Landslides behavior spatial modeling by using evidential belief function model, Promethean II model, and index of entropy in Tabriz, Iran

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Abstract

Due to the increasing construction of clay and marl hills in most areas of Tabriz (Iran), its characteristics in terms of resistance, and its tendency to liquefy during earthquakes, this city is at risk of landslides. This paper studies the landslide vulnerability of Tabriz using visual and statistical evidence. The evaluation of landslide susceptibility was performed using the evidential belief function model (EBF) and the index of entropy. The environmental impact assessment of landslides was carried out using the Promethean II model in three environmental, economic, and social phases. Finally, a landslide strategy plan for decision-makers was developed. The results of the analysis using the EBF model showed that 89.81% of the total area of Tabriz is located in a direct landslide vulnerability zone. The output of the receiver operating characteristics (ROC) curve showed 83.3% accuracy of the EBF model. The impact assessment showed that for the environment, the geological criterion had an output weight of 0.396; for the economy, the road criterion had a weight of 0.477; and for the society, the commercial criterion had a weight of 0.452; all were the most affected by landslides. The results of monitoring studies of the largest landslides in Tabriz in 1957, 1984, and 2020 showed approximately 41.65 m of land sliding over a period of 63 years. To our knowledge, this study is the first in the world to predict the environmental impact assessment and provide a strategy plan for Tabriz.

Keywords Landslide susceptibility assessment · Environmental effects · Mitigation option · Strategy process · Monitoring process

Introduction

Landslides in the form of mass movements pose threats to human safety and security, the environment, and the economy (Pandey et al. 2021; Nsengiyumva et al. 2018). According to the Construction Ministry of Jihad in Iran, 15,000 landslides have occurred in Iran since 2006. The earthquakes of 1721 and 1780 were the worst natural disasters in the North Tabriz Fault: the first killed 100,000 people in the northeastern of Tabriz, and the second killed a total of 200,000 people in Tabriz and Turkey. Considering the occurrence of numerous historical earthquakes and the resulting complete destruction of Tabriz 12 times, the North Tabriz Fault has been propounded as one of the well-known seismic faults of Tabriz (Ahadnezhad Reveshty et al. 2014). Landslide disaster risk reduction is an important common goal in all countries/regions where people living in mountains and slopes are prone to landslides (Akawwi et al. 2018; Vilímek et al. 2020). Landslide susceptibility can be generally defined as the probability of landslide occurring in

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Fig. 1 Location map of the study area (a) Geological map of Tabriz (b)

areas under the coupling action of a series of geological environmental factors and human activities (Chen et al. 2019a). The assessment of landslides in the world

suggests that most developing countries are at greater risk of landslides (Pradhan and Siddique 2020; Sah et al. 2018).

Table 1 Morphometric of Tabriz linked to 1956 landslide

Volume (m ³)	Sphere (m)	Area (m ²)	Width (m)	Length (m)	Landslide of 1957
13539761.74	2539.36	85386.53	327.53	983.39	Main slip boundary
2164892.64	1043.74	25892.85	259.64	372.58	Small slip border, left
317974.86	534.58	6798.63	168.63	213.63	Small slip border, right
17376928.85	4728.09	438967.39	971.53	1987.52	Great slip border

Assessing the risk of landslide occurrence can help predict the probability and return period of landslide in an area (He et al. 2019; Mateos et al. 2020). The consequence of landslides becomes more hazardous if they occur along or near townships (Puente-Sotomayor et al. 2021). This phenomenon has attracted the attention of the global scientific community, leading to the publication of a large number of studies examining landslide risk assessment (Dikshit et al. 2020; Sassa 2019; Bičér and Ercanoglu 2020). All of the above studies concluded that for a landslide risk assessment, it is essential to have access to recorded information and results of previous research studies. However, in Tabriz, despite previous landslides incidents and damage to infrastructure and housing “especially in highly developing areas of the city without respecting the laws and regulations of urban planning and geology,” there is no reliable scientific research to determine vulnerability to future events. The lack of information regarding the potential damage caused by a severe landslide hazard in

Tabriz, being a large metropolis with a particular economic and international situation in Iran, requires an in-depth scientific study and elimination of the research gap in the assessment of landslide in this city. In the event of a landslide, areas that comply with the principles and regulation of urban planning and geology will not significantly be impacted (Skilodimou et al. 2019; Shaaban et al. 2021). The assessment of the environmental effects of landslides showed an inverse relationship between the severity of landslides and the extent of urban infrastructure (Fahad et al. 2019) and the level of noncompliance to urban development regulations (Usman et al. 2020). This study focuses on the vulnerability of areas with low living standards (Ayala 2019) in Tabriz. Reducing landslide losses requires an appropriate method to identify the prone area, causal factors, and likelihood of future occurrence (Li et al. 2020; Confuorto et al. 2019). Landslide susceptibility mapping (LSM) has proven to be an effective module for detecting and predicting

Fig. 2 Map of landslides identified in Tabriz

Table 2 Data describing landslides in the study

	Category	Factors	Data type	Scale	
Digital elevation model	Topographic factors	Slope Aspect Elevation	Grid	1:25000	National geographic information institute (NGII) Iran national geographic center, www.ncc.gov.ir
Soil map	Topography Lithology Landslide Erosion		Polygon	1:5000	Forests, range, and watershed management organization (FRWC)
Fault map		Distance from fault density	Line	1:5000 1:4000	Geological survey and mineral exploration of Iran (gsi.ir) Google Map
Power line map	Infrastructure factors	Distance from oil line Distance from gas network	Line	1:5000	East Azerbaijan agricultural organization, www.eaj.ir
Hydrographic map	Rivers	Distance from main and minor rivers	Line	1:5000	Water and sewerage of East Azerbaijan Province, en.abfaazarbaijan.ir

landslide-susceptible areas (Nhu et al. 2020; Park et al. 2018; Feizizadeh et al. 2014).

Various machine-learning methods have been used for geotechnical applications such as landslide susceptibility mapping, groundwater spring potential mapping, and other environmental applications (Schäfer and Wenzel 2019; Zhao and Chen 2020). Selecting an appropriate mapping unit is an important step for landslide susceptibility evaluation. Statistical models, such as evidential belief function (EBF), have been widely used for generating landslide susceptibility maps (Feby et al. 2020). The EBF model is best suited for integration in different environmental and socioeconomic scenarios enhancing the models for urban allocation tasks (Arasteh et al. 2019; Pradhan et al. 2014; Bui et al. 2016). Successful use of the model by other researchers suggests that the EBF model is suitable for data analysis with GIS (Deng

et al. 2017). Recent advances in remote sensing (RS) and geographic information system (GIS) technology have dramatically improved the efficiency of the LSM module and the reliability of its results (Tavakkoli Piralilou et al. 2019). In this study, due to the investigation of various urban components such as economic, social, and environmental components, the EBF model was used as a dual model for socio-spatial measurement between landslides and conditional factors. The receiver operating characteristic (ROC) is a graphical plot that calculates the area under the ROC curve (AUC) (Thi Ngo et al. 2021); the focus is on the positive rate (Murillo et al. 2019). The second model is the entropy of index (IOE), which is based on the bivariate analysis principle (Shirani et al. 2018). The Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) method has been used by many researchers, for the location of wind farms

Table 3 Types of landslides identified in Tabriz

Distance from the main river	Distance from fault	Distance from residential areas	Distance from the road	Lithology	Landslide position	Type of landslide	
-	-	5 m	1 m	Shill sandstone and red marn	Pasdaran highway	Swing slip	1
50 m	500 m	20 m	-	Green and gray marn	Valiasr	Swing slip	2
100 m	50 m	20 m	-	Granular deposits and tuff	Valiasr	Swing Slip	3
-	500 m	20 m	3 m	Shill sandstone and red marn	Yaghchian	Swing Slip	4
-	-	30 m	1 m	Shill sandstone and red marn	Pasdaran highway	Crushing and overturning	5
-	-	10 m	1 m	Shill sandstone and red marn	Pasdaran highway	Crushing and overturning	6
-	-	5 m	5 m	Shill sandstone and red marn	Baghmishe township	Crushing and overturning	7
-	-	5 m	1 m	Shill sandstone and red marn	Baghmishe township	Stone slip	8

Table 4 Criteria and indicator used in the study

Criterion	Slope	Altitude	Slope direction	Erosion	Fault density	Distance from gas network	Lithology	Distance from main rivers	Distance from minor rivers	Distance from oil lines	Soil type
Criteria classes	1	1	1	1	1	1	1	1	1	1	1
	2	2	2	2	2	2	2	2	2	2	2
	3	3	3	3	3	3	3	3	3	3	3
	4	4	4	4	4	4	4	4	4	4	4
	5	5	5	5	5	5	5	5	5	5	5
Criteria indicator	0–5	1400–1500	Flat	I/II/III	<500	<1700	Stand stone	<1800	<1000	1000–4000	Xur
	5–10	1500–1600	North	IV	500–1000	1700–3000	Tuff	1800–3000	1000–2000	4000–8000	Arid soils
	10–17	1600–1700	Northeast	Urban	1000–1500	3000–5000	conglomerate	3000–5000	2000–3000	8000–12000	Entices
	17–23	1700–1800	East	V	1500–2000	5000–7000	Recent alluvial	5000–7000	3000–4000	12000–16000	Incept
	> 23	>1800	Southwest		>2000	>7000	Urban	>7000	>4000	>16000	sols
Area (m ³)			South								
			Southeast								
			West								
			Northwest								
	6558780	5037960	4103670	4067190	4371780	3256440	3303330	4681170	5347560	44338230	3434040
	1272750	10449160	1426320	1684410	2074230	210407	2115240	2180010	1922160	2005980	1137450
	35504	1914840	105300	1845090	145710	1846020	205203	105123	82305	152704	3616590
	210	18115700	21000	591390	601800	1924850	56340	948270	664950	1015560	292853
		186120	694380			1161270	2713200	378630	253410	728310	
			479130								
			14580								

Table 5 Classification of criteria calculated in EBF model

PLS	UNC	DIS	BEL	Cumulative percentage	Percentage of total layer	Area (m ²)	Class	
<i>0.95</i>	<i>0.7</i>	<i>0.05</i>	<i>0.25</i>	80.10	80.10	6558780	0–5.99	Slope
<i>0.88</i>	<i>0.78</i>	<i>0.12</i>	<i>0.10</i>	95.64	15.54	1272750	5.99–11.98	
<i>0.94</i>	<i>0.74</i>	<i>0.06</i>	<i>0.20</i>	99.99	4.35	356340	11.98–17.97	
<i>0.93</i>	<i>0.78</i>	<i>0.07</i>	<i>0.15</i>	100	0.002	210	17.97–23.96	
<i>0.80</i>	<i>0.75</i>	<i>0.2</i>	<i>0.05</i>	61.52	61.52	5037960	1400–1502	High see level
<i>0.90</i>	<i>0.8</i>	<i>0.1</i>	<i>0.10</i>	74.34	12.81	1049160	1502–1605	
<i>0.94</i>	<i>0.74</i>	<i>0.06</i>	<i>0.20</i>	97.72	23.38	1914840	1605–1707	
<i>0.95</i>	<i>0.7</i>	<i>0.05</i>	<i>0.25</i>	100	2.27	186120	1707–1810	
<i>0.88</i>	<i>0.78</i>	<i>0.12</i>	<i>0.10</i>	49.67	49.67	4067190	I/II/III	Erosion
<i>0.90</i>	<i>0.75</i>	<i>0.1</i>	<i>0.15</i>	70.25	20.57	1684410	IV	
<i>0.95</i>	<i>0.75</i>	<i>0.05</i>	<i>0.20</i>	77.46	7.22	591390	V	
<i>0.93</i>	<i>0.75</i>	<i>0.07</i>	<i>0.18</i>	100	22.53	1845090	Urban	
<i>0.90</i>	<i>0.82</i>	<i>0.1</i>	<i>0.08</i>	50.11	50.11	4103670	Flat	Slope direction
<i>0.92</i>	<i>0.77</i>	<i>0.08</i>	<i>0.015</i>	67.53	17.14	1426320	North	
<i>0.85</i>	<i>0.8</i>	<i>0.15</i>	<i>0.05</i>	68.82	1.28	105300	Northeast	
<i>0.80</i>	<i>0.75</i>	<i>0.2</i>	<i>0.05</i>	69.07	0.25	21000	East	
<i>0.91</i>	<i>0.81</i>	<i>0.09</i>	<i>0.10</i>	69.25	0.17	14580	Southeast	
<i>0.94</i>	<i>0.76</i>	<i>0.06</i>	<i>0.18</i>	75.10	5.85	479130	South	
<i>0.95</i>	<i>0.75</i>	<i>0.05</i>	<i>0.20</i>	83.58	8.48	694380	Southwest	
<i>0.94</i>	<i>0.78</i>	<i>0.06</i>	<i>0.16</i>	93.11	9.52	779580	West	
<i>0.90</i>	<i>0.82</i>	<i>0.1</i>	<i>0.08</i>	100	6.88	564120	Northwest	
<i>0.90</i>	<i>0.8</i>	<i>0.1</i>	<i>0.10</i>	39.77	39.77	3256440	0–2166	Gas network
<i>0.93</i>	<i>0.78</i>	<i>0.07</i>	<i>0.15</i>	62.31	22.54	1846020	2166–4334	
<i>0.91</i>	<i>0.78</i>	<i>0.09</i>	<i>0.13</i>	85.81	23.50	1924850	4334–6500	
<i>0.94</i>	<i>0.78</i>	<i>0.06</i>	<i>0.18</i>	100	14.18	1161270	6500–8667	
<i>0.94</i>	<i>0.76</i>	<i>0.06</i>	<i>0.18</i>	54.20	54.20	4438230	0–5061	Oil pipelines
<i>0.95</i>	<i>0.75</i>	<i>0.05</i>	<i>0.30</i>	78.70	24.49	2005980	5061–10122	
<i>0.93</i>	<i>0.78</i>	<i>0.07</i>	<i>0.15</i>	91.10	12.40	1015560	10122–15184	
<i>0.88</i>	<i>0.8</i>	<i>0.12</i>	<i>0.08</i>	100	8.89	728310	15184–20245	
<i>0.80</i>	<i>0.76</i>	<i>0.2</i>	<i>0.04</i>	40.34	40.34	3303300	Sand stone	Lithology
<i>0.93</i>	<i>0.65</i>	<i>0.07</i>	<i>0.26</i>	66.17	25.83	2115240	Tuff	
							conglomerate	
<i>0.80</i>	<i>0.75</i>	<i>0.2</i>	<i>0.05</i>	66.86	0.68	56340	Recent alluvial	
<i>0.95</i>	<i>0.65</i>	<i>0.05</i>	<i>0.30</i>	100	33.13	2713200	Urban	Fault density
<i>0.95</i>	<i>0.65</i>	<i>0.05</i>	<i>0.30</i>	53.39	53.39	4371780	0–3334	
<i>0.92</i>	<i>0.72</i>	<i>0.08</i>	<i>0.20</i>	78.72	25.33	2074230	3334–6669	
<i>0.92</i>	<i>0.74</i>	<i>0.08</i>	<i>0.18</i>	92.65	13.92	1140270	669–10004	
<i>0.90</i>	<i>0.74</i>	<i>0.1</i>	<i>0.15</i>	100	7.34	601800	10004–13338	Main rivers
<i>0.93</i>	<i>0.7</i>	<i>0.07</i>	<i>0.23</i>	57.17	57.17	4681170	0.2251	
<i>0.90</i>	<i>0.77</i>	<i>0.1</i>	<i>0.18</i>	83.79	26.62	2180010	2251–4502	
<i>0.88</i>	<i>0.78</i>	<i>0.12</i>	<i>0.10</i>	95.37	11.58	948270	4502–6754	
<i>0.85</i>	<i>0.77</i>	<i>0.15</i>	<i>0.08</i>	100	4.62	378630	6754–9005	Minor rivers
<i>0.95</i>	<i>0.72</i>	<i>0.05</i>	<i>0.23</i>	65.30	65.30	5347560	0–1099	
<i>0.91</i>	<i>0.77</i>	<i>0.09</i>	<i>0.14</i>	88.78	23.47	1922160	1099–2198	
<i>0.93</i>	<i>0.75</i>	<i>0.07</i>	<i>0.18</i>	96.90	8.12	664950	2198–3297	
<i>0.86</i>	<i>0.76</i>	<i>0.14</i>	<i>0.10</i>	100	3.9	253410	3297–4397	

(Amarasinghe and Perera 2020 the evaluation of tourist attraction (Tian et al. 2020), sustainable composing technology (Makan and Fadili 2020), the socioeconomic vulnerability of

urban (Contreras et al. 2020). The concept of social vulnerability (SV) to environmental hazards that involves demographic and socioeconomic factors that affect community

Table 6 Degree of vulnerability of Tabriz regions with EBF model

Percentage (%)	Area of each floor (m ²)	Pixel area (m ²)	Number of pixels (n)	
13.14	30880075	25	131465	Very high vulnerability
23.73	56491875	25	237315	High vulnerability
46.03	128550825	25	4603024	Moderate vulnerability
11.34	23178850	25	113475	Low vulnerability
5.76	14134125	25	57633	Very low vulnerability

resilience is considered a hot topic in the current disaster research (Shen et al. 2018). The most common spatial variables used to assess the economic and social vulnerability of a city between 2010 and 2020 include the housing of poor families, the number of important facilities (fire stations and medical centers) (Rezaei et al. 2019), the distance from the fault, and faults causing landslides (Hizbaron et al. 2012). The above studies show that in the context of landslide hazards, especially in urban areas, most landslide sensitivity zoning and comparison of model superiority were carried out (Abbaszadeh Shahri et al. 2019), and the role of proper location and fair distribution of urban infrastructure in reducing the destructive effects of landslides was not considered. The occurrence of an earthquake can shift the movement of the Tabriz fault to a more activated state. The consequences of such rapid developments, regardless of regional potential, will be significant environmental destructions and heavy financial losses for residents and urban settlements.

Two examples of these consequences include first, the landslides in the Valiasr Town residential complexes in Tabriz during 1993–1994 (the slip site remains so far) and second, the landslides and destructions of the Northern Highway of Tabriz and its reconstruction costs.

This study aims to identify the slippery and vulnerable areas of Tabriz, where the consequences of growing low-cost illegal construction must be taken into consideration.

This study also examines the impact of landslide scale on the city's underground infrastructure. The innovative aspect of this paper is that it evaluates the impact of landslide category in an urban environment applying the environmental impact assessment (EIA) tool and including parameters such as landslide sensitivity mapping, landslide impacts assessment, and mitigation, and monitoring.

Study area and data

This research was conducted in the geographical area of Tabriz (Iran). Tabriz is a city situated at north latitude 30°12' and east longitude 46°16'. Tabriz lies on the eastern point of the Tabriz plain and the intersection of two rough ranges in the north and south of the city; its area is 70388 km². Geologically, Tabriz is located in an area with various combinations of formations that show intense tectonic activity (Fig. 1). The most significant landslide in Tabriz occurred in 1956 due to a strong and deadly earthquake with a magnitude of 7.2; in fact, it was the largest and also the most dangerous landslide in Tabriz (Table 1). This paper presents an application development study conducted through diverse methods, including literature review, field observations, modeling, aerial photography, and satellite photo interpretation. First, the potential and susceptible landslide locations were identified using satellite images by completing extensive field

Table 7 Weighting, standardization, and entropy model uncertainty

Adjusted weight	Criteria weight	Uncertainty value	Entropy value	Criterion	
0.117	0.117	0.21	99%	Slope	1
0.296	0.296	0.53	97%	Altitude	2
0.216	0.216	0.039	98%	Slope direction	3
0.063	0.063	0.011	99%	Lithology	4
0.029	0.029	0.005	99%	Erosion	5
0.2	0.2	0.004	99%	Fault density	6
0.007	0.007	0.001	95%	Distance from oil lines	7
0.026	0.026	0.005	96%	Distance from gas network	8
0.096	0.096	0.017	96%	Distance from main rivers	9
0.12	0.12	0.021	97%	Distance from minor rivers	10
0.1	0.1	0.002	96%	Soil type	11

Fig. 3 Social impact assessment

Fig. 4 Results of the entropy model map and the EBF model. The results of the entropy model map revealed the direct and indirect vulnerability of 67.69% of the Tabriz area zone in terms of landslides (a). The results of the EBF model map revealed the direct and indirect vulnerability of 82.90% of the Tabriz area zone in terms of landslides. The difference

between the results of the models is due to the more careful evaluation of the interclass criteria and the intra-class criteria by the EBF model (b). The ROC curve also confirmed the accuracy of the EBF model; the area under the curve was 83.60% which indicates the accuracy of the EBF model (c)

Table 8 The relationship between the effective landslide factors and the sliding points using event weight probabilistic model

C/SC	SC	S2(W-)	S2(W+)	C	W-	W+	FR	%LSD	N-LSD	%CLS	N-PIX	Classic	
-231.1	0.012	0.000	0.000	-2.749	1.690	-1.060	0.38	30.18	10143	80.10	218626	0-5	Slope
178.2	0.011	0.000	0.000	1.949	-0.514	1.435	3.01	46.84	15741	15.54	42425	5-11	
217.7	0.013	0.000	0.000	2.824	-0.243	2.581	5.25	22.96	7717	4.35	11878	11-17	
6.44	0.447	0.000	0.200	2.880	0.000	2.879	5.80	0.01	5	0.00	7	17-23	
-17.90	0.500	0.000	0.250	-8.94	0.650	-8.229	0.00	0.01	4	41.94	114468	ARIDOSOL	Soil
63.07	0.013	0.000	0.000	0.804	-0.143	0.661	1.74	24.12	81.07	13.89	37915	URBAN	
122.57	0.013	0.000	0.000	1.562	-0.915	0.647	1.72	75.86	25495	44.17	120553	INCEPTISOL	Slope direction
-6.54	0.039	0.000	0.002	-0.275	0.821	0.567	0.04	1.97	661	50.12	136789	Flat	
14.60	0.096	0.000	0.009	1.401	0.218	1.618	0.02	0.32	109	17.42	47544	North	
-2.71	0.005	0.000	0.000	-0.015	0.015	0	0.00	0.00	0	1.29	3510	Northeast	
-0.54	0.005	0.000	0.000	-0.003	0.003	0	0.00	0.00	0	0.26	700	East	
118.54	0.046	0.000	0.002	5.495	-0.014	5.481	7.89	1.40	472	0.18	486	Southeast	
377.71	0.011	0.000	0.000	4.199	-0.507	3.63	6.90	40.36	13565	5.85	15971	South	
192.75	0.012	0.000	0.000	2.235	-0.35	1.884	3.90	33.08	11118	8.48	18804	Southwest	
98.3	0.013	0.000	0.000	1.274	-0.18	1.094	2.40	22.84	7677	9.52	25986	West	
-13.15	0.500	0.000	0.250	-6.574	0.082	-6.492	0.00	0.01	4	6.89	564120	Northwest	
-163.43	0.015	0.000	0.000	-2.521	0.984	-1.537	0.24	14.65	4924	61.53	167932	1400-1500	Elevation
97.72	0.012	0.000	0.000	1.186	-0.217	0.967	2.19	28.10	9444	12.81	34972	1500-1600	
114.76	0.011	0.000	0.000	1.255	-0.408	0.847	2.00	46.85	15745	23.39	63828	1600-1700	Erosion
129.51	0.018	0.000	0.000	2.315	-0.098	2.217	4.57	10.39	3493	2.27	6204	1700-1800	
-153.22	0.005	0.000	0.000	-0.836	0.836	0.000	0.00	0.00	0	49.67	135573	3/2/1	Erosion
-70.66	0.028	0.000	0.001	-1.990	0.220	-1.770	0.19	3.90	1312	20.57	56147	4	
113.61	0.013	0.000	0.000	1.531	-0.177	1.354	2.86	20.66	6944	7.22	19713	5	Distance from gas network
224.77	0.013	0.000	0.000	2.848	-1.240	1.608	3.35	75.43	25350	22.53	61503	Urban	
-110.44	0.005	0.000	0.000	-0.603	0.603	0.000	0.00	0.12	40	39.77	108548	0-2166	
-65.37	0.020	0.000	0.000	-1.307	0.197	-1.109	0.36	8.11	2724	22.55	61534	2166-4333	
92.64	0.011	0.000	0.000	1.023	-0.316	0.707	1.80	42.30	14216	23.50	64145	4333-6500	Lithology
2.7.61	0.011	0.000	0.000	2.265	-0.586	1.679	3.49	49.47	16626	14.18	38709	6500-8667	
-109.60	0.005	0.000	0.000	-0.602	0.602	0.000	0.03	1.16	390	40.34	110110	Sandstone	
-64.48	0.061	0.000	0.004	-3.933	0.339	-3.594	0.03	0.81	271	25.83	70508	Tuff	
-1.44	0.005	0.000	0.000	-0.008	0.008	0.000	0.00	0.00	0	0.69	1878	Recent	Distance from fault
128.79	0.039	0.002	0.000	5.059	3.653	1.406	2.96	93.03	32925	33.14	90440	Urban	
92.34	0.016	0.000	0.000	1.450	-1.450	0.000	1.65	87.92	29548	53.39	145726	0-334	
-59.76	0.017	0.000	0.000	-1.001	0.189	-0.812	0.48	12.08	4058	25.33	69141	3434-6669	
-31.70	0.005	0.000	0.000	-0.173	0.173	0.000	0.00	0.00	0	13.93	38009	6669-10004	Distance from Main River
-16.05	0.005	0.000	0.000	-0.088	0.088	0.000	0.00	0.00	0	7.35	20060	10004-13338	
85.14	0.036	0.001	0.000	3.023	-3.023	0.000	1.71	97.64	32813	57.17	156039	0-2251	
-80.05	0.036	0.000	0.001	-2.877	0.333	-2.554	0.09	2.36	793	26.62	72667	2551-4502	
-25.97	0.005	0.000	0.000	-0.142	0.142	0.000	0.00	0.00	0	11.58	31609	4502-6754	Distance from oil lines
-9.93	0.005	0.000	0.000	-0.054	0.054	0.000	0.00	0.00	0	4.62	12621	6754-9005	
-26.78	0.07	0.000	0.000	-0.198	0.198	0.000	0.84	45.63	15336	54.20	147941	0-5061	
140.84	0.011	0.000	0.000	1.542	-0.558	0.985	2.22	54.37	18270	24.50	66866	5061-10122	
-27.96	0.005	0.000	0.000	-0.153	0.153	0.000	0.00	0.00	0	12.40	33852	10122-15184	Distance from Minor river
-19.61	0.005	0.000	0.000	-0.107	0.107	0.000	0.00	0.00	0	8.89	24277	15184-20245	
44.59	0.012	0.000	0.000	0.523	-0.523	0.000	1.20	78.35	26329	65.31	178252	0-1099	
-15.46	0.014	0.000	0.000	-0.210	0.046	-0.163	0.87	20.31	6827	23.48	22165	1099-2198	
-14.86	0.005	0.000	0.000	-0.082	0.082	0.000	0.16	1.34	450	8.12	8447	2198-3296	
-6.59	0.005	0.000	0.000	-0.036	0.036	0.000	0.00	0.00	0	3.09		3297-4397

Scenario 1: Environmental effects of landslide: A_1 (geology) $>$ A_3 (fault) $>$ A_2 (soil) $>$ A_4 (erosion) $>$ A_5 (slope)

(a₁) PROMETHEE I partial ranking of environmental criteria (b₁) Complete ranking of alternatives based on the PROMETHEE II method, taking into consideration of all categories of possible decisions.

Scenario 2: Economic effects of landslide: A_1 (Transportation) $>$ A_2 (Residential) $>$ A_3 (Pressure lines) $>$ A_4 (oil pipes)

(a₂) PROMETHEE I partial ranking of economic criteria (b₂) Complete ranking of alternatives based on the PROMETHEE II method, taking into consideration of all categories of possible decisions.

Scenario 3: Social effects of landslide: A_2 (recreational) $>$ A_1 (population) $>$ A_3 (health)

(a₃) PROMETHEE I partial ranking of social criteria (b₃) Complete ranking of alternatives based on the PROMETHEE II method, taking into consideration of all categories of possible decisions.

Fig. 5 Scenario 1: Environmental effects of landslide: A_1 (geology) $>$ A_3 (fault) $>$ A_2 (soil) $>$ A_4 (erosion) $>$ A_5 (slope) (a₁) PROMETHEE I partial ranking of environmental criteria (b₁) Complete ranking of alternatives based on the PROMETHEE II method, taking into consideration of all categories of possible decisions. Scenario 2: Economic effects of landslide: A_1 (Transportation) $>$ A_2 (Residential) $>$ A_3 (Pressure lines) $>$ A_4 (oil pipes) (a₂) PROMETHEE I partial ranking of economic criteria (b₂)

Complete ranking of alternatives based on the PROMETHEE II method, taking into consideration of all categories of possible decisions. Scenario 3: Social effects of landslide: A_2 (recreational) $>$ A_1 (population) $>$ A_3 (health) (a₃) PROMETHEE I partial ranking of social criteria (b₃) Complete ranking of alternatives based on the PROMETHEE II method, taking into consideration of all categories of possible decisions.

Fig. 6 Areas requiring park and green spaces (a) (areas 3, 4, and 6; dense commercial areas of the city and busy areas) are the areas that encounter a lack of green spaces; meanwhile, Tabriz suffers from a total shortage of 430 ha in terms of green spaces. Accessibility to open and green spaces of

the city in Tabriz (b). The lack of green space per capita in Tabriz leads to increased severity of vulnerability to landslides and similar accidents. The more people have access to the city's open and green spaces, the less causality will result in the hours after the landslide

observations and data recorded by GPS to match the existing landslides accurately. ArcGIS 10 software was used to analyze the data and prepare the maps. A total of 29 landslides

were identified (Fig. 2; Tables 2 and 3). The landslide data set was randomly divided into two parts so that 70% of cases were used for assessment, and 30% were kept for validating

Table 9 Area and per capita of Green spaces in Tabriz

(m ²) Shortage	Per capita standard	(m ²)Per capita	(m ²)Area	region
-	4	4.1	1546	1
-	4	6.7	2095	2
150040	4	3.4	2798	3
150011	4	3.1	2550	4
-	4	8.3	3229	5
300102	4	0.5	7196	6
-	4	11.7	2882	7
-	4	12.2	386	8
400151	4	0.1	762	9
4302154	8.2	4.4	1050	10

the landslide susceptibility map. In the next step, considering the conditions of the study area, eleven factors determining the occurrence of landslides were analyzed in the GIS environment including the slope degree, slope direction, height above mean sea level, distance from the fault, distance from main rivers, distance from minor rivers, distance from oil pipelines, distance from natural gas networks, erosions, soil type, and lithology. It is noteworthy that the study area was local in scale and had homogeneous conditions in terms of climatic variables; therefore, the rainfall criterion was removed (Table 4).

Methods and materials

Evidential belief function

The base of the EBF model used in this study is mainly the Dempster-Shafer theory of evidence algorithms (Dempster 2008; Shafer 1976). The Dempster-Safer theory is a generalization of the Bayesian subjective probability theory, which relates to the effect of confidence index on the probability of related problems. The main advantage of the EBF model is its flexibility which is the result of accepting uncertainty and incorporating many sources of belief (Bui et al. 2012). For this reason, it has already been applied in the construction of landslide susceptibility maps. The EBF model consists of the following four main mathematical functions: Bel (degree of belief), Dis (degree of disbelief), Unc (degree of uncertainty), and Pls (degree of plausibility) (Tables 5 and 6). The values of these functions range from 0 to 1. Multilayer integration of Bel, Dis, Unc, and Pls is expressed as follows:

$$Bel_{x_1x_2} = \frac{bel_{x_1}bel_{x_2} + bel_{x_1}unc_{x_2} + bel_{x_2}unc_{x_1}}{\beta} \quad (1)$$

$$Dis_{x_1x_2} = \frac{dis_{x_1}dis_{x_2} + dis_{x_1}unc_{x_2} + dis_{x_2}unc_{x_1}}{\beta} \quad (2)$$

$$Unc_{x_1x_2} = \frac{unc_{x_1}unc_{x_2}}{\beta} \quad (3)$$

where $\beta = 1 - bel_{x_1}dis_{x_2} - dis_{x_1}bel_{x_2}$ is a normal factor to ensure $BEL + UNC + DIS = 10$.

Index of Shannon entropy

The second model used for landslide susceptibility analysis in the current study is the index of entropy model. The model indicates the extent of the instability, disorder, imbalance, and uncertainty of a system (Youssef et al. 2015) (Table 7). The entropy of a landslide refers to the extent to which various factors influence the development of a landslide. Several important factors provide additional entropy in the index system. Thus, the entropy can be used to calculate the objective weights of the index system. The equations used to calculate the information coefficient W_j , which represents the weight value for the parameter as a whole, are as follows:

$$P_{ij} = \frac{b}{a} \quad (4)$$

$$(P_{ij}) = \frac{P_{ij}}{\sum_{j=1}^{S_j} P_{ij}} \quad (5)$$

PROMETHEE II

The Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) method is a subgroup of the multiple-criteria decision-making (MCDM) method developed in the early 1980s by Brans et al. (Zhou et al. 2018). The PROMETHEE technique is an outranking approach for a finite set of alternative actions to be ranked and selected among often contradictory criteria. Due to its flexibility and ease of use, it can be used in various fields. The use of the PROMETHEE method can reinforce the confidence and reliability of decision-makers (Fig. 3).

Results

To study the geology of Tabriz, a regional geological map at a scale of 1:5000 of lithology was analyzed microscopically using 30 thin sections of existing rock

Fig. 7 Distribution of health facilities in Tabriz (a). The zones that require the construction of the necessary relief centers (b). The zones that require the construction of the necessary health centers. Tabriz suffers from a total of 142.6 ha of shortage in terms of healthcare infrastructure

Table 10 Area and per capita of Health facilities in Tabriz

(m ²) Shortage	Per capita standard	(m ²) Per capita	(%)Portion	(m ²) Area	Region
86325	0.5	0.27	0.34	103059	1
120500	0.5	0.96	0.68	271180	2
29414	0.5	0.5	0.4	103710	3
44855	0.5	0.4	0.4	114435	4
41827	0.5	0.83	1.65	79801	5
500	0.5	0.41	0.33	14348	6
2883	0.5	0.55	0.03	11978	7
4824	0.5	0.05	0.001	461	8
0	0	0	0	0	9
1426528	1.5	0.5	0.3	669946	Tabriz

142
Hectares
shortages

in the region. Regarding the age and structure of the fault and folds of the rocky units of the area, Tabriz geology map at a scale of 1:25000 was used as a reference. In this study, landslide sensitivity in Tabriz city was assessed using EBF and entropy models (Fig. 4; Table 8). The EBF model can be used to summarize the spatial correlation between landslide occurrence and landslide conditioning factor. When the Bel value is zero, the expected landslide risk is also zero. The results of the EBF model showed that the entire Tabriz region was vulnerable at moderate to very high levels; this vulnerability puts 82.9% of the city at risk of direct and indirect landslides. The entropy model results show that 67.69% of the city is at risk of landslide. The environmental impact assessment was carried out using the Promethean II model. DecisionLab

software was used to run the Promethean II model. To rank the effects of landslides, options and criteria of each of the environmental, economic, and social components were selected, and a pairwise comparison of all options was performed. Of the six types of PROMETHEE model preference indicators, types four and five were considered for the criteria. The normalized weights of each indicator were determined by the decision-makers. For the assessment of the environmental impacts of landslides, criteria included geology, soil, fault, erosions, and slope. The evaluation of the environmental effects of landslides showed that the geological option with a weight of 0.396% had the most damage due to the landslides risk ($A_1 > A_3 > A_2 > A_4 > A_5$). Analyzing the economic outcome of landslides in roads, residential areas, high-pressure lines, and oil lines using

Fig. 8 Accessibility to urban facilities in Tabriz. Nearly 85 ha of the regions of Tabriz suffer from deprivation of accessibility to urban facilities

Table 11 Area and per capita of facilities and equipment spaces in areas of Tabriz

(m ²) Shortage	Per capita standard	(m ²) Per capita	(%)Portion	(m ²) Area	Region
86325	0.5	0.27	0.34	103059	1
120500	0.5	0.96	0.68	271180	2
29414	0.5	0.5	0.4	103710	3
44855	0.5	0.4	0.4	114435	4
41827	0.5	0.83	1.65	79801	5
500	0.5	0.41	0.33	14348	6
2883	0.5	0.55	0.03	11978	7
4824	0.5	0.05	0.001	461	8
0	0	0	0	0	9
1426528	1.5	0.5	0.3	669946	Tabriz

the economic impact criteria showed that the road option with a weight of 0.477 had the most damage due to the landslides ($A_1 > A_2 > A_3 > A_4$). The evaluation of the social outcome of landslides in population, commercial-recreational areas, and health ($A_2 > A_1 > A_3$) showed that the commercial/recreational areas had the most damage due to landslides with a weight of 0.452 (Fig. 5). Losses from landslides can be significantly reduced through cooperation between geologists, engineers, and planners, which may reduce the scale of mitigation measures to be taken; therefore, a statistical and detailed study of the quantity and quality of infrastructure in vulnerable physical structures is necessary for dealing with the severity of the effects after a landslide in Tabriz.

Mitigation

Mitigation is the final stage of the risk management process (Ferlisi et al. 2019). One of the mitigation methods is to compensate for the shortcomings. The main infrastructure and parameters of Tabriz which played a significant role in offsetting the effects of a landslide were studied as follows.

Green space

Significant parts of the urban spaces in the northwest, south-east, and western parts of Tabriz have been allocated to green spaces and urban open spaces. However, the urban and outdoor spaces in the central part of the city are limited (Fig. 6; Table 9). The more accessible open spaces are in a city, the less damage there will be in natural disasters such as landslides.

Health facilities

Improving the quantity and quality of medical centers leads to rapid relief of the injured. In the current global Covid-19 pandemic, if any natural disasters occur in Tabriz, medical centers should be able to provide services to the injured people. Tabriz is currently facing a shortage of 142.6 ha of health facilities (Fig. 7; Table 10).

Urban facilities

Infrastructure networks are vital for citizens' and urban life; the absence or vulnerability of these networks affects the lives of citizens. The facilities of Tabriz that have been less studied include water reservoirs, municipal electricity facilities, telecommunication center, gas facilities, emergency facilities, and fire brigade. There are more than 85 ha of shortages of mentioned facilities in Tabriz (Fig. 8; Table 11).

Vital arterial roads

The traffic network per capita in Tabriz is 29.3m², which seems adequate. However, some surveys show a very uneven distribution of the transport network, with 4.9% of the urban population uses 12.5% of the city's urban roads. In comparison, 32.0% of the population living in the suburbs uses 17.08% of the city streets; also in these areas, the building density is very high, which greatly increases the vulnerability (Fig. 9). If Tabriz's per capita traffic network does not increase, in the event of a landslide, the increase in population will prevent the rescue team from providing timely assistance.

Important vital infrastructure

In terms of quality and condition, the structures of the city's vital infrastructure are classified into three types: usable, restored, and destroyed. This research showed that among all important institutions and service centers, the educational centers had the highest frequency in Tabriz and then the administrative, medical, military, and transit system terminals, respectively. Of the identified institutions and centers, 78.7% are in good condition and usable, 20.7% are restored, and 0.6% are destroyed (Fig. 10).

Monitoring

Remediation and early warning strategies are generally focused on continuous monitoring of the slope displacements, which can provide crucial information on the dynamics and

evolution of the landslide (Whiteley et al. 2019). The morphometric monitoring and evaluation of the largest landslides in Tabriz were carried out using RS and GIS at three periods of

time, including 1957, 1984, and 2020. The relevant data of aerial photographs of 1957 and 1984 with a scale of 1:5000 (soil and water studies of Iran) and a satellite image of Google

Fig. 9 The degree of impermeability in Tabriz (a); as shown in the map, the highest impermeability was observed in areas where the greatest risk for landslides occurrence was previously predicted; high-risk areas

mentioned include 1 and 10 and at low levels 3, 6, and 7. Construction density of Tabriz (b); residential parts less than 100 m are the most vulnerable to natural disasters (earthquakes, landslides, floods, etc.)

Fig. 10 Vital and important centers need reconstruction and reinforcement in Tabriz (a); to mitigate landslide impact, it is necessary to reinforce more than 70% of the important and vital centers in Tabriz. Damage ratios of the major centers of the city (b); red spots: some areas such as military, Bazar, and fire station that need to be rehabilitated. The blue dots represent some of the most important and vital new centers, including some training, administrative, military, and fire stations. The yellow dots represent a military site and training site which are in the range of destructive. According to civil engineering and urban

planning, new buildings were 10 to 30% more vulnerable to accidents such as landslides. Buildings that required retrofitting had a vulnerability of about 30 to 70% and buildings that were very old and demolished had a vulnerability of about 70 to 100% to a landslide occurrence. Area requiring police and security centers (c), law enforcement, and security forces play a key role in controlling the psychological and social impacts of natural disasters such as landslides, preparing them to deal with their destructive effects

Fig. 10 continued.

Earth in 2020 with a scale of 1:4000 were entered into the GIS software. The average annual slip movement in a 27-year period (1957 to 1984) was 53.29 cm per year, and in the 36-year period (1984 to 2020), it was 75.72 cm per year. The increase in human activity in landslide-sensitive areas has led to the ascending increases in landslides between 1984 and 2020; over time, landslide areas have become more unstable. The results showed that the average speed of Tabriz landslides during 63 years is 41.65 m (Fig. 11; Table 12).

Discussions

This study showed that the EBF model is well able to detect landslides in urban areas; this deduction is consistent with the results of a credible study. The results of the landslide sensitivity assessment using the EBF model showed that 82.9% of the Tabriz area is at risk of landslide vulnerability. The output of the ROC curve showed 89.81% accuracy of the EBF model. This study showed that landslides occur at certain altitudes (Chen et al. 2019b). Areas above 1,700 m from sea level are more at risk of landslides due to human activities. In addition to similar and main criteria used in related articles (Hong et al. 2018), in this study, others such as distance from oil lines and

gas networks were also used. The highest risk of explosion due to landslides in Tabriz in these high-risk lines is at a distance of 5,000 m. Some researchers looking at the environmental impact of landslides also studied the impact of landslide vulnerability economic criteria (Postance et al. 2017). In this study, we also assessed environmental and social criteria. Regarding the economic impact, the road criterion, with an output weight of 0.477, is the most vulnerable to landslides as a direct effect (road damage and blockage) and an indirect effect (traffic delay and reduced transport efficiency). Moreover, for the environmental impact, the output weight of the geological criterion was 0.396, and for the social impact, the output weight of the recreation areas was 0.452, which all showed the highest vulnerability to landslides in Tabriz. A survey of vital infrastructures in Tabriz revealed shortages in several areas, including medical and rescue facilities, security and enforcement centers, distribution of city facilities users, distribution of essential and vital centers, and green spaces; the quantity and quality of each play a critical role in reducing (or increasing) the severity of landslide vulnerability. The general trend of the results of this study revealed that the areas with a higher population density suffered from a poor economic situation; these areas were located downstream of the mountainous area and were more

Fig. 11 Aerial photo and satellite image of the largest landslide in Tabriz. **a** Landslide aerial photo 1956. **b** Landslide aerial photo 1983. **c** Landslide satellite image 2020. The results showed that the average landslide movement in Tabriz over 63 years was about 41.65 m. The graph of displacement rate and morphometric changes of landslide in Tabriz, slip volume difference (**d**), slip sphere difference (**e**), slip area comparison (**f**),

slip width comparison (**g**), and slip length comparison (**h**). Analysis of the information obtained in the above diagrams shows that, due to the influence of lithological and human factors, the morphometric characteristics of the Tabriz landslide during the period 1956 to 2020 increased significantly

Table 12 Total motion rate and annual average slip motion in the years studied

2020–1956	2020–1983	1983–1956	Documents
66.11	75.72	53.29	Average annual slip motion (cm/year)
41.65	27.26	14.39	Total amount of slip motion (M)

vulnerable. The results showed that in terms of medical and rescue centers, there was 142 ha shortage, which directly affects approximately 6815 people in the northern and south-eastern regions of Tabriz. In terms of equipment and facilities, 85-ha shortage affects 1814 people in the southwest, central, and northeast regions of Tabriz. Regarding per capita green and open areas, 430 ha shortage affected 3094 people in the southwest region and two regions in central Tabriz. Some vital centers in Tabriz need improvement, including educational centers, security, and market centers. In general, the severity of vulnerability to landslides can be minimized if the city's vital infrastructure is improved. The results of monitoring studies of the largest landslide in Tabriz in 1957 (first landslide occurrence first), 1984 (beginning of human activity in the landslide area), and 2020 showed approximately 41.65 m of landslide during 63 years. The statistical results of the Tabriz landslide monitoring program showed a gradual increase in the rate of landslide movement over time; the average annual sliding during 1983–2020 was higher than that from 1956 to 1983. This shows that Tabriz landslides have become more unstable and frequent over time, especially as human activities have recently increased in the area. The lack of geological documented data related to urban planning policy was the only statistical limitation in this research work. Different insights of this study provide a valuable and useful basis for more extensive regional and trans-regional research. The mentioned insights deal with the environmental behavior of landslides and the design of strategic policies to mitigate the effects of landslides. The importance of applying the results on an international scale can be summarized into three topics as follows. First, due to the high vulnerability of road criterion in terms of landslide potential, the importance of maintaining the infrastructure of the Tabriz-Turkey road network is revealed; it is the most important international transit road.

Table 13 Relationship between building size and degree of vulnerability

Vulnerability degrees	Building size
High	area<200
Average	200<area<500
Low	500<area

The average size of residential plots is one of the factors affecting the slip vulnerability of urban structures

Second, due to the extent of the plateaus and interconnection of faults in neighboring countries, the occurrence of geological events in one of two neighboring border cities of neighboring countries leads to the stimulation of faults in the latter. Third, according to the 2009 cooperation agreement between Iran and the United Nations (UN) Office on Transatlantic Affairs, the study results are useful as internationally documented applicable spatial data concerning landslides, strategic policies in crisis management of geological events, and monitoring programs in the physical control of landslides.

Conclusions

Previous studies in Iran have focused on assessing the vulnerability to landslides. However, the influence of landslides in urban areas has not been analyzed by examining environmental, economic, and social vulnerabilities and needs to be investigated. This study is a prototype for assessing vulnerability in urban areas of a developing country. The objective of this study was to identify and predict locations of landslides in Tabriz, as it is one of the most important cities in Iran in terms of geography, economy, and politics. In this study, to improve the performance of government agencies and nongovernmental organizations (NGOs), it was necessary to assess the environmental behavior of landslides concerning the vulnerability of the population living in slippery areas. The results showed that the most landslide vulnerable areas were residential areas with a high population density and weak financial situations (Table 13). Moreover, these areas include low-density and compact structures with dramatically increasing vulnerability. Therefore, corrective measures must be taken in terms of the quantity and quality of services provided by the government and the health agencies. A natural disaster such as an earthquake or heavy rain will then lead to the destruction of high-risk buildings, significant casualties, and financial losses. Several general strategies can be proposed to manage the situation and reduce the effects of landslides in Tabriz. Short-term strategies include public education and low-cost mitigations such as gully and other drainage facilities. Monitoring and recording landslide data can also be useful to local authorities for the development and management of the city. Meanwhile, midterm strategies can include establishing an evidence-based decision-making guideline for defining essential projects and governance in areas highly affected by the landslide. Long-term strategies include changing the legal policy and administrative structure of urban development in areas at high landslide risk. In the long run, the high costs of these measures are offset, due to the prevention of post-slip maintenance and its associated costs. Control and maintenance measures may include daily observation, forecast, and assessment of slope slip fences and meteorological devices. Although these measures are described as low-cost operations, they have a significant impact on reducing slip risks.

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Declarations

Conflict of interest The authors declare that they have no competing interests.

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