An assessment on the use of bivariate, multivariate and soft computing techniques for collapse susceptibility in GIS environ

IŞIK YILMAZ^{1,*}, MARIAN MARSCHALKO² and MARTIN BEDNARIK³

¹*Department of Geological Engineering, Cumhuriyet University, 58140 Sivas, Turkey.*

²*Institute of Geological Engineering, VŠB-Technical University of Ostrava, 17. listopadu 15, 708 33 Ostrava, Czech Republic.*

³*Department of Engineering Geology, Comenius University, Mlynská dolina, 842 15 Bratislava, Slovak Republic.*

**Corresponding author. e-mail: iyilmaz@cumhuriyet.edu.tr*

The paper presented herein compares and discusses the use of bivariate, multivariate and soft computing techniques for collapse susceptibility modelling. Conditional probability (CP), logistic regression (LR) and artificial neural networks (ANN) models representing the bivariate, multivariate and soft computing techniques were used in GIS based collapse susceptibility mapping in an area from Sivas basin (Turkey). Collapse-related factors, directly or indirectly related to the causes of collapse occurrence, such as distance from faults, slope angle and aspect, topographical elevation, distance from drainage, topographic wetness index (TWI), stream power index (SPI), Normalized Difference Vegetation Index (NDVI) by means of vegetation cover, distance from roads and settlements were used in the collapse susceptibility analyses. In the last stage of the analyses, collapse susceptibility maps were produced from the models, and they were then compared by means of their validations. However, Area Under Curve (AUC) values obtained from all three models showed that the map obtained from soft computing (ANN) model looks like more accurate than the other models, accuracies of all three models can be evaluated relatively similar. The results also showed that the conditional probability is an essential method in preparation of collapse susceptibility map and highly compatible with GIS operating features.

1. Introduction

Collapse structures in gypsum terrains are serious geological hazards because they can damage engineering structures, produce settlement areas, form natural lakes and allow infiltration of contaminant into the groundwater. Presentation of engineering geological data in the form of a hazard map is a useful tool in urban planning. There have been few studies carried out on collapse hazard

and/or susceptibility mapping, such as Forth *et al.* (1999), Tolmachev *et al.* (1999), Kaufman and Quinif (2002), Zhou *et al.* (2003), Yilmaz (2007), Bruno *et al.* (2008), Guerrero *et al.* (2008), Galve *et al.* (2008).

Forth *et al.* (1999) had produced a map showing relative risk of hazard occurrence along the coast of the Algarve (Portugal). They had taken into consideration of sinkholes, caving, gullyng, slope angle, tension cracks, fissuring, rock falls,

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mechanical strength and vegetation cover as controlling factors. Selected sizes of cells unfortunately were 100 m² in a quite small study area (<1 km²), and so they obtained a very rough map. Tolmachev *et al.* (1999) prepared a sinkhole hazard zonation for a 25 km long section of the Moscow–Nizhny Novgorod high-speed line based on the spatio-temporal frequency of sinkholes in the railway right-of-way. Kaufman and Quinif (2002) reported a methodology for drawing geo-hazard map of cover collapse sinkhole occurrences in limestones overlain by a Mesozoic cover consisting of marls, sand and clay in the ‘Tournaisis’ area (Belgium). They used parameters such as the dewatering of limestone, thickness of cover formation, density of former collapses. They found that zones of high sinkhole occurrence coincide with the zones of heavy lowering of piezometric heads. They delineated the zones of low, moderate and high collapse hazard by combining the density of former collapses with the dewatering of the limestone. Zhou *et al.* (2003) presented a sinkhole susceptibility zonation for the Maryland interstate highway I-70 based on spatial distribution analyses of recorded sinkholes and the application of a scoring system to several controlling factors. The probabilistic method for assessment of collapse susceptibility was first used by Yılmaz (2007), and he took into account the collapse factors, directly or indirectly related to the causes of collapse occurrences in a given region, such as lithology, drainage system, structural lineaments (such as faults and folds), morphology (slope angle, slope aspect, elevation), springs, roads, settlement areas and vegetation cover, etc., in order to produce collapse susceptibility map in gypsum terrain in Sivas basin (Turkey). Higher quality of the map by means of its performance had been obtained and the map was considered as satisfactory. Bruno *et al.* (2008) explained the development of sinkholes in coastal plains selected from southern Italy and proposed a method for producing a collapse susceptibility map in karst terrains in their paper. The susceptibility map had unfortunately roughly drawn using cells having a dimension 62.5 × 62.5 m in ~2 km² study area as discussed by Yılmaz (2008a). Guerrero *et al.* (2008) presented a methodology for producing sinkhole susceptibility zonations along linear infrastructures based on the analysis of the subsidence and dissolution features exposed in the adjacent cuttings and the distribution of karstic depressions along the stretch of high-speed Madrid–Barcelona railway built on halite- and glauberite-bearing evaporites of the Tertiary Zaragoza Gypsum Formation in Spain. They discussed that the approach described in their paper, based on analysis of dissolution features and subsidence structures exposed in the

railway cuttings, may constitute a highly useful and inexpensive method to produce sinkhole susceptibility zonations and to identify particularly dangerous points. Galve *et al.* (2008) carried out the analysis of sinkhole susceptibility in a stretch 50 km² in area of the Ebro valley alluvial evaporite karst (NE Spain). They used thematic maps of sinkholes, topography, geomorphology, geology, hydrogeology, hydro-geochemistry and human structures in their analysis and found that ~75% of the sinkholes occur on the 10% of the pixels with the highest susceptibility according to validation curves.

In this paper, collapse susceptibility maps of a selected area in Sivas basin (Turkey) were prepared by use of bivariate – conditional probability (CP), multivariate – logistic regression (LR) and soft computing – artificial neural networks (ANN) models. At the end of the study, the maps obtained from four models were then compared according to their validation degrees. This paper will also add an extra value to the literature of the collapse susceptibility mapping as a comparative study of very basic techniques (CP) with both statistical (LR) and soft computing techniques (ANN).

2. Study area

Gypsum provides actual numbers of coverage, and is extensively karstified with numerous sinkholes, dolines and other depressions (figures 1 and 2), and the entire area in the region is composed of gypsum. Collapse structures were generally classified as cover collapse based on their genesis. They were formed by the failure of the rock roof of an underlying cave and characterized by steep walls and large voids in the rock beneath.

Depressions in the study area are especially observed as a form of doline. Dolines have been subdivided into three groups by Karacan and Yılmaz (1997). The first group comprises partially collapsed dolines; the second group appears to develop together with cracks on the surface; the third group comprises olders (Karacan and Yılmaz 1997; Yılmaz and Karacan 2005). The first two groups of dolines are very young, while the others are older.

In the region, urbanization is developing towards east of Sivas city, and the study area is especially valuable for sites of plants and waste disposal. In order to produce a collapse susceptibility map, which will also serve to regional planning, 1:25,000 scaled map was chosen. Collapses in the gypsum terrains in Sivas basin are a current problem where they can cause extensive damage to property.

Hafik Lake to the east of Sivas, Tödürge Lake to the west of Zara and Ulaş Lake to the south

Figure 1. Location map of the case study area.

of Sivas have filled karst depressions. Most of the sinkholes have been formed along faults, and groundwater discharge to the river can be observed in some places (Karacan and Yilmaz 1997). In addition, dolines and collapse passages play an important role in the groundwater flow system (Karacan and Yilmaz 1997).

3. Susceptibility mapping

An understanding of the karst breakdown mechanism is crucial for assessment, prediction and management of subsidence hazards in karst terrains. A set of component agencies and a shifting of the breakdown process proper (i.e., breakdown mechanism) depends on many factors and conditions. The most important factors can be considered as the presence and structure of overburden, lithological properties of individual units in the cover, hydrogeological conditions such as piezometric levels and hydraulic gradients, degree of karstification and characteristics of the primitive initiating cavities (Klimchouk and Andrejchuk 2005).

As stated by Yilmaz (2007), interpretation of future collapse occurrence requires an understanding

of conditions and processes controlling collapse event. In order to predict collapse, it is necessary to assume that collapse occurrence is determined by collapse-related factors, and that future collapses will occur under the same conditions as past collapses. On this basis, the relationship between areas where a collapse has occurred and collapse-related factors can be distinguished from the relationship between areas without past collapses and collapse-related factors. The evidence of collapse structures such as dolines and sinkholes is the most important factor in the prediction of future collapses.

Preparation of the karst inventory map, which presents karst affected area, is the first primary goal for assessment of the hazard and vulnerability in a given area. A karst inventory map should provide data for hazard and vulnerability mapping and assist to landscape level planning. However, preparation of the karst inventory requires significant amount of field works, satellite imagery and other remote sensing data, including recent and historical air photos, surficial and bedrock geological maps and detailed topographic information, etc., that will provide useful data in order to facilitate and complete data for inventory mapping.

Figure 2. Distribution of the collapse structures on the DEM of study area.

Attributes and descriptions in the content of karst inventory preparation should include polygons corresponding to boundaries of karst structure. The database of collapse-related factors such as, geological, hydrological, topographical, environmental, surficial material was obtained, and both inventory and collapse-related factors were then inserted to GIS environ in a GIS software of ArcGIS 9.1. Hazard and susceptibility maps

were constructed by using statistical and/or soft computing techniques (figure 3).

3.1 Database used in the models

Point data in GIS can be described by a single (X, Y) coordinate and does not reflect the collapse affected area, and this type of feature may be used when the areal extend of a small collapse cannot be drawn due to the scale of the map. However, the logic way is to reveal the collapse responsible pixels. In the study area, collapses were only observed if they were larger than one cell (10×10 m) used in the analyses. In collapse inventory mapping, for each surficial collapse zone as polygon feature drawn from Landsat TM satellite images (May 2006), 1:35,000 aerial photographs, field work, and converted to the raster format (figure 2).

As discussed by Yılmaz (2009), capability of cell numbers depends on the cell size and resolution used in the analyses. Digital elevation models (DEM) (figure 2) having a resolution of 1353 rows and 1037 columns, and totally 14,03,061 cells (10×10 m) enclosing a rectangle of ~ 140.3 km² was first implemented from 1:25,000 scaled topographic maps, and slope angle, slope aspect and topographical elevation maps were then produced from the DEM. Collapse-affected factors, directly or indirectly related to the causes of collapse occurrence in a given region, such as distance from faults, slope angle and aspect, topographical elevation, distance from drainage, topographic wetness index (TWI), stream power index (SPI), normalized difference vegetation index (NDVI) by means of vegetation cover, distance from roads and settlements (figures 4, 5, 6 and 7) parameters, were obtained. Topographic wetness index and stream power index are the second derivatives of the digital elevation models indirectly describing

Figure 3. Flowchart of the works for production of collapse susceptibility maps.

Figure 4. Collapse-related geological factor maps: (a) geological map and (b) distance from faults.

Figure 5. Collapse-related hydrological factor maps: (a) distance from drainage, (b) SPI and (c) TWI.

the hydrological situation of the relevant terrain (Wilson and Gallant 2000). The theoretical background of the parameters could be found in Nefeslioglu *et al.* (2012).

In order to understand the significance of the selected factors, frequency ratios of each factor

were calculated and the variables were included in the model. The frequency ratio method is very easy to apply, and results obtained by Lee and Talib (2005), Lee and Sambath (2006), Lee and TuDan (2005) and Yilmaz (2007) are very intelligible. The frequency ratio, which was calculated

Figure 6. Collapse-related topographical factor maps: (a) slope gradient, (b) slope aspect and (c) topographical elevation.

Figure 7. Collapse-related land-use and vegetation cover factor maps: (a) distance from roads, (b) distance from settlements and (c) NDVI.

as the ratio of the probabilities of a collapse occurrence to a non-occurrence for a given attribute, was used to obtain relationships between collapse-related factors chosen and collapse occurrence area. Frequency ratio values greater than 1 indicate a high probability of collapse occurrence. In order to find the relationships between collapse-related factors chosen and collapse occurred area, graphs of the probabilities of a collapse occurrence versus classes of given attribute were drawn and

significant factors were considered in the collapse susceptibility analyses (figures 8–11). All of the selected factors were found to be significant in assessment of collapse susceptibility.

3.2 Models

In this study, three different models (bivariate, multivariate and soft computing) were applied in

Figure 8. Relationships between collapse-related geological factors and collapse occurrence.

Figure 9. Relationships between collapse-related hydrological factors: (a) distance from drainage, (b) SPI and (c) TWI and collapse occurrence.

Figure 10. Relationships between collapse-related topographical factors: (a) slope gradient, (b) slope aspect and (c) topographical elevation and collapse occurrence.

gypsum terrain for assessment of collapses by means of collapse susceptibility. Models used in the article consist of basic conditional probability (CP), complicated statistical method of logistic regression (LR) and more sophisticated artificial neural network (ANN) as a soft computing method.

Conditional probability is one of the basic bivariate methods for producing a susceptibility map and highly compatible with GIS (Ramakrishnan *et al.* 2005). Non-specialists can also produce the maps easily. Number of factors related to occurrences can be considered in the conditional probability approach.

Logistic regression, which is a multivariate analysis model, is useful for predicting the presence or absence of a characteristic or outcome based on

values of a set of predictor variables. The advantage of logistic regression is that, through the addition of an appropriate link function to the usual linear regression model, the variables may be either continuous or discrete, or any combination of both types, and they do not necessarily have normal distributions (Menard 1995).

The use of ANNs, which is very well-known soft computing method is an alternative method for susceptibility mapping and risk zonation. Because, ANNs, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Trained neural networks can be thought of as an ‘expert’ in the

Figure 11. Relationships between collapse-related land-use and vegetation cover factors: (a) distance from roads, (b) distance from settlements and (c) NDVI and collapse occurrence.

category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer ‘what if’ questions. Other advantages include: adaptive learning, self-organization, real-time operation and fault tolerance via redundant information coding (Singh *et al.* 2003).

3.2.1 Bivariate model – conditional probability

Conditional probability is one of the basic methods for producing a susceptibility map and highly compatible with GIS. Number of factors related to occurrences can be considered in the conditional probability approach. The data layers containing each factor subdivided into a convenient number

of classes are crossed in order to obtain possible combinations of the various classes of the different factors (Clerici *et al.* 2002). Each specific combination represents a pixel, and the collapse spatial frequency is subsequently determined within each pixel. The resulting collapse density equals the collapse susceptibility, assuming that the collapse in future will be more likely occurred under those conditions which led to the past instability and frequency of an event equals the probability that the same event will occur (Clerici *et al.* 2002).

In order to categorize the conditioning factors, the quantile method was used. In this method, every 10% fraction of the relevant factor assigned as different parameter subclass, and then, the collapse distribution was evaluated by using these subclasses of the conditioning factors.

Conditional probability is denoted mathematically as $P(A|B)$ (equation 1) (Negnevitsky 2002; Gokceoglu et al. 2005).

$$P(A|B) = \frac{\text{(the number of times } A \text{ and } B \text{ can occur)}}{\text{(the number of times } B \text{ can occur)}} \quad (1)$$

The number of times A and B can occur, or the probability that both A and B will occur, is also called ‘joint probability’ of A and B . It represents mathematically as $P(A \cap B)$. The number of ways B can occur is the probability of B , $P(B)$:

$$P(A|B) = P(A \cap B) / P(B) \quad (2)$$

$$P(B|A) = P(B \cap A) / P(A) \quad (3)$$

$$P(B \cap A) = P(B|A) \times P(A) \quad (4)$$

$$P(A \cap B) = P(B \cap A) \quad (5)$$

Bayesian rule is given in equation (6) and equation (7) can be written as event A being dependent on a number of mutually exclusive events $B_1, B_2, \dots, B_n$.

$$P(A|B) = [P(B|A) \times P(A)] / P(B) \quad (6)$$

By using equation (5), we can derive the following conditional probability equations for different thematic layer:

$$P(A \cap B_1) = P(A|B_1) \times P(B_1)$$

$$P(A \cap B_2) = P(A|B_2) \times P(B_2)$$

:

$$P(A \cap B_n) = P(A|B_n) \times P(B_n)$$

Then, we can combine the equations and write the final conditional probability equation for each mapping unit (equation 7).

$$P(A) = \sum_{i=1}^n P(A \cap B_i) = \sum_{i=1}^n P(A|B_i) * P(B_i) \quad (7)$$

The mapping unit in the present study is the grid cell. So, each spatial domain in study area corresponds to a unique grid cell in the present research. This means that every grid cells have their own information on ‘ n ’ conditioning factors. Obviously, as it can be clearly realized that each spatial domain contains only one subclass for each conditioning factor and each subclass has its own conditional probability value. Therefore, the total conditional probability for each spatial domain in the study area is the summation of ‘ n ’ conditional probability values on each grid cell.

Collapse susceptibility maps were then produced using equation (7) for study area (figure 12a). The $P(A|B)$, $P(A)$ and $P(B)$ values are tabulated in tables 1–4.

Figure 12. Collapse susceptibility maps produced from conditional probability CP (a), Logistic Regression – LR (b), artificial neural networks – ANN (c) models.

Table 1. Frequency ratio of geological factors to collapse occurrences and results of the $P(A/B_i)$ obtained from the Conditional Probability model.

Class	CA (%)	Grid (%)	FR	$P(A)$	$P(B_i)$	$P(A/B_i)$
Distance from faults						
0–250	31.54725	11.14442	0.001756	0.01422	0.433095	0.032834
250–500	25.24886	11.6166	0.005384	0.011381	0.451445	0.02521
500–750	15.90881	11.97382	0.007036	0.007171	0.465328	0.015411
750–1000	15.23289	12.25342	0.010251	0.006866	0.476194	0.014419
1000–1250	6.329114	10.69733	0.012751	0.002853	0.41572	0.006863
1250–1500	4.504117	9.04558	0.022483	0.00203	0.35153	0.005776
1500–1750	0.989308	7.607795	0.021906	0.000446	0.295655	0.001508
1750–2000	0.239646	6.766064	0.020009	0.000108	0.262943	0.000411
2000–2250	0	5.368904	0.005104	0	0.208647	0
2250–4663	0	13.52607	0.00021	0	0.525651	0

CA: collapse affected grid percent, Grid (%): grids in domain percent, FR: collapse affected grid (%) / grids (%).

Table 2. Frequency ratio of hydrological factors to collapse occurrences and results of the $P(A/B_i)$ obtained from the Conditional Probability model.

Class	CA (%)	Grid (%)	FR	$P(A)$	$P(B_i)$	$P(A/B_i)$
Distance from drainage						
0–250	1.149072	33.21288	0.034597	0.000518	1.290722	0.000401
250–500	14.97481	21.58124	0.693881	0.00675	0.838692	0.008048
500–750	18.85216	15.26092	1.235323	0.008498	0.593071	0.014328
750–1000	19.71857	11.34491	1.738098	0.008888	0.440887	0.02016
1000–1250	17.37741	8.261793	2.103346	0.007833	0.32107	0.024397
1250–1500	13.02077	5.43754	2.394607	0.005869	0.211314	0.027775
1500–1750	6.507312	2.420921	2.687949	0.002933	0.094082	0.031177
1750–2000	3.170702	1.053482	3.009734	0.001429	0.040941	0.03491
2000–2250	2.525501	0.762618	3.311618	0.001138	0.029637	0.038411
2250–2707	2.703699	0.663692	4.073727	0.001219	0.025792	0.047251
SPI						
0–0.5	84.08504	55.6469	1.511046	0.037902	2.162554	0.017527
0.5–1.0	11.97001	16.66371	0.718328	0.005396	0.647586	0.008332
1.0–1.5	2.292	12.53324	0.182874	0.001033	0.487068	0.002121
1.5–2.0	1.118348	7.723755	0.144793	0.000504	0.300161	0.001679
2.0–2.5	0.4117	4.227471	0.097387	0.000186	0.164288	0.00113
2.5–3.0	0.092172	1.865421	0.049411	4.15E-05	0.072494	0.000573
3.0–3.5	0.030724	0.747508	0.041102	1.38E-05	0.02905	0.000477
3.5–4.0	0	0.323578	0	0	0.012575	0
4.0–4.5	0	0.161789	0	0	0.006287	0
4.5–5.853	0	0.106624	0	0	0.004144	0
TWI						
0.53–1.5	0	0.007056	0	0	0.000274	0
1.5–3.0	0	0.031004	0	0	0.001205	0
3.0–4.5	0	0.227859	0	0	0.008855	0
4.5–6.0	0.030724	0.77281	0.039756	1.38E-05	0.030033	0.000461
6.0–7.5	0.184343	0.948498	0.194353	8.31E-05	0.036861	0.002254
7.5–9.0	0.755807	3.818009	0.197958	0.000341	0.148376	0.002296
9.0–10.5	3.133833	7.243092	0.432665	0.001413	0.281482	0.005018
10.5–12	31.94052	31.86547	1.002355	0.014397	1.238359	0.011626
12–13.5	29.63623	29.04271	1.020436	0.013359	1.12866	0.011836
13.5–13.6	34.31854	26.04349	1.31774	0.015469	1.012104	0.015284

CA: collapse affected grid percent, Grid (%): grids in domain percent, FR: collapse affected grid (%) / grids (%).

Table 3. Frequency ratio of topographical factors to collapse occurrences and results of the $P(A/B_i)$ obtained from the Conditional Probability model.

Class	CA (%)	Grid (%)	FR	$P(A)$	$P(B_i)$	$P(A/B_i)$
Slope gradient						
0–3	71.92454	46.53433	1.545623	0.032421	1.808421	0.017928
3–6	16.49871	12.88739	1.280221	0.007437	0.500831	0.014849
6–9	6.175495	9.894438	0.624138	0.002784	0.384518	0.007239
9–12	2.654541	8.672396	0.306091	0.001197	0.337027	0.00355
12–15	1.093769	7.022075	0.155762	0.000493	0.272892	0.001807
15–18	0.700504	5.164138	0.135648	0.000316	0.200689	0.001573
18–21	0.522306	3.712241	0.140698	0.000235	0.144265	0.001632
21–24	0.282659	2.559832	0.110421	0.000127	0.09948	0.001281
24–27	0.061448	1.6072	0.038233	2.77E-05	0.062459	0.000443
27–58.5	0.086027	1.94596	0.044208	3.88E-05	0.075624	0.000513
Slope aspect						
Flat	48.01524	22.43295	2.140389	0.021643	0.871791	0.024826
N	0.995453	4.265246	0.233387	0.000448	0.165756	0.002707
NE	5.272213	11.78929	0.447203	0.002376	0.458157	0.005187
E	10.82709	9.83015	1.101416	0.00488	0.38202	0.012775
SE	11.7488	11.468	1.024486	0.00529	0.44567	0.011883
S	8.074229	10.14361	0.795992	0.003639	0.394202	0.009233
SW	8.621113	10.50731	0.820487	0.003886	0.408336	0.009517
W	2.310434	8.060875	0.286623	0.001041	0.313262	0.003325
NW	2.875753	7.434744	0.386799	0.001296	0.28893	0.004486
N	1.259678	4.06782	0.309669	0.000567	0.158084	0.003592
Topographical elevation						
1270–1300	5.198476	34.38717	0.151175	0.002343	1.336357	0.001753
1300–1350	12.8057	19.94596	0.64202	0.005772	0.775142	0.007447
1350–1400	8.240138	8.741031	0.942696	0.003714	0.339695	0.010934
1400–1450	12.29569	9.258899	1.327986	0.005542	0.35982	0.015403
1450–1500	37.00381	12.00461	3.082467	0.01668	0.466524	0.035753
1500–1550	14.64299	7.9581	1.840011	0.0066	0.309268	0.021342
1550–1600	9.708738	6.421032	1.512021	0.004376	0.249535	0.017538
1600–1650	0.104461	0.751714	0.138964	4.71E-05	0.029213	0.001612
1650–1700	0	0.387154	0	0	0.015046	0
1700–1730	0	0.144327	0	0	0.005609	0

CA: collapse affected grid percent, Grid (%): grids in domain percent, FR: collapse affected grid (%) / grids (%).

The values of collapse susceptibility were classified using equal areas. The proportions are sorted from the smallest to the largest. This range of values is broken into five groups to represent the relative susceptibility in the study area.

3.2.2 Multivariate model – logistic regression

As it is well known, the logistic regression technique is a kind of multivariate statistical analysis, and due to its stepwise multivariate analysis nature, the multicollinearity is completely eliminated. On the other hand, the conditional probability approach usually suffers from multicollinearity problems. For this reason, more attention should be paid during the selection of appropriate conditioning factors for the relevant-dependent hazard.

Obviously, when applying such type of bivariate analyses, the expert opinions are more crucial and dominant.

Multiple regression analysis is the most common statistical method used in earth sciences, and expressed as a linear equation below.

$$Y = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n \quad (8)$$

where Y is the dependent variable representing the presence (1) or absence (0), b_0 the intercept of model, $b_1, \dots, b_n$ the partial regression coefficients, $x_1, \dots, x_n$ the independent variables.

As stated by Lee and Sambath (2006) logistic regression, which is a multivariate analysis model, is useful for predicting the presence or absence of a characteristic or outcome based on values of a set of predictor variables. Additionally, Yesilnacar

Table 4. Frequency ratio of land-use and vegetation cover factors to collapse occurrences and results of the $P(A/B_i)$ obtained from the Conditional Probability model.

Class	CA (%)	Grid (%)	FR	$P(A)$	$P(B_i)$	$P(A/B_i)$
Distance from roads						
0–300	21.82623	12.60865	1.731052	0.009838	0.489998	0.020078
300–600	22.26865	11.22047	1.984645	0.010038	0.436051	0.02302
600–900	20.69559	10.37025	1.995668	0.009329	0.40301	0.023148
900–1200	9.721027	9.588963	1.013773	0.004382	0.372647	0.011759
1200–1500	9.807054	9.169024	1.069585	0.004421	0.356327	0.012406
1500–1800	8.430626	8.296931	1.016114	0.0038	0.322436	0.011786
1800–2100	4.608578	7.461899	0.617615	0.002077	0.289985	0.007164
2100–2400	0.54074	5.274325	0.102523	0.000244	0.204971	0.001189
2400–2700	0.362541	4.548412	0.079707	0.000163	0.176761	0.000925
2700–6624	1.73897	21.46108	0.081029	0.000784	0.834022	0.00094
Distance from settlements						
0–500	8.84847	4.231177	2.091255	0.003989	0.164432	0.024256
500–1000	14.78432	11.44056	1.292273	0.006664	0.444604	0.014989
1000–1500	21.18717	14.75396	1.436033	0.00955	0.573369	0.016656
1500–2000	14.686	14.87676	0.987178	0.00662	0.578142	0.01145
2000–2500	13.51235	15.57937	0.867324	0.006091	0.605447	0.01006
2500–3000	13.89333	15.95569	0.870745	0.006263	0.620071	0.0101
3000–3500	8.774733	10.94243	0.8019	0.003955	0.425246	0.009301
3500–4000	3.232149	7.370599	0.438519	0.001457	0.286437	0.005086
4000–4500	1.08148	4.128331	0.261965	0.000487	0.160436	0.003039
4500–4874	0	0.721138	0	0	0.028025	0
NDVI						
–0.9–0.1	62.64594	44.69421	1.401657	0.028238	1.73691	0.016258
0.1–0.3	25.15669	31.81309	0.790766	0.01134	1.236323	0.009172
0.3–0.6	12.14207	23.35152	0.519969	0.005473	0.907488	0.006031
0.6–0.83	0.055303	0.141191	0.391688	2.49E-05	0.005487	0.004543

CA: collapse affected grid percent, Grid (%): grids in domain percent, FR: collapse affected grid (%) / grids (%).

and Topal (2005) mentioned that the key to logistic regression is that the dependent variable is dichotomous. The independent variables in this model are predictors of the dependent variable and can be measured on a nominal, ordinal, interval or ratio scale. The datasets, in vector format, were converted into raster format. The conversion of parameters from nominal to numeric can be done through the creation of dummy variables or by coding and ranking the classes based on the relative percentage of the area affected by occurrence. The two methods are similar but the latter is to be preferred for two reasons: (i) it avoids the creation of an excessively high number of dummy variables and (ii) allows consideration of the so-called ‘previous knowledge’ of susceptibility (Carrara 1983; Yesilnacar and Topal 2005). In this study, each class in the geology map was ranked based on the latter technique.

At the beginning of the analysis, a map showing the area affected by collapse and factor maps in raster format were converted into ASCII format. Statistical software (SPSS 10.0) was then used to

estimate the correlation between collapse event and collapse affecting factors. An equation predicting the collapse occurrence was obtained as following

$$\begin{aligned}
 Y = & 8.112 + (ASPECT^{(*)}) + (-0.0483*FAULT) \\
 & + (0.0396*DRAIN) + (-0.0401*SLOPE) \\
 & + (-0.0331*SPI) + (0.0296*TWI) \\
 & + (-0.0302*ROAD) + (-0.0291*SETTL) \\
 & + (-0.0013241*NDVI) + (-0.0091*ELEV)
 \end{aligned}
 \quad (9)$$

(*)logistic regression coefficients of categorical data of ‘ASPECT’ can be seen in table 5.

In order to calculate the probability of collapse occurrence in each grid cell, the following equation was implemented (equation 10).

$$p = \frac{1}{1 + e^{-Y}}. \quad (10)$$

Finally, susceptibility map was obtained by converting the file into the raster format (figure 12b).

Table 5. Logistic regression coefficients of categorical data.

Category	Coefficient
Slope aspect	
Flat	0.017124
N	-0.000122
NE	0.000411
E	0.009163
SE	0.007231
S	0.000631
SW	0.000742
W	-0.000112
NW	-0.000103
N	-0.000237

3.2.3 Soft computing model – artificial neural networks

Soft computing techniques have the ability to handle imprecise and fuzzy data; they can work with continuous, categorical and binary data without violating any assumptions. As assessment of probability for collapse is performed through the forecast of future events from experience of past collapses, it may be considered an ideal application for soft computing techniques.

As mentioned previously, ANNs is one of the most applied soft computing techniques in recent scientific literature (Negnevitsky 2002; Nefeslioglu et al. 2008; Ramakrishanan et al. 2008). ANNs consist of a large class of different architectures. In many cases, the issue is approximating a static nonlinear, mapping $f(\mathbf{x})$ with a neural network $f(\mathbf{x})_{NN}$, where $\mathbf{x} \in \mathbf{R}^K$. There are many kinds of ANN models, among which the back propagation (BP) model is the most widely used, and it is

an instructive training model. It is accepted that the most useful neural networks in prediction and decision algorithm are BP and radial basis function (RBF) networks. In this paper, BP algorithm, created by generalizing the Widrow–Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer function, is used. A back propagation consists of an input layer, several hidden layers, and output layers. All of those layers may contain multiple nodes (Yılmaz and Yüksek 2008, 2009).

The inputs x_n , $n = 1, \dots, n$, to the neuron are multiplied by weights w_{ni} and summed up together with the constant bias term Q_i . The resulting n_i is the input to the activation function y . The activation function was originally chosen to be a relay function, but for mathematical convenience a hyperbolic tangent ($\tan h$) or a sigmoid function is most commonly used. Connecting several nodes in parallel and series, an MLP network is formed. A typical network is shown in figure 13.

MatLab 7.0 was used for training and testing for the neural networks. A three-layer feed-forward network that consists of an input layer (10 neurons), one hidden layer (21 neurons) and one output layer was used as a network structure of 10-21-1 (figure 13). In order to find the number of hidden layer nodes, equation (11) proposed by Hecht-Nielsen (1987) was used.

$$N_h = 2 * N_i + 1 \quad (11)$$

where N_i is the number of input nodes and N_h is the number of hidden nodes.

Initial weight range is also an important parameter influencing the convergence of learning rule. In this study, weights were randomly initialized in a small range of -0.25 to 0.25 as proposed by

Figure 13. Neural network structure used in the study.

Kavzoglu (2001). Kavzoglu (2001) has also suggested that the minimum number of training samples should be more than $30 * N_i^* (N_i + 1)$ where N_i is the number of input nodes. Learning and momentum parameters were set as follows as proposed by Foody *et al.* (1996). Almost 18,000 pixels were randomly selected from the two classes (collapse and non-collapse) as training samples, and parameters were then adjusted as below.

Learning parameters: 0.1.

Momentum parameters: 0.9.

Networks training function: variable learning rate with momentum (traingdx).

Activation (transfer) function for all layers: tansig.

Moreover, training areas were checked in the field for accuracy and completeness. As in many other network training methods, models and parameters were used to be able to reach minimum Root Mean Square Error (RMSE) values. RMSE goal for stopping criterion was set to 0.1. After the network goal was reached, the whole study area was fed into the network in order to estimate the collapse susceptibility. The set of susceptibility values obtained in each grid cell were then converted to raster file in GIS environment, and collapse susceptibility map was produced (figure 12c).

3.3 Validation of the models

The collapse susceptibility maps can be tested using the known collapse locations. Validation was performed by comparing the known collapse location data, which were not included in the susceptibility

analyses, with the susceptibility map obtained. The area under curve (AUC) is a good indicator to evaluate the prediction performance of the model, and the largest AUC, varying from 0.5 to 1.0, is the most ideal model (Swets 1988; Yesilnacar and Topal 2005). By the use of 100 subdivisions of CSI values of all cells in the study area and cumulative percentage of collapse occurrence in the classes, curves were drawn to calculate AUC (figure 14). Additionally, in order to evaluate the receiver operating characteristic (ROC) curve for the conditional probability results, the resultant probabilities were stretched between 0 and 1. The obtained values of AUC from the four mapping models are given in figure 14. Although ANN is the most accurate method, the results for all three used methodologies do not show significant difference; i.e., all three approaches lead to very similar results and, therefore, can be used in collapse susceptibility mapping. Moreover, validation by field investigations was also performed by comparing the known collapse location data with the classes of collapse susceptibility in maps. The results obtained from field observation were also found to be harmonious with results of AUC.

4. Results and discussion

The use of bivariate, multivariate and soft computing methods such as conditional probability (CP), logistic regression (LR) and artificial neural networks (ANN) models in GIS based collapse susceptibility mapping in an area from Sivas basin (Turkey) was compared and discussed in this article. Collapse-related factors, directly or indirectly related to the causes of collapse occurrence, such as distance from faults, slope angle and aspect, topographical elevation, distance from drainage, topographic wetness index (TWI), stream power index (SPI), normalized difference vegetation index (NDVI) by means of vegetation cover, distance from roads and settlements, were used in susceptibility analyses, and the following results were obtained.

Figure 14. Area under curve (AUC) representing the quality of the models used.

- Analyses of distance from lineaments (figure 4b) showed that frequency ratios greater than 1 were obtained at a distance lower than 1000 m, indicating a high probability of collapse occurrence (figure 8; table 1). It can be seen that as the distance from faults decreases, the number of collapses increase, because the weathering and fracturing of rocks increase with increasing proximity to the lineament.
- Frequency ratios of distance to drainage (figure 5a) indicated a low collapse probability at a distance lower than 500 m (figure 9a; table 2).

This can be explained as the first 500 m refers to the river bed where the occurrence of very deep erosion in gypsum did not allow the development of any karstic structure.

- As a measure of erosive power of the overland flow, frequency ratio values were found to be greater than 1 in areas having a lower SPI values (figure 5b) than 0.50 (figure 9b; table 2). The parameter SPI is a measure of the erosional power of water related with the channel geometry. Therefore, the geomorphic features derived from gypsum karst, as could be clearly understood, could be suppressing due to the possible high erosion rates sourced from high stream power.
- The higher probabilities of collapse occurrence were found in cells having the higher TWI value (figure 5c) which is a measure of moisture (figure 9c; table 2).
- It has been observed that most of the recorded collapses occurred in areas with a slope less than 6°. Surficial cover materials are generally removed by the surface water flows where the slopes are steep. As seen in table 3, showing the distribution of collapses in relation to slope, it can be concluded that the slope factor has an inverse effect on the development of collapse (figure 10a).
- In the case of the relationship between collapse occurrence and aspect (figure 6b), collapses were most abundant on east-facing and flat areas (figure 10b; table 3) depending on the regional/local groundwater flow regime.
- Topographical elevation map (figure 6c) showed that collapses occur in areas with an elevation between 1350 and 1600 m as seen in figure 10(c). Table 3 shows the relationships between collapse occurrence and topographical elevation. It may be concluded that the dolines occur in relatively flat areas, because the hilly and mountainous areas generally have high slope angles.
- Analyses were carried out to assess the influence of road lines on collapse occurrence. For this purpose, the proximity to road lines was identified by buffering (figure 7a). For distances lower than ~1000 m, frequency ratio values higher than 1 were obtained (table 4), indicating the high collapse occurrence probability (figure 11a). This result means that the collapse occurrence probability increases with decreasing proximity to the roads. The main road crossing the study area from SW to NE is especially important for transportation from the west of Turkey to the east. It can be thought that vibrations sourced from high load of traffic may be triggering the collapse event in very young doline locations.
- In order to analyse the influence of the proximity to the settlement area, a buffering method

was used (figure 7b). In the case of the relationship between collapse occurrence and distance from settlement, it was seen that as the distance increases, collapse frequency decreases (figure 11b; table 4). At a distance lower than ~1500 m, frequency ratio was higher than 1, indicating a high probability of collapse occurrence. This can be attributed to the human use effect such as stresses induced by foundation loadings and live loadings, human-made sources of water, lowering of the groundwater by dewatering and vibrations from adjacent site activities. This parameter was found as affecting factor in collapse event in very young doline locations, particularly.

- NDVI is a measure of surface reflectance and gives a quantitative estimate of the vegetation growth and biomass (Hall *et al.* 1995). Satellite maps of vegetation show the density of plant growth over the entire globe. Very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand or snow. Moderate values represent shrub and grassland (0.2 to 0.3), while high values indicate temperate and tropical rainforests (0.6 to 0.8) (Weier and Herring 2005). Using the satellite image of Landsat Thematic Mapper (TM), the NDVI was taken into consideration as a collapse-related factor (figure 7c). The relationship between collapse occurrence and NDVI can be seen in table 4. The results show that collapse probability increases with decreasing of NDVI. It was observed that the collapses were focused in rocky barren areas with an NDVI value smaller than 1 (figure 11c).

The results of this study showed that the map obtained from ANN model look like having a better accuracy than the conventional statistical methods, however all the models were found having relatively similar accuracies. The main problem in the use of ANN and LR is time-consuming input process, calculations and output process. Because they require conversion of data used in analyses into ASCII or other formats, and it is also very hard to process the large amount of data in statistical software. As stated by Yılmaz (2008a, 2008b) “It should not be forgotten that ‘*simple is the best*’ in engineering applications”, that’s why the Conditional Probability Model can be used as an essential tool in the assessment of collapse susceptibility and the preparation of maps. Moreover, ANNs are one of a large array of black-box prediction methods. The main disadvantage of black-box methods is that the causal relationships can not be seen, whereas regression methods allow quantification of the importance of the factors. This paper has also an extra value with its comparative nature, because the use of conventional (conditional probability, logistic regression) and soft computing (ANN) in

collapse susceptibility mapping were compared for the first time.

Preparation of collapse susceptibility maps will help the planners and engineers for choosing suitable locations to implement developments. These results can be used as basic data to assist land-use planning, but the methods used are valid for generalized planning and assessment purposes, although they may be less useful at the site-specific scale.

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