability is part of non-structural measures to prevent and reduce flood destructive  
21 effects. Hence, the current study proposes a methodology for assessing the flood vulnerability in  
22 the area of watershed in a severely flooded area of Iran (i.e., Kashkan Watershed). First  
23 interdependency analysis among criteria (including population density, PD; livestock density, LD;  
24 percentage of farmers and ranchers, PFR; distance to industrial and mining areas, DTIM; distance  
25 to tourist and cultural heritage areas, DTTCH; land use; distance to residential areas, DTRe;  
26 distance to road, DTR; and distance to stream, DTS) was conducted using the decision-making  
27 trial and evaluation laboratory (DEMATEL) method. Hence, the cause and effect factors and their  
28 interaction levels in the whole network were investigated. Then, using the interdependency  
29 relationships among criteria, a network structure from flood vulnerability factors to determine their  
30 importance of factors was constructed and the analytical network process (ANP) was applied.  
31 Finally, with aim of overcome ambiguity, reduce uncertainty, and keep the data availability, an  
32 appropriate Fuzzy membership function was applied to each layer by analyzing the relationship of  
33 each layer with flood vulnerability. Importance analysis indicated that the variables of land use  
34 (0.197), DTS (0.181), PD (0.180), DTRe (0.140), and DTR (0.138) were the most important  
35 variables. The flood vulnerability map produced by the integrated method of DEMATEL-ANP-  
36 FUZZY showed that about 19.2% of the region has a high to very high flood vulnerability.

37 **Keywords:** Flood vulnerability; DEMATEL; Interdependency; Analytical network process;  
38 Fuzzy

39

## 40 **1. Introduction**

41 Flood is abundant water that flows rapidly and covers a large area of land, which has not been  
42 naturally submerged, and it is known as one of the most destructive disasters (Getahun and Gebre  
43 2015). Among natural disasters, flood is increasingly recognized as a serious worldwide concern  
44 that causes the most damages in parts of agriculture, fishery, housing, and infrastructure, and  
45 strongly affects economic and social activities (Demir and Kisi 2016). During the past several  
46 decades, flood has led to high economic damages and human casualties in different regions of the  
47 world (Guo et al. 2014). Surveys showed that just in 2010, more than 178 million people  
48 worldwide have been affected by floods, and from 1960 to 2017 about 34% of natural disasters  
49 have been caused by floods, resulting yearly about 1254 deaths and \$ 2.5 billion in socio-economic  
50 damage (Petit-Boix et al., 2017). In Iran, due to the arid and semi-arid climate, the rainfall is mostly  
51 short-term and intense which this condition will be exacerbated by climate change. After 1985 the  
52 frequency of more extreme floods because of rangeland degradation and intense deforestation has  
53 been increased in this country (Modarres et al. 2016). For instance, one of the most devastating  
54 events in the contemporary history of Iran was occurred in March 2019, that it involved 28  
55 provinces and about 70% of the country's area with an economic cost of about \$ 3.5 billion U.S.D.  
56 (Aminyavari et al. 2019; Hosseini et al. 2020). Thus, one of the basic steps to reduce the harmful  
57 effects of floods is to identify flood-prone areas and grade these areas in terms of flood  
58 vulnerability (Patial et al. 2008).

59 Sustainable management of natural resources requires the identification of vulnerable regions that  
60 is one of the main steps in the protection framework (Sahoo et al., 2016). According to the  
61 Intergovernmental Panel on Climate Change (IPCC) (2014), vulnerability is a degree of sensitivity  
62 in a system to the lateral effects of a particular hazard or strain (Field et al., 2014). Understanding  
63 effective factors is essential for assessing environmental vulnerability (Burger, 1997). In general,  
64 vulnerability refers to the economic, social, physical, and environmental conditions that show the  
65 sensitivity of the elements to hazard effects (UNISDR, 2009). Spatial analysis of flood  
66 vulnerability is part of non-structural measures to prevent and reduce flood destructive effects  
67 (Demir and Kisi 2016).

68 A major area of interest within the field of flood studies is paid attention to flood  
69 susceptibility/hazard assessment (e.g., Islam et al. 2020; Nachappa et al. 2020; El-Haddad et al.  
70 2020; Costache et al. 2020; Costache and Bui 2020; Tang et al. 2020), but far too little attention  
71 has been paid to flood vulnerability assessment and there is not entirely a guideline for its  
72 analyzing. However, flood vulnerability analysis is usually conducted using decision-making  
73 approaches (Lee et al. 2013). Although, in a study, Connor and Hiroki (2005) analyzed the flood  
74 vulnerability using the multiple linear regression through considering the vulnerability as a  
75 function of the number of casualties, number of populations, and amount of costs; due to lack of  
76 any observed data that can assign as a dependent variable, application of other methods such as  
77 machine learning is not feasible. Among the decision-making approaches, analytical hierarchy  
78 process (e.g., Ouma and Tateishi 2014; de Brito et al. 2018), Delphi (e.g., de Brito et al. 2017;  
79 Boulomytis et al. 2019), TOPSIS (e.g., Lee et al. 2013; Yang et al. 2018) have been applied to  
80 flood vulnerability analysis. But the main limitation of these methods is that they have not  
81 considered interdependency among criteria (Khadivi and FatemGhomi, 2012). Some studies such

82 as de Brito et al. (2018) have addressed this issue by using the analytical network process (ANP)  
83 method which considers the interdependency among factors through network analysis. However,  
84 how to determine the interdependency among factors is another major issue that is not well  
85 documented in the flood vulnerability analysis. In this study, we tried to fill this gap by applying  
86 the decision-making trial and evaluation laboratory (DEMATEL) method, which can extract  
87 interdependencies among variables (Sajedi-Hosseini et al. 2018).

88 This study, therefore, set out to assess the flood vulnerability at the watershed level. We integrated  
89 the DEMATEL, ANP, and Fuzzy theories to develop a methodology for flood vulnerability  
90 assessment. It should be noted that one of the main aspects and effective ways in modern flood  
91 management and flood damage mitigation is increasing the awareness and perception of people to  
92 floods (Kellens et al. 2011). To achieve this purpose, having flood vulnerability maps may help  
93 managers to gain a deeper understanding of vulnerable areas.

94

## 95 **2. Materials and methods**

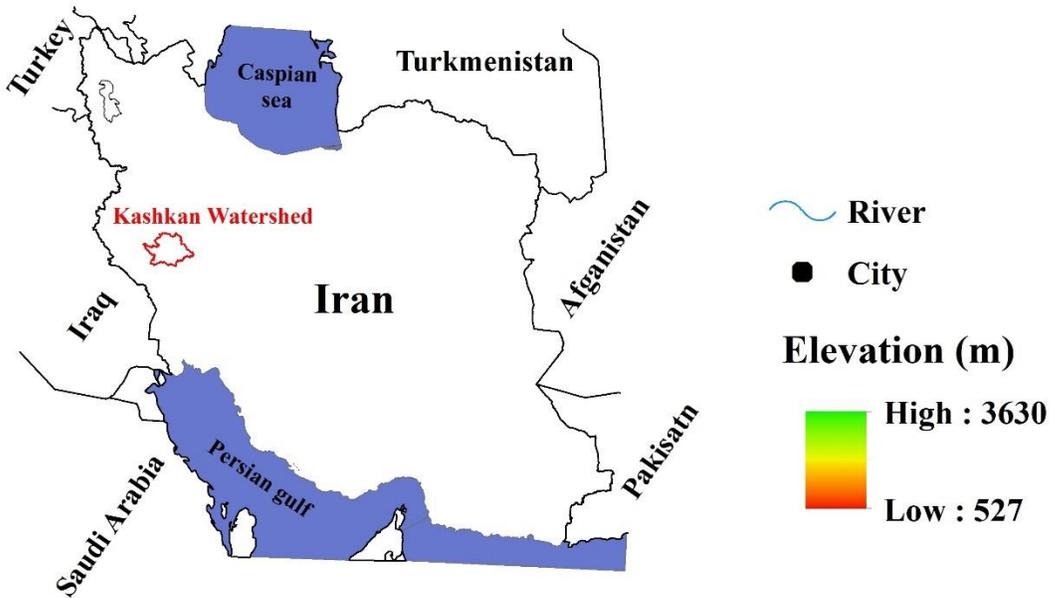
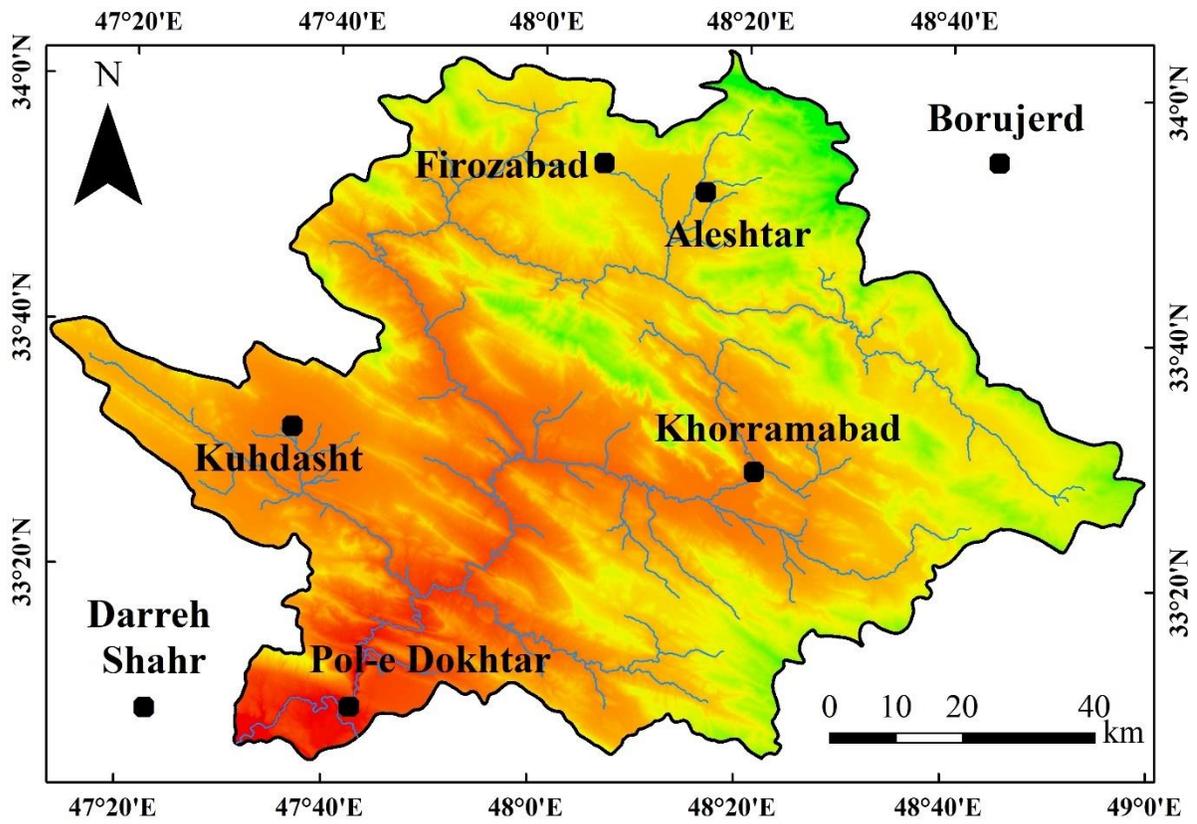
### 96 *2.1. Study area*

97 Kashkan Watershed located in the Lorestan Province, west of Iran, has an area of about 9510 km<sup>2</sup>  
98 which extends from longitudes 47° 12' 03" to 48° 59' 42" east and latitudes 33° 04' 24" to 34° 03'  
99 36" north (Figure 1). The basin is an important tributary of the Karkheh River Basin (the main  
100 River Basin in the west of Iran). Variation of the elevation in the watershed is high and vary  
101 between 527 m to 3630 m. Cites of Khorramabad, Kuhdasht, Aleshtar, Firozabad, and Pol-e  
102 Dokhtar with a sum of about 800,000 people are in this watershed (National Statistics Center of  
103 Iran, 2016) (Figure 1). The long-term mean precipitation of the Kashkan Watershed is about 620  
104 mm (JAMAB, 1999). According to available statistics during the last fifty years, this watershed is

105 the most flooded area in the Lorestan Province and Iran. For example, one of the biggest and most  
106 destructive floods in this watershed was occurred in March 2019, with a peak of 3000 m<sup>3</sup>/s (~300-  
107 yr return period) (Geravand et al. 2020). Figure 2 indicates a small part of the damage of this flood  
108 in the region. The main land uses of the watershed are rangeland (34.87 %), forest (34.44 %),  
109 agriculture (27.57 %), residential (2.0 %), orchard (0.92 %), and others (0.2%).

110

111



**Figure 1.** Location of the study area.

112  
113  
114  
115



116 **Figure 2.** Some photos of the flood damage in March 2019. Photos were taken by Shahram  
117 Khalighi Sigaroodi.

118

## 119 *2.2. Flood vulnerability factors*

120 According to the surveys in literature, applied factors for vulnerability assessment are consist of  
121 physical, economic, and social conditions (e.g., Karmaoui et al. 2016; Sadeghi-Pouya et al. 2017;  
122 Kumar and Bhattacharjya 2020). Thus, in this study, we considered important physical and socio-  
123 economic factors based on the available data in the area of the watershed; that are described as  
124 follows:

### 125 *2.2.1. Socio-economic factors*

126 Socio-economic factors are including the population density (PD), livestock density (LD),  
127 percentage of farmers and ranchers (PFR), distance to industrial and mining areas (DTIM),

128 distance to tourist and cultural heritage areas (DTTCH), and land use (Figure 3a to 3f). For  
129 preparing the above-mentioned factors, data including the number of population, number of  
130 livestock, PFR, location of industrial and mining areas, and location of tourist and cultural heritage  
131 areas were obtained from the National Statistics Center of Iran according to the general population  
132 and housing census and agricultural census during 2016 (National Statistics Center of Iran, 2016).  
133 PD and LD indicate respectively the number of people and livestock in a given area (usually at  
134 km<sup>2</sup>). Everywhere the PD and LD are more, the flood vulnerability is greater. PFR shows the  
135 percentage of people engage in agriculture and rancher, which vulnerability can increase as the  
136 PFR increases. To prepare the maps of DTIM and DTTCH, the Euclidean distance tools in ArcGIS  
137 10.3 was used. By increasing the DTIM and DTTCH, the flood vulnerability is decreased. Land  
138 use was another effective factor that was used for flood vulnerability assessment. Different land  
139 uses have different values and different reactions to flood; for example, residential areas and  
140 infrastructures such as roads are most important, while they reduce soil infiltration capacity and  
141 increase runoff (Ouma and Tateishi, 2014). To prepare the land use map, the required frames of  
142 the Sentinel 2 in April 2017 were obtained. Then after taking the data samples from Google Earth  
143 and field surveys, the area was classified into seven categories (including forest, rangeland,  
144 agriculture, barren, orchard, residential, and waterbody) using the Maximum Likelihood  
145 Classification (MLC) method in ENVI 5.4 environment.

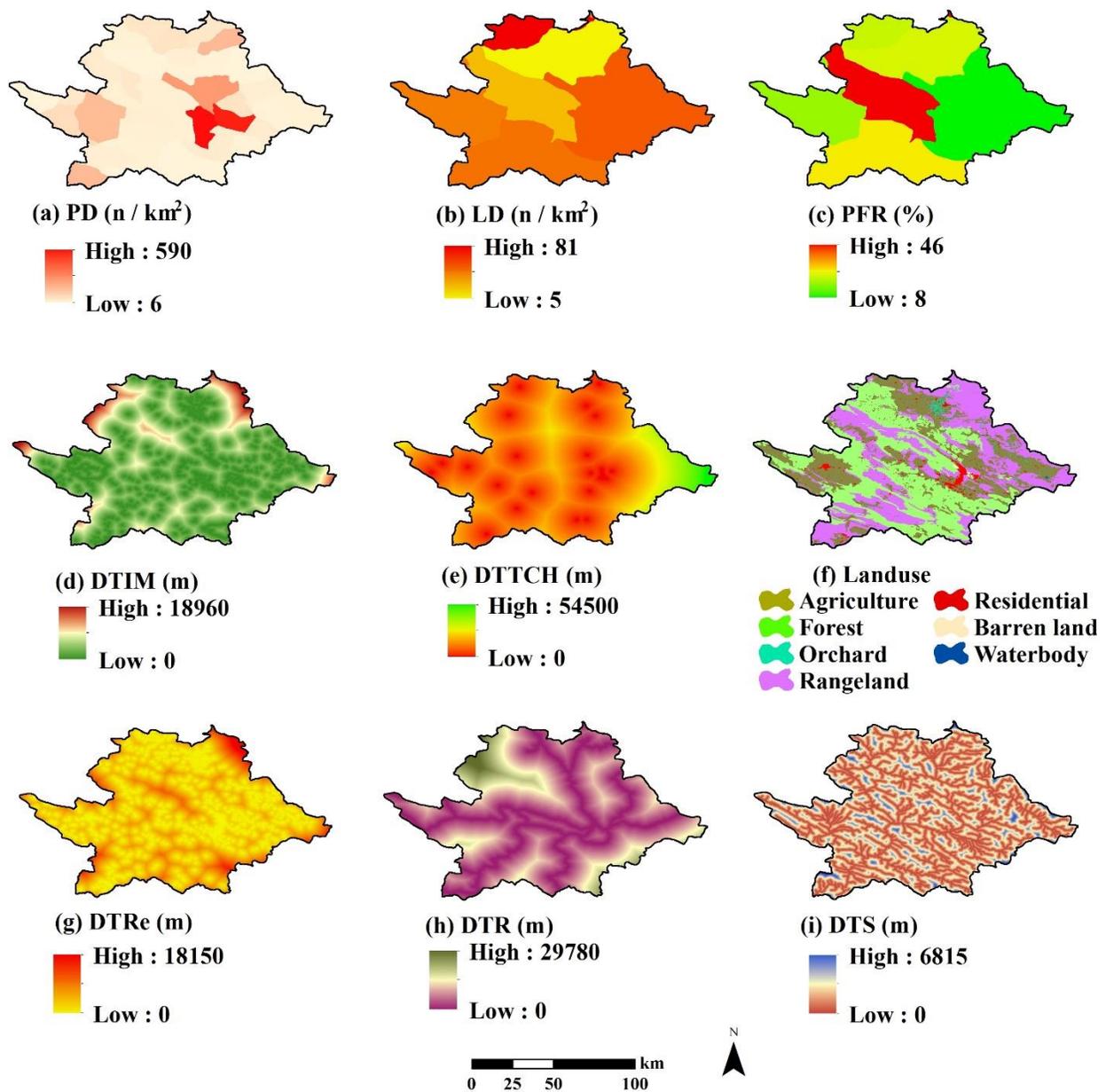
#### 146 2.2.2. *Physical factors*

147 Physical factors are including the distance to residential areas (DTR<sub>e</sub>), distance to road (DTR),  
148 and distance to stream (DTS) (Figure 3g to 3i). By decreasing the distance to residential areas,  
149 roads, and streams, the vulnerability is increased. The location of residential areas was extracted  
150 by the land use map. The road layer was received from the Iranian Water Resources Management

151 Company (IWRMC). For extracting the stream layer, we used a Digital Elevation Model (DEM)  
152 with a pixel size of about  $13 \times 13$  m (for the study area in Iran) which was obtained from Sentinel  
153 1 satellite images. Then, the stream layer was prepared in the ArcGIS 10.3 software by extension  
154 of the ArcSWAT 2012.10.3.19. For preparing the all physical factors shown in Figure 3g to 3i, the  
155 Euclidean distance tools in ArcGIS 10.3 was applied.

156 It should be mentioned that all socio-economic and physical factors were resampled to a pixel size  
157  $13 \times 13$  m to be equal with land use and DTS layers obtained from the Sentinel images.

158



159

160 **Figure 3.** Flood vulnerability variables: (a) population density (PD), (b) livestock density (LD),  
 161 (c) percentage of farmers and ranchers (PFR), (d) distance to industrial and mining areas (DTIM),  
 162 (e) distance to tourist and cultural heritage areas (DTTCH), (f) land use, (g) distance to residential  
 163 areas (DTRe), (h) distance to road (DTR), and (i) distance to stream (DTS).

164

165

166

167 2.3. Flood vulnerability assessment

168 The procedure of flood vulnerability assessment in this study is divided into four steps: (i)  
169 investigation of the relationships among factors using the Decision Making Trial and Evaluation  
170 Laboratory (DEMATEL), (ii) calculation of the weight of factors using the Analytical Network  
171 Process (ANP) and identified relationships from step (i), (iii) standardizing pixels based on the  
172 relevance fuzzy membership functions, and (iv) flood vulnerability mapping; which, they are  
173 described as follows:

174

175 2.3.1. Investigation of the relationships among factors using the DEMATEL

176 The DEMATEL method in this study was used to identify the causal relationships among the  
177 variables, that it is important in the designing network in the ANP method. According to this  
178 method, number of 30 questionnaires was distributed and completed by the related specialists, and  
179 the influence of the factors on each other was investigated via values of 0, 1, 2, 3, and 4 respectively  
180 for ‘No’, ‘Very low’, ‘Low’, ‘High’, and ‘Very high’ effects (Gabus and Fontela 1972; Azareh et  
181 al. 2019). The steps of the DEMATEL method can be summarized as follows (Gabus and Fontela  
182 1972; Sajedi-Hosseini et al. 2018):

183 (i) A matrix  $M_{n \times n}$  is prepared based on the experts’ knowledge that indicates the influence  
184 of the factors on each other (base on the above-mentioned values).

185 (ii) The matrix  $M_{n \times n}$  is normalized ( $N$ ) using the Eq.s 1 and 2:

186 
$$N = K \cdot M_{n \times n} \quad \text{Eq. 1}$$

187 
$$K = \frac{1}{\max \sum_{j=1}^n a_{ij}} \quad \text{and } 1 \leq i \leq n \quad \text{Eq. 2}$$

188 where  $K$  is the inverse of the maximum value among the sum of the rows and columns  
189 in the matrix  $M_{n \times n}$ , and  $a_{ij}$  denotes the influence of factor  $i$  on factor  $j$ .

190

191 (iii) Total relation matrix ( $T$ ) is calculated by using the identity matrix ( $I$ ) through the Eq.  
192 3:

$$193 \quad T = N(I - N)^{-1} \quad \text{Eq. 3}$$

194 (iv) Finally, the causal relationships among variables are identified using Eq.s 4 to 6:

$$195 \quad T = [t_{ij}]_{n \times n} \quad \text{and} \quad i, j = 1, 2, \dots, n \quad \text{Eq. 4}$$

$$196 \quad R_i = [\sum_{j=1}^n t_{ij}]_{1 \times n} \quad \text{Eq. 5}$$

$$197 \quad C_j = [\sum_{i=1}^n t_{ij}]_{1 \times n} \quad \text{Eq. 6}$$

198 where  $t_{ij}$  is the value of matrix  $T$  in row  $i$  and column  $j$ .  $R_i$  and  $C_j$  are respectively sum  
199 of rows and sum of columns within the matrix  $T$ , which respectively indicate the  
200 amount of cause and effect of the variables in the whole network.

201 In the current research, the DEMATEL method was run in the MATLAB R2016b.

202

### 203 2.3.2. Weight calculation of the factors using the ANP

204 In this study, the ANP method was used to determine the weight of factors. The method is one of  
205 the last multi-criteria decision-making methods represented by Saaty in 2001 to solve the problems  
206 related to dependency among the factors (Saaty 2001). In this method, the problem is shown as a  
207 network that nodes display levels. Elements in a node may affect all or part of the elements in other  
208 nodes. In the network structure, the relationships between elements are shown with arrows, and  
209 the direction of the arrows determines the direction of the dependency. The interdependence  
210 between two nodes is called the external dependence that represented by the two-way arrow, and  
211 the internal interdependence between the elements in a node is represented by a loop arrow (Saaty  
212 2005). According to Saaty (2001), the ANP method can be summarized in five steps as follows:

- 213 (i) Design and conversion of the problem to a network structure. In this study, the cause  
214 and effect factors and their dependencies were determined by the DEMATEL method.
- 215 (ii) Pairwise comparison. In this step, the comparison of factors was done using the  
216 linguistic terms and scale 1 to 9 Saaty (2001).
- 217 (iii) Creation of the primary supermatrix according to the weights obtained from step (ii).
- 218 (iv) Creation of the weighted supermatrix by multiplying the primary supermatrix by  
219 weight of clusters.
- 220 (v) Eventually, calculation of the limited supermatrix was done by multiplying the  
221 weighted supermatrix n times by itself.

222 More information about the ANP method has been described by Saaty (2001). In this study, the  
223 ANP method was implemented within the environment of SuperDecision 2.8 software.

224

### 225 *2.3.3. Standardizing pixels based on the fuzzy membership functions*

226 After calculating the layers' weight using the DEMATEL-ANP method, the pixels of each layer  
227 were standardized based on the relative fuzzy membership functions. According to the scholars  
228 (e.g., Sajedi-Hosseini et al. 2018; Azareh et al. 2019), providing the continuous values based on  
229 the Fuzzy keep the data variability of variables that is more realistic than other ways such as  
230 categorizing inputs. Also, the Fuzzy can overcome ambiguity and reduce uncertainty (Samanlioglu  
231 and Aya 2016; Sajedi-Hosseini et al. 2018). Thus, by analyzing the relationship of each layer with  
232 flood vulnerability, an appropriate fuzzy membership function was applied for standardizing each  
233 layer between 0 and 1. In this study, we used the Fuzzy membership tools in the ArcGIS 10.3 for  
234 this objective.

235

236 2.3.4. Flood vulnerability mapping

237 Following the above steps, the flood vulnerability map was calculated using the Raster Calculator

238 Tools in the ArcGIS 10.3 by the Eq. 7:

239 
$$FV = \frac{\sum_{i=1}^{i=n} W_i \times N_i}{\sum_{i=1}^{i=n} W_i} \quad \text{Eq. 7}$$

240 where  $FV$  indicates the flood vulnerability,  $W_i$  is the weight of variable  $i$  calculated by the  
241 DEMATEL-ANP method,  $N_i$  is a normalized layer of variable  $i$  by the related fuzzy membership  
242 function, and  $n$  is the number of variables. A higher value of the  $FV$  shows a higher flood  
243 vulnerability.

244 After calculating the  $FV$  layer, it is reclassified into five classes of very low, low, moderate, high,  
245 and very high flood vulnerability using the Equal interval method (via an interval 0.2 from 0 to 1)  
246 in the ArcGIS 10.3.

247

248 **3. Results and Discussion**

249 *3.1. Causal relations between factors based on the DEMATEL method*

250 Finding the causal relationships between factors is important for designing an appropriate network  
251 from the problem across the ANP method. Results of causality analysis by the DEMATEL are  
252 presented in Table 1 and Figure 4.  $R_i$  and  $C_i$  are respectively sum of rows and columns within the  
253 total relation matrix (Eq. 3), which indicates the magnitude of the cause and effect of each variable.

254 Accordingly,  $R_i - C_i$  is named as ‘relation’ that is used to determine whether a variable is a cause  
255 ( $R_i - C_i > 0$ ) or effect ( $R_i - C_i < 0$ ) factor in the whole network (Sajedi-Hosseini et al. 2018; Azareh  
256 et al. 2019). According to the results (Table 1 and Figure 4), variables of distance to stream (DTS),  
257 distance to industrial and mining areas (DTIM), distance to residential areas (DTRe), and distance

258 to road (DTR) are causal factors in the whole network, while variables of land use, distance to  
 259 tourist and cultural heritage areas (DTTCH), percentage of farmers and ranchers (PFR), population  
 260 density (PD), and livestock density (LD) are effect factors in the whole network.  $R_i + C_i$  is named  
 261 as ‘prominence’ that is used to indicate which variables have the highest total interaction in the  
 262 whole network. The results indicated that the variable of distance to road (DTR), land use,  
 263 population density (PD), and distance to stream (DTS) have the highest interaction with other  
 264 variables (Table 1 and Figure 4).

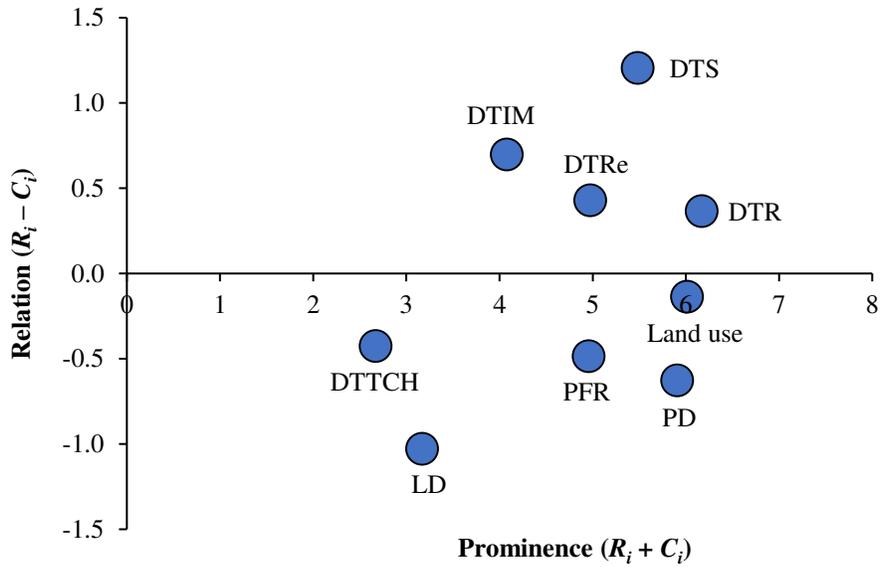
265 Finally, according to the DEMATEL results by defining a threshold on values of the total relation  
 266 matrix, the structure of the network among the flood vulnerability factors are designed (Figure 5).  
 267 The direction of the arrows shows the effect of a factor on another. The interdependency effect  
 268 between two variables represented by a two-way arrow (Figure 5).

269

270 **Table 1.** Results of causality analysis by the DEMATEL method

Factor	$R_i$ (Cause)	$C_i$ (Effect)	$R_i - C_i$ (Relation)	$R_i + C_i$ (Prominence)
Distance to stream (DTS)	3.34	2.14	1.2	5.48
Distance to industrial and mining areas (DTIM)	2.39	1.69	0.7	4.08
Distance to residential areas (DTRe)	2.7	2.27	0.43	4.97
Distance to road (DTR)	3.27	2.9	0.37	6.17
Land use	2.94	3.07	-0.14	6.01
Distance to tourist and cultural heritage areas (DTTCH)	1.12	1.55	-0.42	2.67
Percentage of farmers and ranchers (PFR)	2.24	2.72	-0.49	4.96
Population density (PD)	2.64	3.27	-0.63	5.91
Livestock density (LD)	1.07	2.1	-1.03	3.17

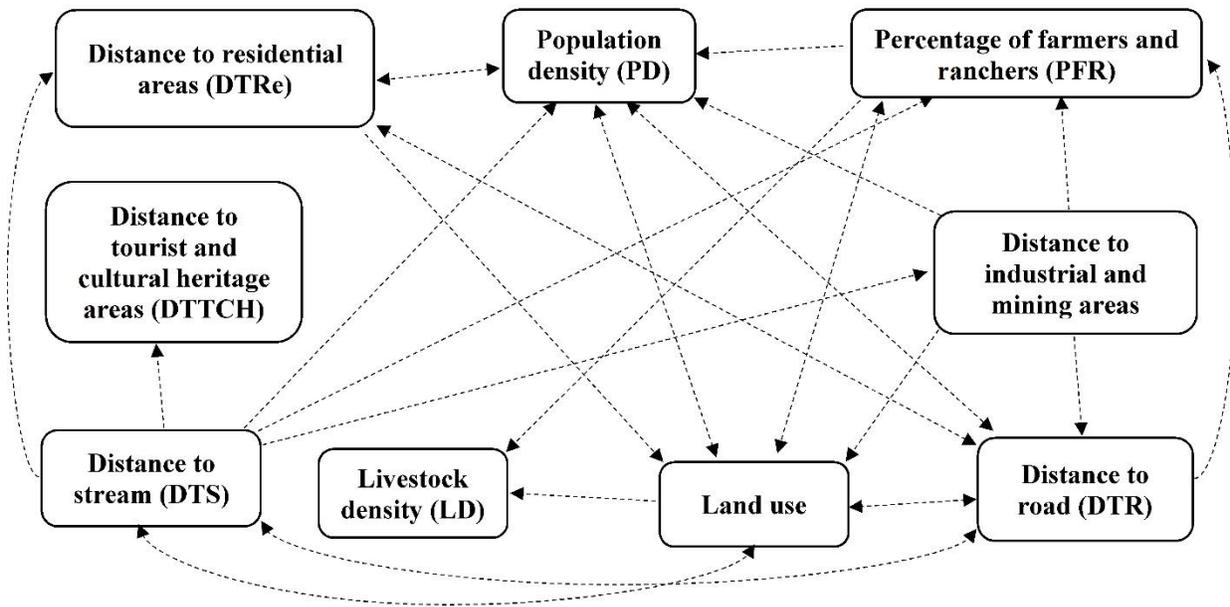
271



272

273 **Figure 4.** Causal diagram representing the relation (cause/effect) and prominence (interaction) of  
 274 the variables in the whole network.

275



276

277 **Figure 5.** Designed network structure among the flood vulnerability variables by the DEMATEL  
 278 method

279 *3.2. Importance of the variables based on the ANP method*

280 After determining the relationships between variables and designing the network structure, the  
281 ANP method was used for extracting the importance and weight variables. According to the ANP-  
282 DEMATEL results, variables of land use (0.197), distance to stream (DTS) (0.181), population  
283 density (PD) (0.180), distance to residential areas (DTRe) (0.140), and distance to road (DTR)  
284 (0.138) were the most important variables, respectively (Table 2). While, variables of distance to  
285 tourist and cultural heritage areas (DTTCH) (0.010), livestock density (LD) (0.019), distance to  
286 industrial and mining areas (DTIM) (0.065), and percentage of farmers and ranchers (PFR) (0.070)  
287 were the less important factors, respectively, that calculated by the ANP- DEMATEL method  
288 (Table 2).

289 No reference has used the DEMATEL-ANP method for flood vulnerability assessment in the area  
290 of the watershed. So, it is not possible to compare the results with previous studies. Although in  
291 other fields such as flood susceptibility mapping this method has been used (e.g., Azareh et al.  
292 2019), the comparison of the results is not the right way because the concepts and effective factors  
293 of the flood susceptibility are different from the flood vulnerability. Indeed, the flood vulnerability  
294 detects the potential weaknesses and strengths in the region, not the actual flood hazard (Fekete,  
295 A., 2009.).

296

297 **Table 2.** Importance of the factors based on the ANP method

Factors	Weight
Land use	0.197
Distance to stream (DTS)	0.181
Population density (PD)	0.180

Distance to residential areas (DTR <sub>e</sub> )	0.140
Distance to road (DTR)	0.138
Percentage of farmers and ranchers (PFR)	0.070
Distance to industrial and mining areas (DTIM)	0.065
Livestock density (LD)	0.019
Distance to tourist and cultural heritage areas (DTTCH)	0.010

298

299 *3.3. Validation of the results*

300 One of the most important steps in network analysis is to assess the validity and consistency of  
301 pairwise comparisons. It derives us to decompose complexity into a network structure for a better  
302 understanding of the relationship between its components and to create priorities for them within  
303 that structure (Ozdemir 2005). The issue of consistency is important in complex and multi-criteria  
304 issues, hence, the existence of a technique that can comment on the consistency of any decision is  
305 of great importance. Inconsistency causes errors and a lack of certainty to get logical and true  
306 results (Davvodi 2009). Inconsistency rate (IR) is an indicator that reflects the possible  
307 contradictions and inconsistencies in the pairwise comparison matrix. A valid result is obtained  
308 when the inconsistency rate is less than 0.1 (Tummala and Wan 1994). Accordingly, the  
309 inconsistency values of the pairwise comparisons for each node across the ANP method are  
310 presented in Table 4. The pairwise comparisons in all the nodes indicate the validity of the results  
311 (IR < 0.1).

312

313 **Table 3.** Inconsistency value of pairwise comparisons for each node across the ANP method

Node	Inconsistency rate
------	--------------------

Land use	0.097
Distance to stream (DTS)	0.00
Population density (PD)	0.091
Distance to residential areas (DTRe)	0.028
Distance to road (DTR)	0.061
Percentage of farmers and ranchers (PFR)	0.015
Distance to industrial and mining areas (DTIM)	0.00
Livestock density (LD)	0.00
Distance to tourist and cultural heritage areas (DTTCH)	0.00
Flood vulnerability	0.079

314

315 *3.4. Flood vulnerability mapping*

316 After validation of the ANP-DEMATEL model and ensuring the results, an appropriate  
317 membership function (MF) was applied for standardizing each layer between 0 and 1. The applied  
318 fuzzy MF for each variable is presented in Table 4. Linear-increasing MF was used for  
319 standardizing the layers of LD, PD, and PFR. It means that by increasing the pixels' value of these  
320 layers, the flood vulnerability is increased. Linear-decreasing MF was applied for standardizing  
321 the layers of DTS, DTR, DTRe, DTIM, and DTTCH. It means that by increasing the pixels' value  
322 of these layers, the flood vulnerability is decreased (Table 4). So, in linear-increasing (linear-  
323 decreasing) MF, the higher (lower) value of a layer converts to 1 and the lower (higher) value  
324 converts to 0, and other values change between them. For land use layer, fuzzy values of 0.2, 0.4,  
325 0.4, 0.4, 0.7, 0.8, and 1 respectively for barren land, rangeland, forest, waterbody, orchard,  
326 agriculture, and residential area were considered (according to the expert knowledge). By defining  
327 an appropriate membership function to each layer, each pixel gets a value that indicates  
328 vulnerability of that pixel to flooding. Accordingly, values of pixels in each layer convert into a

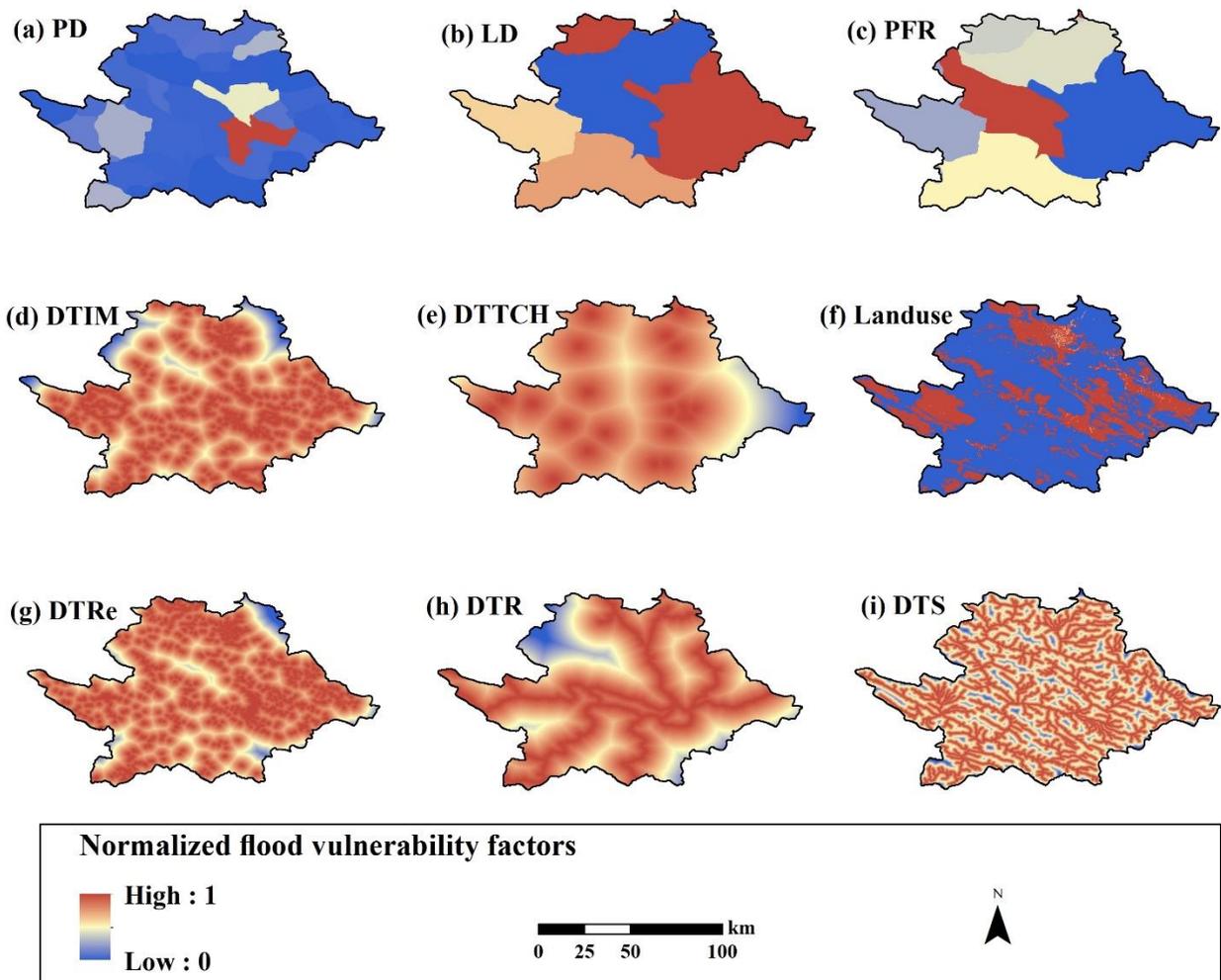
329 continuous scale from 0 to 1 based on the target (i.e., flood vulnerability) that keeps the data  
 330 availability in the overlaying process (Sajedi-Hosseini et al. 2018; Azareh et al. 2019). Figure 6  
 331 shows the normalized factors after applying the fuzzy MF to each layer.

332

333 **Table 4.** Applied fuzzy membership function for each layer

Factor	Membership function
Livestock density (LD)	Linear-increasing
Population density (PD)	Linear-increasing
Distance to stream (DTS)	Linear-decreasing
Distance to road (DTR)	Linear-decreasing
Distance to residential areas (DTRe)	Linear-decreasing
Distance to industrial and mining areas (DTIM)	Linear-decreasing
Distance to tourist and cultural heritage areas (DTTCH)	Linear-decreasing
Percentage of farmers and ranchers (PFR)	Linear-increasing
Land use	User defined (0.2, 0.4, 0.4, 0.4, 0.7, 0.8, and 1 for barren land, rangeland, forest, waterbody, orchard, agriculture, and residential area, respectively)

334



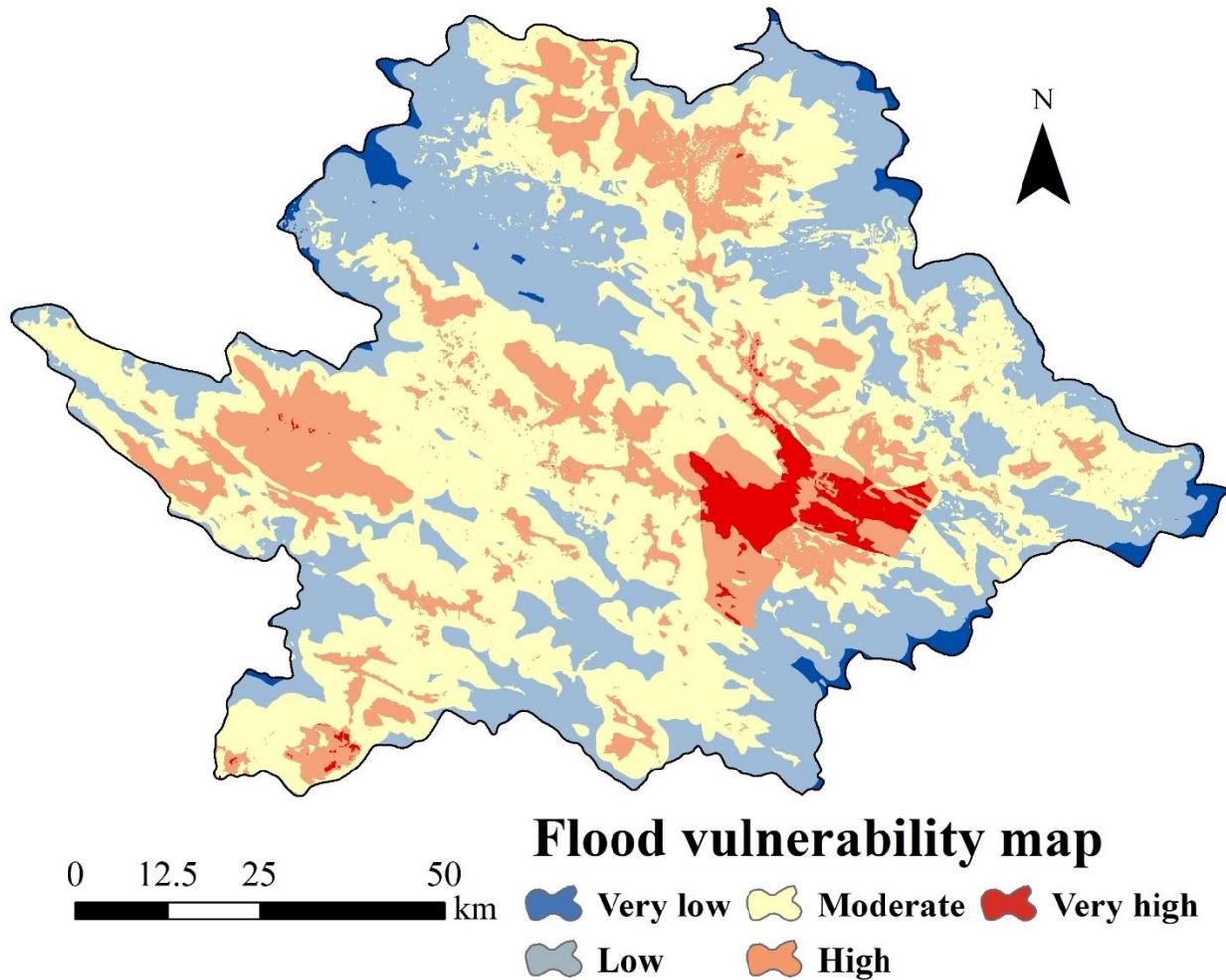
335  
 336 **Figure 6.** Normalized flood vulnerability factors: (a) population density (PD), (b) livestock density  
 337 (LD), (c) percentage of farmers and ranchers (PFR), (d) distance to industrial and mining areas  
 338 (DTIM), (e) distance to tourist and cultural heritage areas (DTTCH), (f) land use, (g) distance to  
 339 residential areas (DTRe), (h) distance to road (DTR), and (i) distance to stream (DTS).

340

341 Finally, by applying the weights achieved from the DEMATEL-ANP method into each Fuzzy  
 342 layer within ArcGIS 10.3, the overlaying of the layers was conducted using Eq. 7. So, a flood  
 343 vulnerability map with pixel size  $13 \times 13$  m for the area of Kashkan watershed was produced  
 344 (Figure 7). According to the flood vulnerability map (Figure 7), 47.2 % area of the region (about  
 345  $4489.5 \text{ km}^2$ ) indicates a moderate vulnerability, while other classes of very low, low, high, and

346 very high contain 1.9% (182.5 km<sup>2</sup>), 31.7% (3010.5 km<sup>2</sup>), 16.9% (1605.2 km<sup>2</sup>), and 2.3% (222.6  
347 km<sup>2</sup>) of the region, respectively. Results indicated that the high and very high vulnerability areas  
348 correspond to high population density, land use of residential, and low distance to streams. The  
349 very high class in Figure 7 is correspond with the location of Khorramabad, Pol-e Dokhtar, and  
350 Kuhdasht cities (presented in Figure 1). Some of these very high vulnerable locations (such as  
351 vulnerable areas in the Pol-e Dokhtar city) have been previously confirmed by the authors  
352 observations from flood damages in March 2019 (Figure 2), after occurring one of the biggest and  
353 most destructive floods in this watershed.

354



355

356

**Figure 7.** Flood vulnerability map in the Kashkan watershed.

357

### 358 **Conclusion**

359 The current study tried to develop a flood vulnerability analysis using an integrated approach by  
 360 combining the DEMATED, ANP, and Fuzzy methods. The DEMATEL, as a causality analysis  
 361 method identified the interdependency among factors of flood vulnerability, the ANP determined  
 362 the importance of factors, and the fuzzy was used to keep the data availability by assigning a

363 continuous scale to each layer (based on its relationship with flood vulnerability). The ANP-  
364 DEMATEL results indicated that the variables of land use (0.197), distance to stream (0.181),  
365 population density (0.180), distance to residential areas (0.140), and distance to road (0.138) were  
366 the most important variables. According to the flood vulnerability map, 16.9% (1605.2 km<sup>2</sup>) and  
367 2.3% (222.6 km<sup>2</sup>) of the region, respectively are located in high and very high flood susceptibility,  
368 which are correspond to high population density, land use of residential, and low distance to  
369 streams. Validation of the vulnerability areas is an inevitable limitation in the vulnerability studies,  
370 even though some of the very high vulnerable locations have been validated by the authors’  
371 observations from flood damages after occurred flood in March 2019. Unlike the flood hazard  
372 studies, there is not any data for validation of the flood vulnerability map, because the flood  
373 vulnerability only detects the potential weaknesses and strengths in the region, not the actual flood  
374 hazard. So, the flood vulnerability is regarded as independent of the flood hazard and the location  
375 of flooded areas can not be used for flood vulnerability validation. However, in this research, the  
376 validity of the DEMATEL-ANP method was confirmed by assessing the inconsistency rate in the  
377 network structure. Thus, it is not surprising that there is not any feasible way for additional  
378 validation, yet, and it can be an outlook for future researches.

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385 **Declarations**

386 **Ethics approval:** Not applicable

387 **Consent to participate:** Not applicable

388 **Consent to Publish:** Not applicable

389 **Authors Contributions:** Conceptualization, FSH; Data preparation, FSH; Formal analysis, FSH,  
390 AS, and BC; Investigation, FSH, AM, and AS; Methodology, FSH and SKS; Project  
391 administration, FSH and SKS; Supervision, SKS; Validation, SKS; Visualization, FSH and BC;  
392 Writing – original draft, FSH and BC; Writing – review & editing, SKS and AM

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394 **Competing interests:** The authors declare that they have no conflict of interests.

395 **Availability of data and materials:** The data that support the findings of this study are available  
396 from the corresponding author, [S.K.S.], upon reasonable request.

397

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# Figures

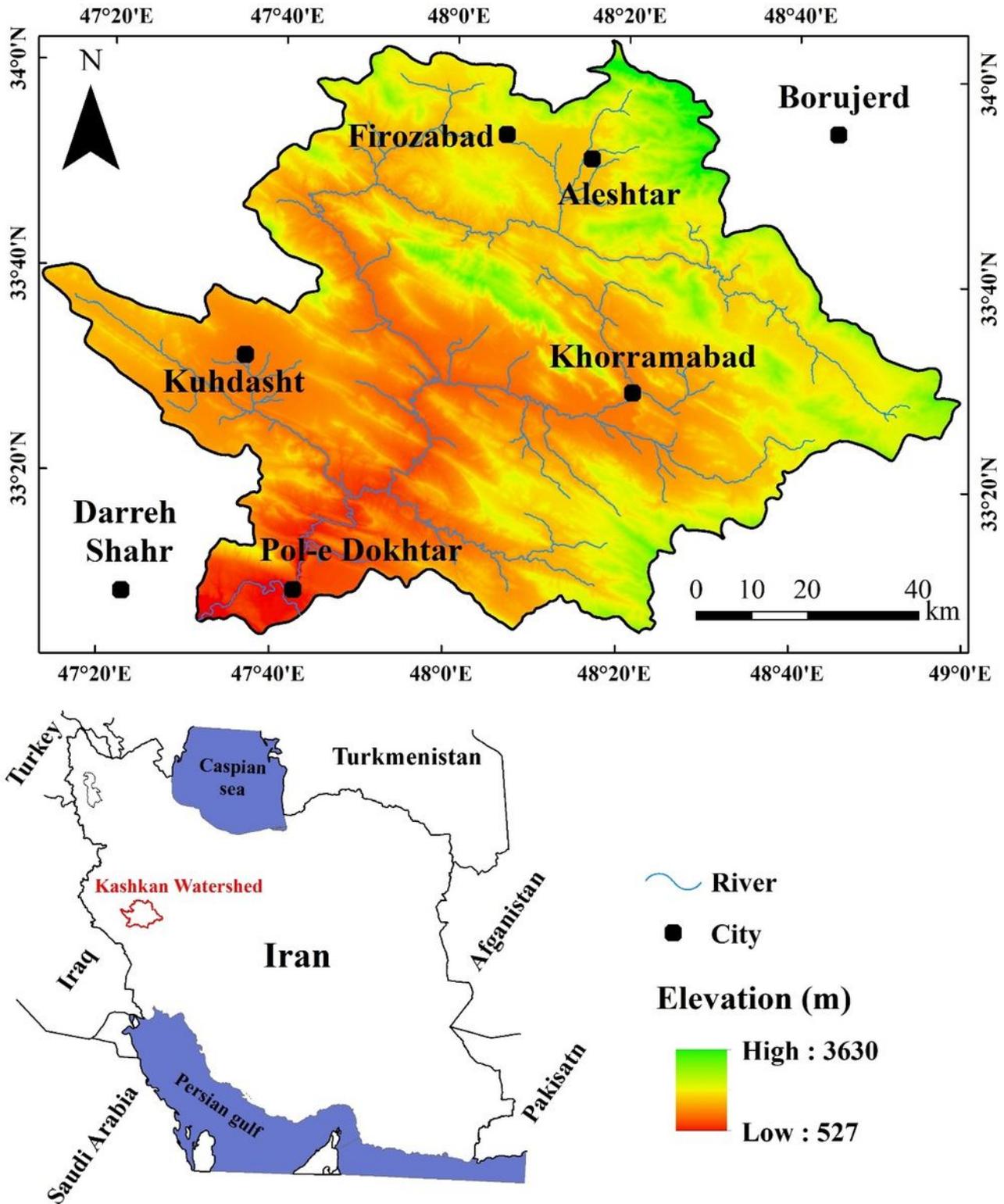


Figure 1

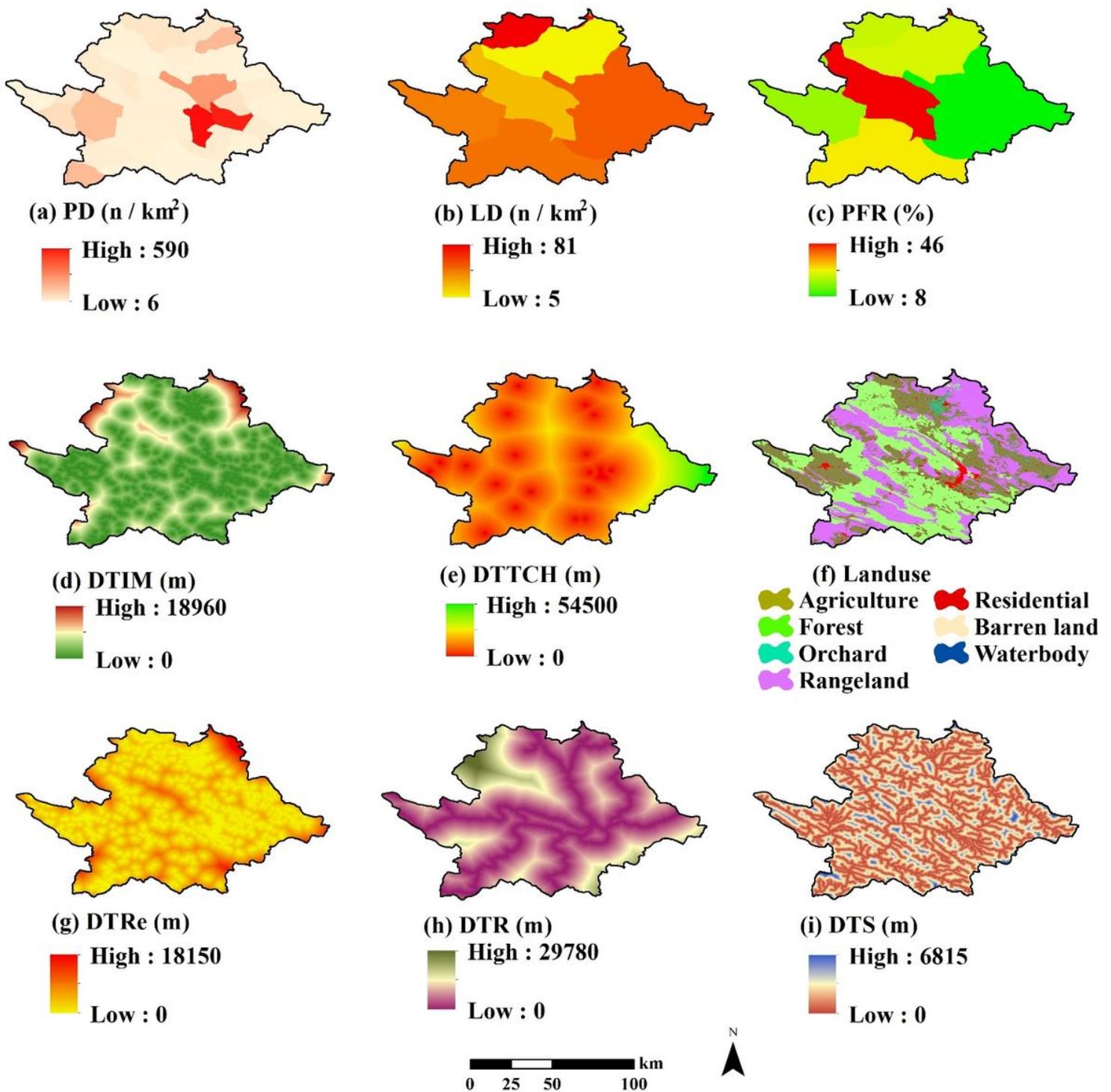
Location of the study area Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning

the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 2**

Some photos of the flood damage in March 2019. Photos were taken by Shahram Khalighi Sigaroodi.



**Figure 3**

Flood vulnerability variables: (a) population density (PD), (b) livestock density (LD), (c) percentage of farmers and ranchers (PFR), (d) distance to industrial and mining areas (DTIM), (e) distance to tourist and cultural heritage areas (DTTCH), (f) land use, (g) distance to residential areas (DTRe), (h) distance to road (DTR), and (i) distance to stream (DTS). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research

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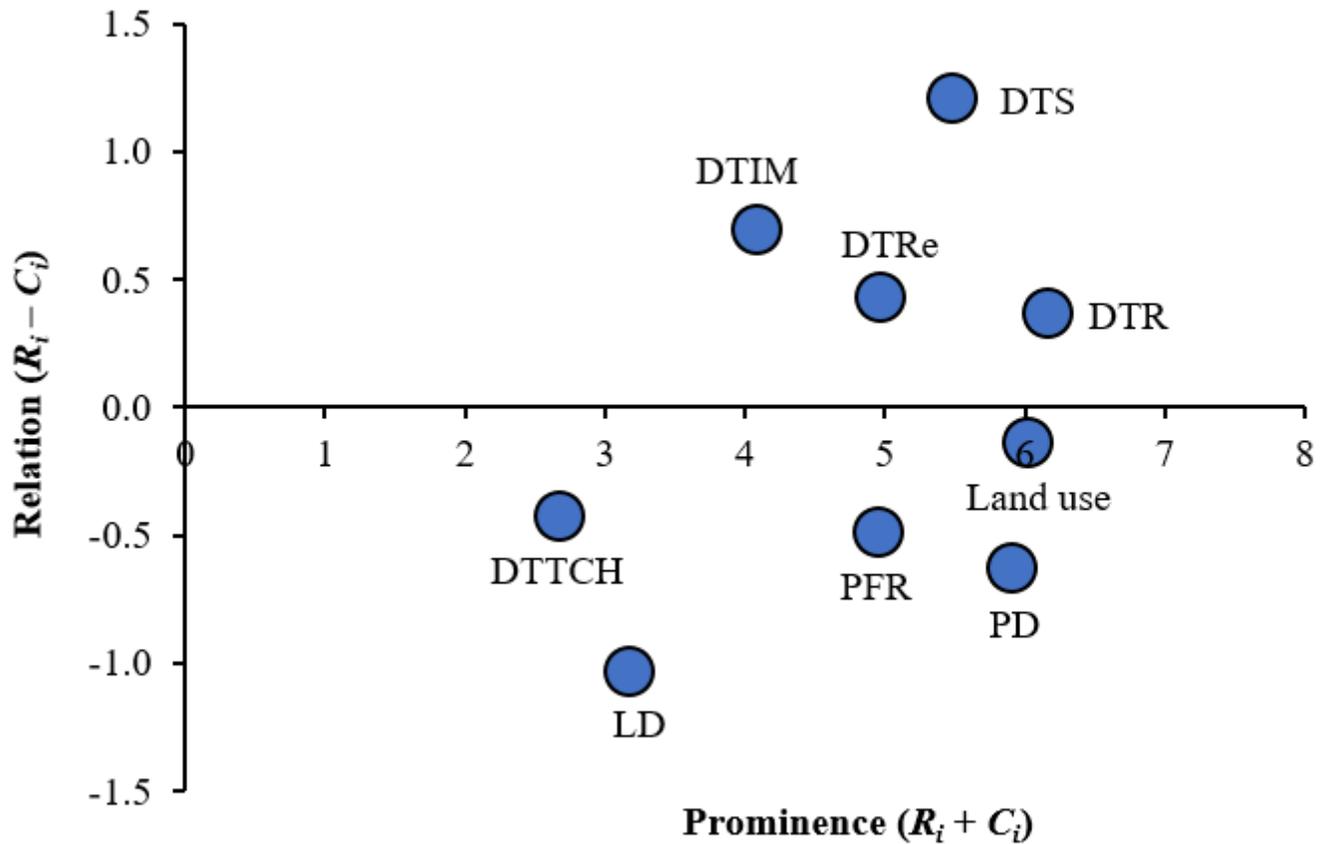
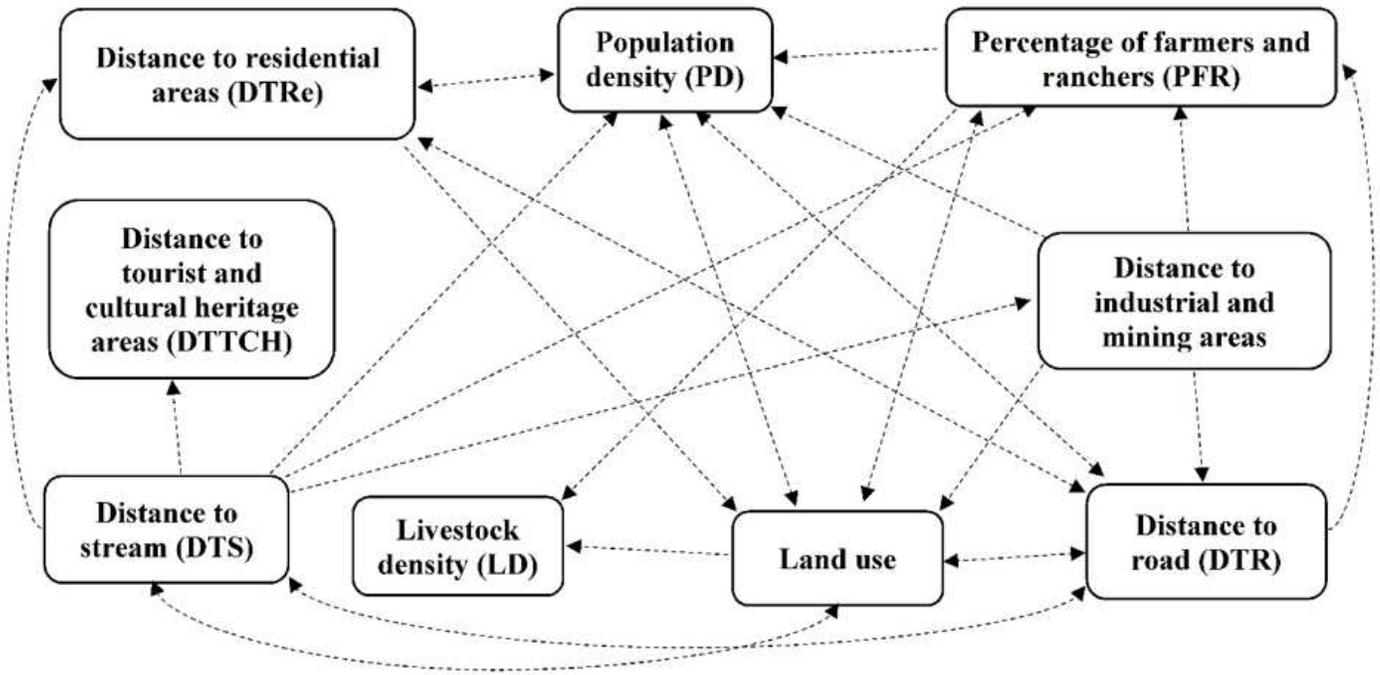


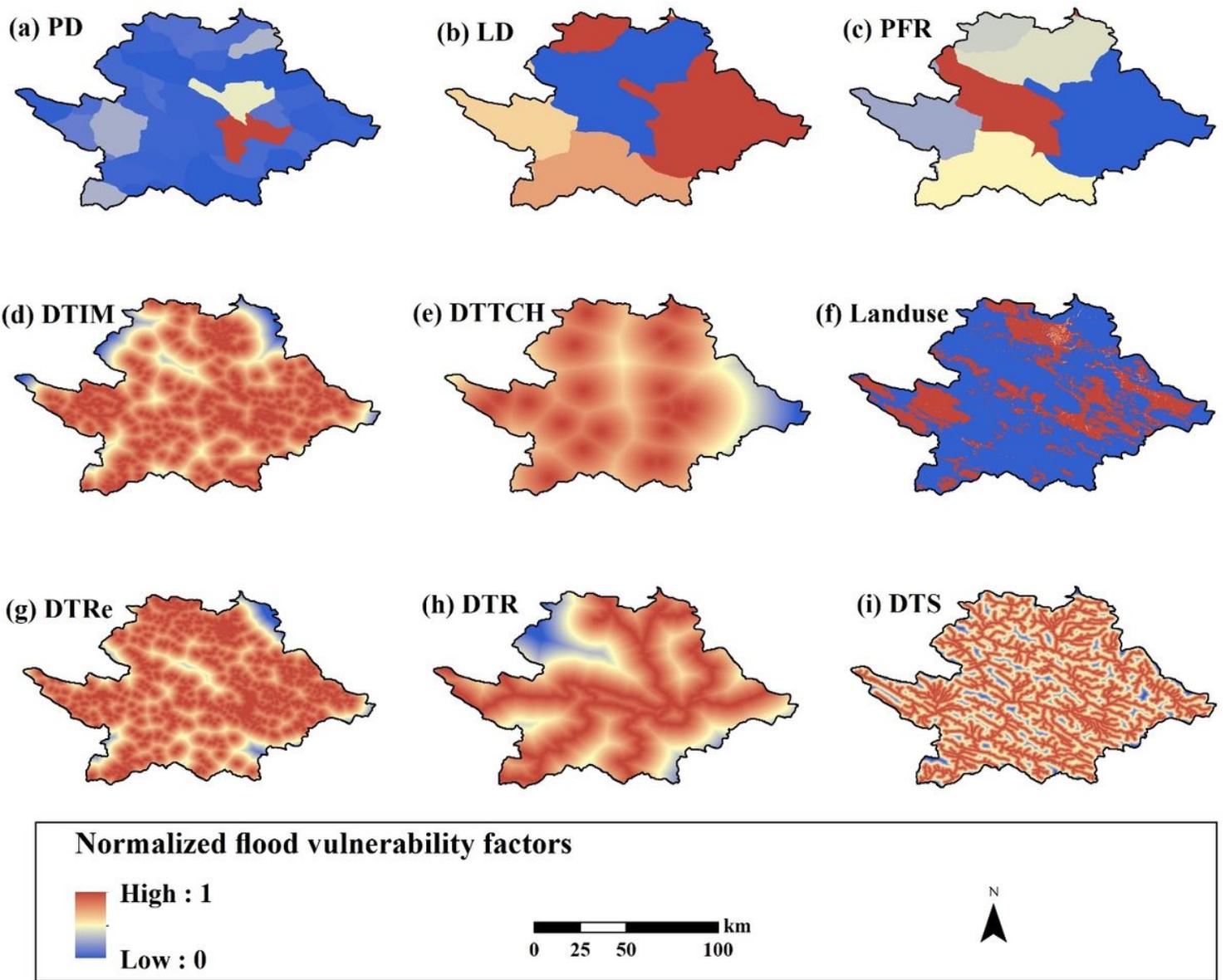
Figure 4

Causal diagram representing the relation (cause/effect) and prominence (interaction) of the variables in the whole network.



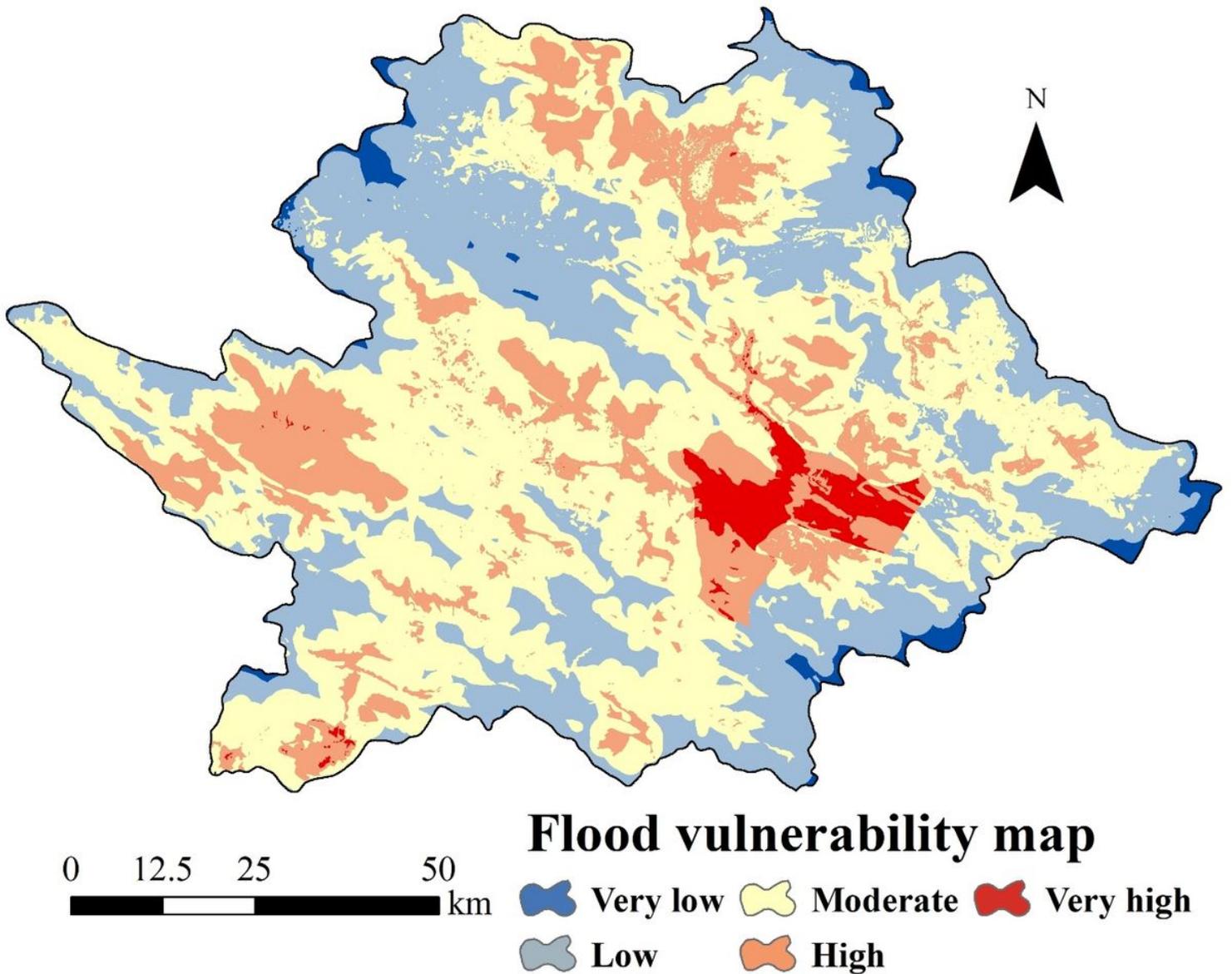
**Figure 5**

Designed network structure among the flood vulnerability variables by the DEMATEL method



**Figure 6**

Normalized flood vulnerability factors: (a) population density (PD), (b) livestock density (LD), (c) percentage of farmers and ranchers (PFR), (d) distance to industrial and mining areas (DTIM), (e) distance to tourist and cultural heritage areas (DTTCH), (f) land use, (g) distance to residential areas (DTRe), (h) distance to road (DTR), and (i) distance to stream (DTS). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 7**

Flood vulnerability map in the Kashkan watershed. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.