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A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey

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ABSTRACT

Over the last few decades, many researchers have produced landslide susceptibility maps using different techniques including the probability method (frequency ratio), the analytical hierarchy process (AHP), bivariate, multivariate, logistics regression, fuzzy logic and artificial neural network In addition, a number of parameters such as lithology, slope, aspect, land cover, elevation, distance to stream, drainage density, distance to lineament, seismicity, and distance to road are recommended to analyze the mechanism of landslides. The data quality is a very important issue in landslide studies, and more accurate results will be achieved if the data is adequate, appropriate and drawn from a wide range of parameters. The aim of this study was to evaluate the susceptibility of the occurrence of landslides in Trabzon province, situated in north east Turkey. This was achieved using the following five methods the frequency ratio model, AHP, the statistical index (*Wi*), weighting factor (*Wf*) methods, and the logistics regression model, incorporating a Geographical Information System (GIS) and remote sensing techniques. In Trabzon province there has been an increasing occurrence of landslides triggered by rainfall. These landslides have resulted in death, significant injury, damage to property and local infrastructure and threat of further landslides continues. In order to reduce the effects of this phenomenon, it is necessary to scientifically assess the area susceptible to landslide. To achieve this, landslide susceptible areas were mapped the landslide occurrence parameters were analyzed using five different methods. The results of the five analyses were confirmed using the landslide activity map containing 50 active landslide zones. Then the methods giving more accurate results were determined. The validation process showed that the *Wf* method is better in prediction than the frequency ratio model, AHP, the statistical index (Wi), and logistics regression model.

1. Introduction

Landslides are amongst the most damaging natural hazards in mountainous regions. Every year, hundreds of people all over the world lose their lives in landslides; furthermore there are large impacts on the local and global economy from these events. Over the past 25 years, many government and international research institutions across the world have invested considerable resources in assessing landslide susceptibilities and in attempting to produce maps portraying their spatial distribution (Guzzetti et al., 1999). In Turkey, landslides are the second most common natural hazard after earthquakes (Ildir, 1995) and the Eastern Black Sea region is especially affected. This region exhibits mountainous topographical features, and is frequently subjected to heavy precipitation. This combination results in the region being prone to extensive and severe landslides. In Turkey, during the last 50 years, natural hazards caused losses related to housing amounting to an estimated US$15.5 billion. The annual economic loses emanating from landslides are about US $80 million, and the majority of the losses are in the Eastern Black Sea region (Yalcin, 2007). A number of different methods for landslide susceptibility mapping have been utilized and suggested. The process of creating these maps involves several qualitative or quantitative approaches. Early attempts defined susceptibility classes by the qualitative overlaying of geological and morphological slope-attributes to landslide inventories (Nielsen et al., 1979). More sophisticated assessments involved, for example, AHP, bivariate, multivariate, logistics regression, fuzzy logic and artificial neural network analysis (Carrara, 1983; van Westen, 1997; Lee and Min, 2001; Ercanoglu and Gokceoglu, 2004; Lee et al., 2004; Komac, 2006; Yalcin, 2008).

Landslide susceptibility mapping may be defined as qualitative or quantitative, and direct or indirect (Guzzetti et al., 1999). Qualitative methods are subjective; they represent the susceptible levels in

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descriptive expressions, and depend on expert opinions. The most common types of qualitative methods basically use landslide inventories to recognize sites of comparable geological and geomorphologic characteristics that are susceptible to failure. However, weights of the parameters are determined from the knowledge of specialists on the subject and the area. The designating weights are thus, highly personal and may be include some virtual admission. Quantitative methods are based on numerical expressions of the relationship between controlling factors and the landslides. There are two types of quantitative methods: deterministic and statistical (Aleotti and Chowdhury, 1999). Deterministic methods are based on slope stability studies, expressed in terms of the safety factor (Refice and Capolongo, 2002; Zhou et al., 2003). The statistical approaches analyze the historical link between landslide-controlling factors and the distribution of landslides. Quantitative methods may be used to decrease the personality and bias in the weight assessment process. Therefore, more realistic susceptibility maps can be produced from an objective measure of values. During the past few years, quantitative methods have been implemented for landslide susceptibility zonation studies in different regions (Clerici et al., 2002; Suzen and Doyuran, 2004; Ercanoglu and Gokceoglu, 2004; Yesilnacar and Topal, 2005; Kanungo et al., 2006; Yalcin and Bulut;, 2007; García-Rodríguez et al., 2008; Nefeslioglu et al., 2008; etc.).

The aim of this study was to use widely-accepted models, a statistical method (frequency ratio model), a multi-criteria decision making approach (AHP), bivariate, and multivariate approaches (logistic regression) and evaluate their performances.

Frequency ratio model is based on the observed associations between allocation of landslides and each associated factors of landslide occurrence to display the correlation between landslide locations and the parameters controlling landslide occurrence in the area (Lee, 2005). Therefore, the method gives very good results for determining the landslide inventory with rigorous accuracy. The weights of the parameters and the decision alternatives used in producing landslide susceptibility map are determined with the AHP. When these weights are determined, both the comparison of the parameters relative to each other, and determination of the effect values of the decision alternatives, namely the sub-criteria, are based on a landslide inventory map obtained with the help of aerial photos and satellite images. As a result of dual comparisons, a pair-wise comparison matrix is obtained for each parameter and sub-criteria. Consequently, the weight values were determined correctly for the real land data. It has been shown that the use of the AHP method produces a practical and realistic result to define the factor weights in the landslide susceptibility model. In statistical models, using bivariate or multivariate techniques for landslide susceptibility analysis, is widespread (Nandi and Shakoor, 2009). There are a number of ways to apply bivariate and multivariate statistics to assess landslide susceptibility of a region. More than a few instability parameter variables are used in the present bivariate approach; the influence of each variable on the occurrence of landslide is evaluated independently and the variables are combined in the form of a unique equation (Conoscenti et al., 2008; Nandi and Shakoor, 2009). In multivariate approaches, logistic regression was detected to be the most appropriate approach for the present study. In this analysis, spatial distribution of landslides is assessed on the basis of interaction of only statistically significant instability factor data; insignificant data are excluded from consideration. Additionally, logistic regression analysis is free of data distribution issues and can handle a variety of datasets, such as continuous, categorical, and binary, common types of instability factor data used in landslide studies (Dai et al., 2001; Lee and Min, 2001; Lee and Sambath, 2006; Akgun et al., 2008; Nandi and Shakoor, 2009). Any effort to make certain landslide susceptibility in a region needs proper validation. Confirmation should establish the quality (i.e., consistency, robustness, degree of fitting and prediction skill) of the proposed susceptibility estimate. The excellence of a landslide susceptibility model can be ascertained using the same landslide data used to obtain the susceptibility estimate, or by using independent landslide information not available to construct the model (Chung and Fabbri, 2003; Guzzetti et al., 2005; 2006). In this paper, we provide a comprehensive validation of a landslide susceptibility model prepared through five different methods for the Trabzon City (Fig. 1).

2. Description of the study area

The study area, in Trabzon province, consisted of approximately 4660 km^2 located between 39° 15′ and 40° 15′ west–east longitudes and 41° 8′ and 40° 30′ north–south latitudes in the middle of Eastern Black Sea region (Fig. 1). Altitudes reach 3400 m in parts of the region and steep slopes are very common. The climate is characteristic of the Black Sea region, with temperate climate summers and a rainy season normally lasting from September to April. Nevertheless, the rainfall regime is irregular, with some periods of rare precipitation with long-lasting heavy rains. Very intense precipitation has caused disastrous flash floods in river basins and many landslides on slopes (Reis and Yomralioglu, 2006; Yalcin, 2008). According to observations result 22 yearly in Trabzon province, February is the coldest month with an average temperature of 6.7 °C, the hottest month is August with an temperature average of 23.2 °C. The annual precipitation of Trabzon city is 838 mm, and precipitations disperse every month symmetrical. The main commercial agricultural products in the region are hazelnuts and green tea. Apart from the agricultural areas, the other main land cover types are forest and pasture. The population of the province was 740,569 in 2007 year (TUIK, 2008).

3. Thematic data layers

The study began with the preparation of a landslide inventory map based on extensive field work, a previous inventory map, and satellite images. Furthermore, the following seven possible landslide causing layers; lithology, slope, aspect, land cover, elevation, distance to stream, and distance to road were analyzed for landslide susceptibility mapping using the logistic probability method (frequency ratio method — FRM), the analytical hierarchy process (AHP), bivariate (*Wi* and *Wf*), and logistics regression (LR) methods. Finally, the susceptibility maps produced from the five different methods were compared and evaluated using validation data sets.

3.1. Landslide inventory map

The maps show the locations and properties of landslides that have moved in the past. These slope failures were related to geological, topographical, and climatic conditions, thus, they can often facilitate the prediction of locations and conditions of future landslides. For this reason, it is important to determine the location and area of the landslide accurately when preparing the landslide susceptibility maps. Landslide susceptibility assessment is performed in a range of phases. The initial phase is identifying and evaluating landslide-prone areas, and constructing a landslide inventory map for future use. Landslide inventory mapping is the systematic mapping of existing landslides in a region using different techniques such as field survey, air photo/satellite image interpretation, and literature search for historical landslide records. A landslide inventory map provides the spatial distribution of locations of existing landslides. The landslides in the study area were determined by comprehensive field surveys. The landslides which are currently indefinite in characteristics and boundaries were identified using old dated satellite images. As a result, the satellite images were very useful in determination of landslides inventory map (Yalcin and Bulut, 2007). In this study, the susceptibility mapping started with the preparation of an inventory map of 250 landslides from field studies, a previous inventory map,

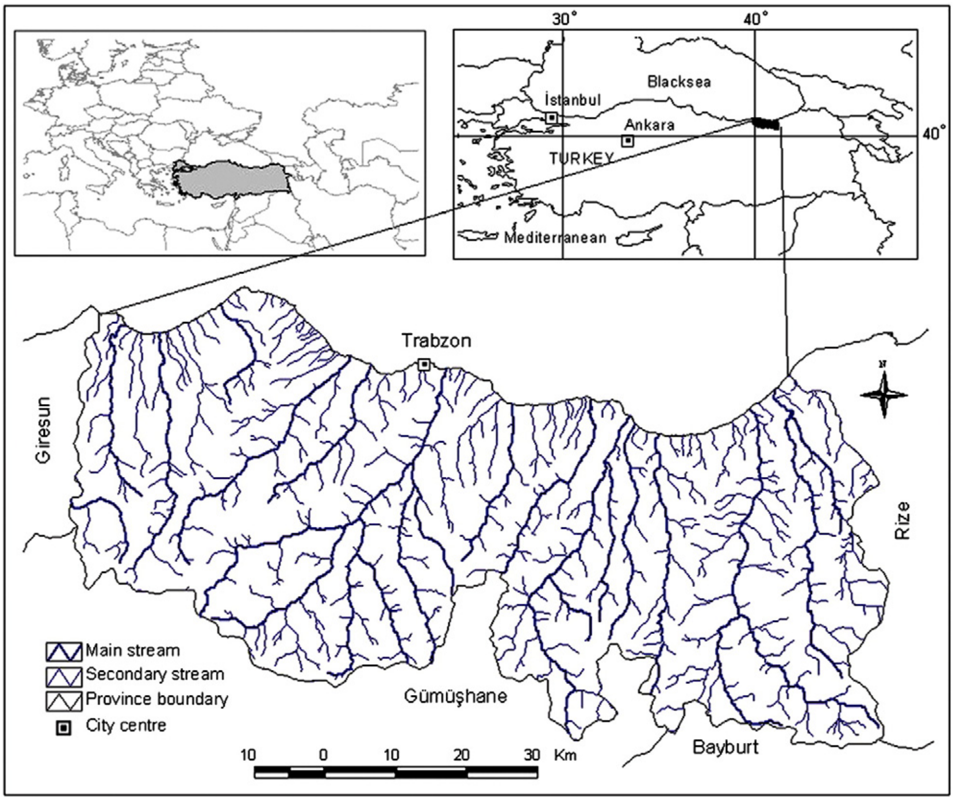

Fig. 1. Location map of the study area.

and satellite image analyses from Quickbird (Fig. 2). Also, to confirm the practicality of producing five susceptibility maps, 50 active landslides zones were determined separately from the inventory map. In the Trabzon region the rough topography, susceptible weathering units and the temperate climate means that many new landslides appear from time to time, as a result of heavy rainfalls. High

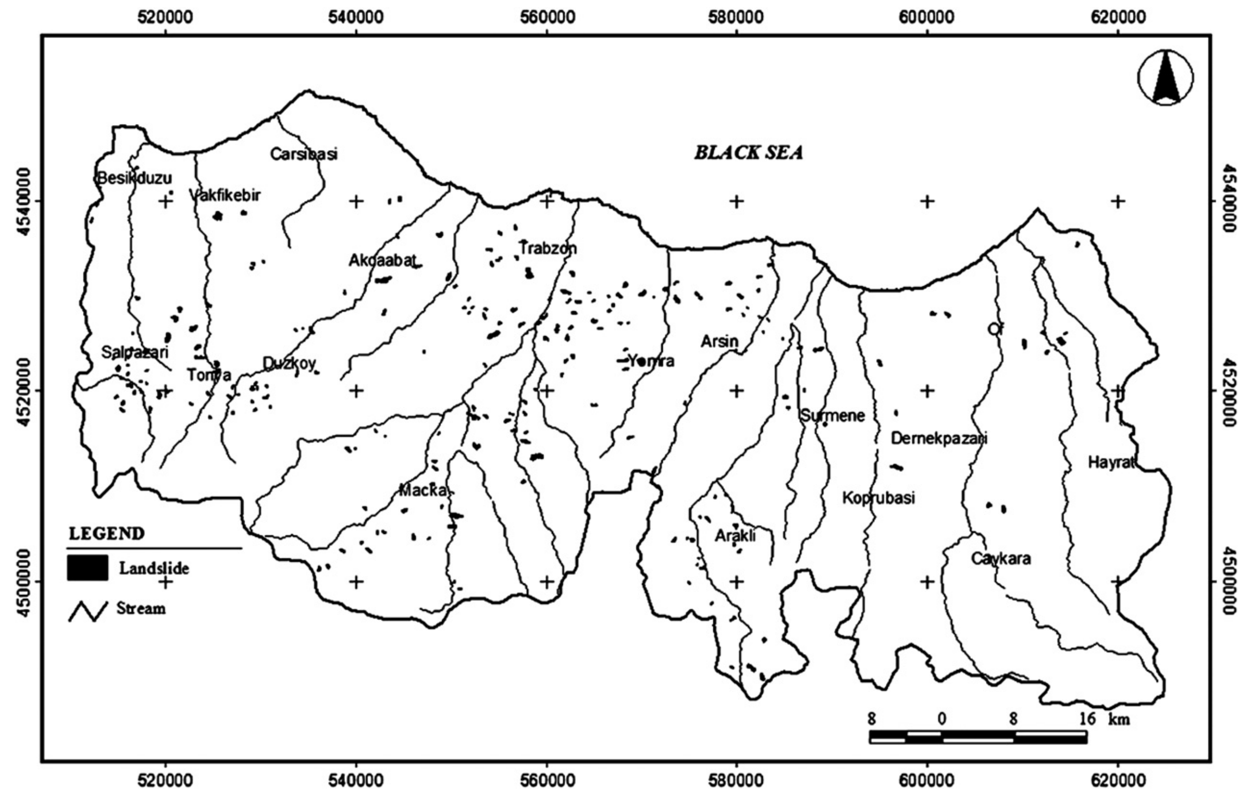

Fig. 2. Landslide inventory map.

intensity rainfalls produce flash floods which cause shallow landslides. So, the landslides in this region show shallow translational characteristics. The field surveys and drilling data with previous studies were used to determine the depth of the weathering zones in rocks and the groundwater table. The weathering zone has reached to maximum approximately 20 m. However, the groundwater table wasn't observed 30 m depth and thus there were no landslides with deeper slip surfaces.

3.2. Lithology map

Lithology is one of the most important parameters in landslide studies because different lithological units have different susceptibility degrees (Dai et al., 2001; Yesilnacar and Topal, 2005; Yalcin and Bulut;, 2007; Garcia-Rodriguez et al., 2008; Nefeslioglu et al., 2008). The landslide event, a component of the geomorphological research, is related to the lithological characteristics of the land. It is extensively accepted that lithology significantly influences the occurrence of landslides, because lithological variations often lead to a difference in the strength and permeability of rocks and soils. The lithology maps of the study area were differentiated into eight lithological units. As a result of the aerial distributions analysis performed according to the lithological units, most landslides (25.62%) are located within basalt, andesite, pyroclastics, and intercalations of mudstone, sandstone and tuffs (Table 1).

3.3. Slope map

The major parameter of slope stability analysis is the slope angle (Lee and Min, 2001). Slope angle is very regularly used in landslide susceptibility studies since landsliding is directly related to slope angle (Dai et al., 2001; Cevik and Topal, 2003; Lee, 2005; Yalcin, 2008; Nefeslioglu et al., 2008). The slope map of the study area was divided into five slope categories. ArcGIS 9.2 analysis was performed to discover in which slope group the landslide happened and the rate of occurrence was observed. The landslide percentage in each slope group class is determined as a percentage of slopes. The result indicates that most of landslides (49.26%) occur when the percentage of the slope more than 50% (Table 1).

3.4. Aspect

Aspect is also considered an important factor in preparing landslide susceptibility maps (Cevik and Topal, 2003; Lee, 2005; Yalcin and Bulut, 2007; Galli et al., 2008). Aspect associated parameters such as exposure to sunlight, drying winds, rainfall (degree of saturation), and discontinuities may affect the occurrence of landslides (Suzen and Doyuran, 2004; Komac, 2006). The association between aspect and landslide is shown with aspect maps. Aspect regions are classified in nine categories according to the aspect class as; flat (−1°), north (0°–22.5°; 337.5°–360°), northeast (22.5°–67.5°), east (67.5°–112.5°), southeast (112.5°–157.5°), south (157.5°–202.5°), southwest (202.5°–247.5°), west (247.5°–292.5°), and northwest (292.5°–337.5°). Analyses were performed using aspect and landslide inventory maps to determine the distribution of landslides, according to the aspect class, and the percentage of landslides that occurred in each aspect class (Table 1).

3.5. Elevation

Elevation is useful to classify the local relief and locate points of maximum and minimum heights within terrains. To calculate landslide densities for different relief classes, the relief map was divided into seven altitude classes on 500-m basis and the study area reveals that the elevation ranges from 0 to 3,500 m above mean sea level. However, landslides below 1500 m are dominant (89.28%) due to the lithological character of the units that have pyroclastic compositions.

Table 1
Frequency ratio values of the landslide-conditioning parameters.

Parameter	Classes	% of total area (a)	% of landslide area (b)	Frequency ratio (b/a)
Geology[a]	Alv	3.86	1.54	0.40
	Pl	2.39	2.23	0.94
	Ev	36.63	13.17	0.36
	Kru	54.65	80.02	1.46
	Jkr	0.11	0.00	0.00
	Jlh	0.67	0.00	0.00
	γ_2	1.63	3.04	1.87
	Kk	0.07	0.00	0.00
Slope (%)	0–10	13.72	2.41	0.18
	10–20	6.94	5.71	0.82
	20–30	11.07	11.79	1.07
	30–50	26.82	30.83	1.15
	>50	41.45	49.26	1.19
Aspect	Flat	10.55	0.72	0.07
	North	12.39	8.74	0.71
	Northeast	12.90	12.65	0.98
	East	11.86	17.14	1.45
	Southeast	9.24	11.17	1.21
	South	8.68	8.49	0.98
	Southwest	10.54	11.46	1.09
	West	11.73	16.36	1.40
	Northwest	12.12	13.27	1.10
Elevation (m)	0–500	23.77	25.33	1.07
	500–1000	22.23	29.67	1.33
	1000–1500	19.85	34.28	1.73
	1500–2000	17.69	6.36	0.36
	2000–2500	13.96	4.35	0.31
	2500–3000	2.33	0.00	0.00
	3000–3500	0.17	0.00	0.00
Land cover	Tea	1.09	1.69	1.56
	Hazelnut	15.39	23.15	1.50
	Deciduous	37.99	42.85	1.13
	Coniferous	2.31	1.65	0.72
	Mix wood	5.17	4.77	0.92
	Rocky	1.14	1.02	0.89
	Pasture	18.61	8.03	0.43
	Agriculture	17.14	16.48	0.96
	Settlement	1.16	0.35	0.30
The distance to stream (m)	0–25	29.20	28.21	0.97
	25–50	10.68	9.62	0.90
	50–75	19.71	20.37	1.03
	75–100	11.26	11.28	1.00
	100–150	9.17	9.80	1.07
	150–200	9.75	10.38	1.06
	200–250	10.23	10.33	1.01
The distance to road (m)	0–25	19.89	21.09	1.06
	25–50	20.01	20.20	1.01
	50–75	20.07	19.52	0.97
	75–100	20.04	19.46	0.97
	100–125	19.98	19.72	0.99

[a] Alv—Alluvium, Pl—Pliocene, continental units, Ev—Eocene, volcanic facies, Kru—Basalt, andesite, pyroclastics, and intercalations of sandstone clayey limestone and siltstone, Jkr—Jurassic–Cretaceous units, Jlh—Lias units, γ_2—Kaçkar granites, Kk—Carboniferous units.

3.6. Land cover

The effect of land cover on slope stability can be clarified by an amount of hydrological and mechanical effects. Land cover acts as a shelter and reduces the susceptibility of soil erosion, landslides and the get water on action of the precipitation. Vegetation extensively changes soil hydrology by increasing rainfall interception, infiltration, and evapo-transpiration. Interception and evapo-transpiration decrease the quantity of water that reaches the soil and is stored in it. They don't play a vital function during the short heavy rainfall events generally required to trigger shallow landslides, but they can be of importance for the long term evolution of water in soil, and thus for initial moisture conditions when an extreme event occurs. Roots increase soil permeability and thus infiltration and conductivity, which cause greater accumulation of water in the soil during both short term events and long rainfall periods. The vegetation cover also introduces some mechanical changes through soil reinforcement and slope loading. The increase in soil strength due to root reinforcement has great potential to reduce the rate of landslide occurrence (Wu and Swanston, 1980; Blijenberg, 1998; Cannon, 2000; Beguería, 2006). Several researchers (Ercanoglu and Gokceoglu, 2004; Tangestani, 2004; Reis and Yomralioglu, 2006; Yalcin, 2007) have emphasized the importance of land cover on slope stabilities. In this study, a single date image of Landsat ETM+ (Path 173; Row: 32) on October 19, 2000 was used to generate the land cover types. Using the image, after extracting an application area of approximately 120×90 km covering the administrative boundaries of Trabzon province, other studies, as required, were implemented on this area. The Landsat ETM+ image has six multi-spectral bands with 28 m resolution, one thermal band with a 60 m resolution and a panchromatic band with 15 m resolution (Reis and Yomralioglu, 2006). The study area was divided into nine land cover classes (Table 1), being mostly covered with deciduous, pasture, and agriculture areas. Landslides are largely observed in deciduous and hazelnut areas. The deciduous areas include different tree types of tree growth such as brake, thicket and small wood. These types obstruct the surface flow of precipitations and this increases the pore water pressure of soil, thus the potential of the occurrence of landslides has increased in these areas.

3.7. Distance to stream

Distance to stream is one of the controlling factors for the stability of a slope. The saturation degrees of the materials directly affect slope stability. The proximity of the slopes to the drainage structures is also important factor in terms of stability. Streams may negatively affect stability by eroding the slopes or by saturating the lower part of material until the water level increases (Dai et al., 2001; Saha et al., 2002). In this respect, the relation streams and groundwater are also important. Groundwater exchanges directly the characteristics of surface water by sustaining stream base flow. Groundwater affects surface water by providing moisture for riparian vegetation, and controlling the shear strength of slope materials, thereby affecting slope stability and erosion processes. Low river flow during periods of no rain or snowmelt input is called base flow, which represent the normal condition of rivers. Groundwater provides base flow for essentially all rivers and has a major effect on the amount of water and chemical composition of rivers. In smaller, low-order streams, groundwater also provides much of increased discharge during and immediately following storms. The effect of streams to landslide increases all of these events. The study area was divided into seven different buffer ranges. Primary streams and secondary streams were branched and the proximity buffers were constructed for intervals of 100–250 m, although extra classes were defined for 0–25 m, 25–50 m, 50–75 m, and 75–100 m.

3.8. Distance to roads

The road density is one of the causal factors for landslides and is parallel to the effect of the distance to streams. The load in the toe of slope can be reduced by road-cuts. A drop-down road section may behave like a wall, a net source, a net sink or a corridor for water flow, and depending on its location in the mountains, this type of road is usually a contributing factor in causing landslides (Ayalew and Yamagishi, 2005; Yalcin, 2008). The study area was divided into five different buffers categorized to designate the influence of the road on the slope stability. The landslide percentage distribution was determined according to the buffer zones by comparing the map of the distance to the road and the landslide inventory (Table 1).

4. Landslide susceptibility analyses

In this study, the landslide susceptibility analyses were implemented using the methods of frequency ratio, analytical hierarchy process, bivariate (*Wi* and *Wf*) and logistics regression. In order to achieve this, landslide factors related to the causes of landslide occurrence in the study area, such as the geology, slope, aspect, elevation, land cover, distance to streams, and distance to roads layers were used. The Digital Elevation Model (DEM) was digitized from 1/25.000 scaled Standard Topographic Maps and the contours on these maps are drawn at 10 m intervals. The DEM of the study area was created using ArcGIS 9.2 software. 10×10 m pixel dimensions of the landslide and parameter maps were chosen. Precipitation data was not included in the susceptibility analyses because it was approximately same over the whole area. Seismic data was also discounted because the study area is far away from seismic activity. Landslide areas were determined using previous inventory map and Quickbird satellite images. Furthermore, the landslide data were achieved and confirmed in the field studies.

4.1. Frequency ratio method

When evaluating the probability of landsliding within a specific period of time and within a certain area, it is of major importance to recognize the conditions that can cause the landslide and the process that could trigger the movement. The correlation between landslide areas and associated factors that cause landslides can be allocated from the connections between areas without past landslides and the landslide-related parameters. In order to prepare the landslide susceptibility map quantitatively, the frequency ratio method was implemented using GIS techniques. Frequency ratio methods are based on the observed associations between distribution of landslides and each landslide-related factor, to expose the correlation between landslide locations and the factors in the study area. Using the frequency ratio model, the spatial associations between landslide location and each of the factors contributing landslide occurrence were derived. The frequency is calculated from the analysis of the relation between landslides and the attributed factors. Therefore, the frequency ratios of each factor's type or range were calculated from their relationship with landslide events as shown in Table 1. The frequency ratio was calculated for sub-criteria of parameter, and then the frequency ratios were summed to calculate the landslide susceptibility index (*LSI*) (Eq. 1) (Lee and Talib, 2005).

$$LSI = Fr_1 + Fr_2 + Fr_3 + \ \dots\dots + Fr_n \tag{1}$$

where, *Fr* is rating of each factor's type or range.

According to the frequency ratio method, the ratio is that of the area where the landslide occurred, to the total area, so that a value of 1 is an average value. If the value is >1, it means the percentage of the landslide is higher than the area and refers to a higher correlation, whereas values lower than 1 mean a lower correlation (Akgun et al., 2007).

The geological characteristics of the study area are very important factors in susceptibility analyses. There are eight classes of lithological units in the study area, Kru-basalt, andesite, pyroclastics, and intercalations of sandstone clayey limestone and siltstone (*Kru*) and Kaçkar granites (γ2) units were found to be more susceptible lithology. *Kru* and γ2 include 1.46%, 1.87% of the higher frequency ratio, respectively.

The slope angle is a one of the most important factors controlling slope stabilities and landslides mostly occur at certain critical slope angles. Mild slopes are estimated to have a low frequency for shallow-domiciled landslides because of the minor shear stresses commonly related to low slopes. Frequency ratio analyses showed that a slope angle in a range of 20–50% and >50% shows high probability of landslide occurrence. As expected, a low gradient indicated a low frequency ratio, in a range of 0–10% giving a 0.18 ratio (Table 1).

Like slope, aspect is another important parameter in preparing landslide susceptibility maps. In the study area, landslides generally occurred on east-southeast and west-northwest-southwest side slopes. The aspect assessments showed that landslides were not likely to happen on the slope surfaces. The assessment of the aspect factor on east-facing slopes shows high probability (1.45) of landslide occurrence (Table 1).

The elevation–landslide analyses showed that landslides mostly occurred from sea level to 1500 m, in particular, the frequency ratio is very high in the elevation range of 1000–1500 m (Table 1). The results are related to geological characteristics because the areas in the elevation range of 0–1500 m are generally overlaid to volcanic units as rhyolite, rhyodacite, dacite, andesite and pyroclastics.

The land cover type is very important for landslide studies, especially the areas that are covered with intense vegetation. As in tea plantations, intensely vegetated areas exhibit more saturation and greater instabilities than forest. Land cover analyses showed that landslides commonly occurred in the tea and hazelnut areas, the frequency ratio being 1.56 and 1.50, respectively (Table 1).

The degree of soil saturation is one of the controlling factors for slope stabilities. The rivers rose to water content of soil until water level and around in the slope. The connection between landslides and distance to streams gives reverse values. Normally, the distance from streams augments the landslide constituting should be declines. However, in the study, the distance from streams increases the landslide constituting ascends (Table 1). The reason for this is related to the topographical modification resulting from the caving of the slopes in the study area, and thus, retrogressive failures were formed in the slopes.

A road constructed alongside slopes causes a decrease in the load on both the topography and on the heel of slope. Tension cracks may be created as a result of an increase in stress on the back of the slope because of changes in topography and the decrease of load (Yalcin, 2008). The distance from roads increases the landslide constituting declines in the study and this is compatible with what is expected. The distance to roads analyses showed that landslides usually occurred at the distance range of 0–50 m (Table 1). On completion of the analyses the frequency ratio of each layer's classes was determined, and a landslide susceptibility map (Fig. 3) was produced by the LSI map using Eq. (1).

4.2. Analytical hierarchy process (AHP)

The AHP improved by Saaty (1980) supplies a flexible and easily understood way of analyzing complicated problems. The AHP is a multi-objective, multi-criteria decision-making approach that enables the user to arrive at a scale of preferences drawn from a set of alternatives. The AHP gained wide application in site selection, suitability analysis, regional planning, and landslide susceptibility analysis (Ayalew et al., 2005). The AHP is a problem-solving construction and a methodical process for representing the elements of any problem (Saaty and Vargas, 1991). To apply this approach, it is necessary to break a complex unstructured problem down into its component factors; arrange these factors in a hierarchic order; assign numerical values to subjective judgments on the relative importance of each factor; and synthesize the judgments to determine the priorities to be assigned to these factors (Saaty and Vargas, 2001). One set of models was enhanced using the values from the statistics to manually describe the relationships between the different parameters according to the AHP methodology and later these values were imported into the AHP matrixes. The other set of models was developed by automatically importing the calculated relationship values of different factors, based on the statistical values, into the AHP matrixes (Table 2). The pair-wise comparison matrix was created by making dual comparisons made in this context. The weights are calculated from the pair-wise comparison matrix undertaking an eigenvalues and eigenvectors calculation. It has been demonstrated that the eigenvector corresponding to the largest eigenvalue of the matrix provides the relative priorities of the factors, i.e., if one factor has preference; its eigenvector component is larger than that of the other. The components of the eigenvector sum to unity. Thus, a vector of weights is obtained, which reflects the relative importance of the various factors from the matrix of paired comparisons.

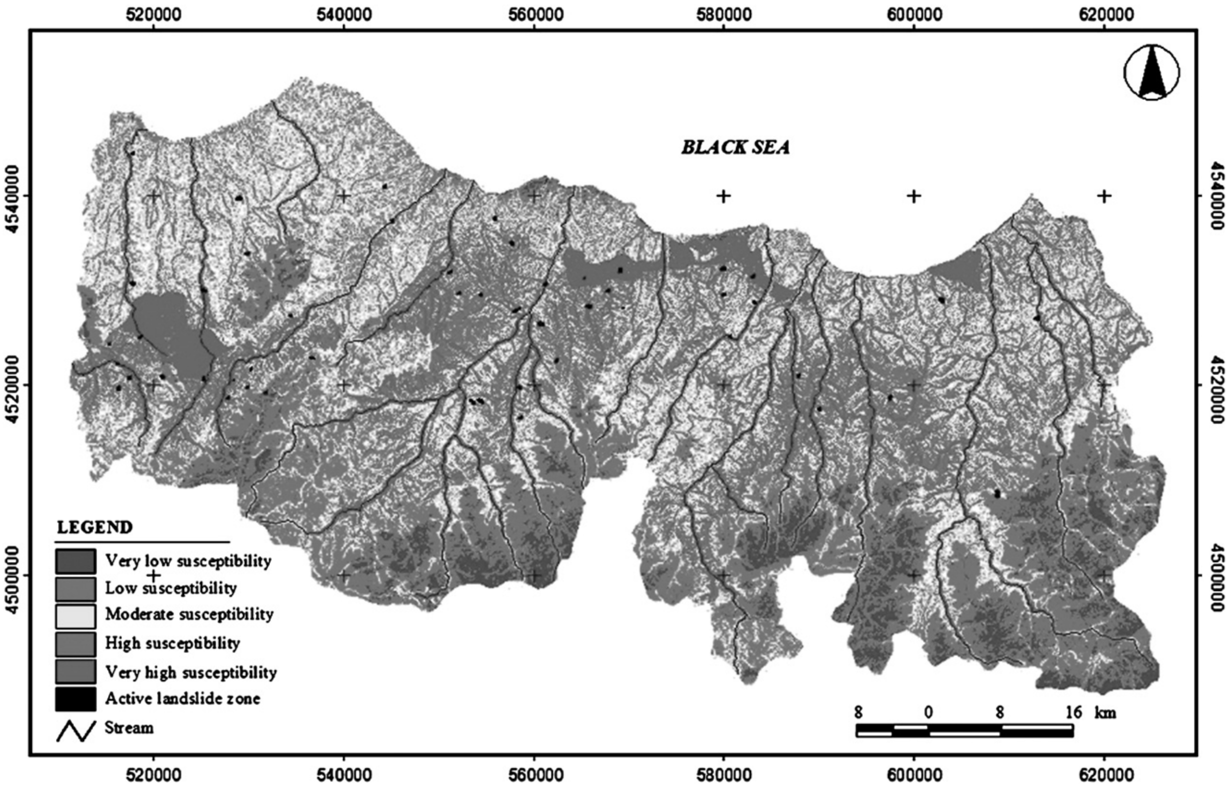

Fig. 3. The landslide susceptibility map produced by FR.

Table 2
Pair-wise comparison matrix, factor weights and consistency ratio of the data layers.

Factors	1	2	3	4	5	6	7	8	9	10	11	12	Weights
Lithology													
(1) Alv	1												0.057
(2) Pl	2	1											0.097
(3) Ev	5	4	1										0.178
(4) Kru	9	8	6	1									0.486
(5) Jkr	1/2	1/3	1/4	1/9	1								0.037
(6) Jlh	1/2	1/3	1/4	1/9	1	1							0.037
(7) γ_2	2	1/2	1/3	1/8	2	2	1						0.070
(8) Kk	1/2	1/3	1/4	1/9	1	1	1/2	1					0.037
Consistency ratio: 0.038													
Slope (%)													
(1) 0–10	1												0.043
(2) 10–20	2	1											0.068
(3) 20–30	4	2	1										0.123
(4) 30–50	6	5	3	1									0.288
(5) >50	8	7	5	2	1								0.479
Consistency ratio: 0.021													
Aspect													
(1) Flat	1												0.024
(2) North	4	1											0.064
(3) Northeast	5	2	1										0.112
(4) East	6	3	2	1									0.200
(5) Southeast	5	2	1	1/2	1								0.112
(6) South	4	1	1/2	1/3	1/2	1							0.064
(7) Southwest	5	2	1	1/2	1	2	1						0.112
(8) West	6	3	2	1	2	3	2	1					0.200
(9) Northwest	4	2	1	1/2	1	2	1	1/2	1				0.110
Consistency ratio: 0.008													
Land cover													
(1) Tea	1												0.039
(2) Hazelnut	5	1											0.207
(3) Deciduous	7	2	1										0.349
(4) Coniferous	1	1/5	1/7	1									0.042
(5) Mix wood	2	1/4	1/7	2	1								0.062
(6) Rocky	1	1/5	1/7	1	1/2	1							0.042
(7) Pasture	3	1/3	1/6	3	2	3	1						0.093
(8) Agriculture	4	1/2	1/3	4	3	4	2	1					0.144
(9) Settlement	1/2	1/7	1/9	1/3	1/3	1/3	1/4	1/6	1				0.022
Consistency ratio: 0.074													
Elevation (m)													
(1) 0–500	1												0.179
(2) 500–1000	2	1											0.254
(3) 1000–1500	3	2	1										0.360
(4) 1500–2000	1/3	1/4	1/5	1									0.104
(5) 2000–2500	1/4	1/5	1/6	1/2	1								0.079
(6) 2500–3000	1/8	1/9	1/9	1/7	1/6	1							0.023
(7) 3000–3500	1/8	1/9	1/9	1/7	1/6	1	1						0.023
Consistency ratio: 0.065													
Distance to stream (m)													
(1) 0–25	1												0.323
(2) 25–50	1/4	1											0.080
(3) 50–75	1/2	3	1										0.208
(4) 75–100	1/3	2	1/3	1									0.114
(5) 100–150	1/4	1	1/2	1/2	1								0.084
(6) 150–200	1/3	1	1/2	1	1	1							0.095
(7) 200–250	1/3	1	1/2	1	1	1	1						0.095
Consistency ratio: 0.016													
Distance to road (m)													
(1) 0–25	1												0.394
(2) 25–50	1/2	1											0.234
(3) 50–75	1/3	1/2	1										0.124
(4) 75–100	1/3	1/2	1	1									0.124
(5) 100–125	1/3	1/2	1	1	1								0.124
Consistency ratio: 0.002													
Data layers													
(1) Lithology	1												0.386
(2) Slope	1/3	1											0.230
(3) Aspect	1/4	1/3	1										0.129
(4) Elevation	1/4	1/3	1	1									0.098

Table 2 (*continued*)

Factors	1	2	3	4	5	6	7	8	9	10	11	12	Weights
Consistency ratio: 0.002													
Data layers													
(5) Land cover	1/5	1/4	1/3	1	1								0.083
(6) Dist. to stream	1/7	1/5	1/4	1/3	1/3	1							0.037
(7) Dist. to road	1/7	1/5	1/4	1/3	1/3	1	1						0.037
Consistency ratio: 0.038													

Normally, the determination of the values of the parameters relative to each other is a situation that is dependent on the choices of the decision-maker. However, in this study, both the comparison of the parameters relative to each other and the determination of the decision alternatives, namely the effect values of the sub-criteria of the parameters (weight), were based on the comparison of landslide inventory maps which were constructed using field studies, previous inventory map, and satellite image with the other data layers (Yalcin, 2008). In AHP, an index of consistency, known as the consistency ratio (CR), is used to indicate the probability that the matrix judgments were randomly generated (Saaty, 1977).

$$CR = CI / RI \tag{2}$$

where RI is the average of the resulting consistency index depending on the order of the matrix given by Saaty (1977) and CI is the consistency index and can be expressed as

$$CI = (\lambda_{max} - n) / (n - 1) \tag{3}$$

where λ_{max} is the largest or principal eigenvalue of the matrix and can be easily calculated from the matrix, and n is the order of the matrix.

For all the models, where the AHP was used, the CR (Consistency Ratio) was calculated. If the CR values were greater than 0.1, the models were automatically discarded. Using a weighted linear sum procedure (Voogd, 1983) the acquired weights were used to calculate the landslide susceptibility models (Komac, 2006). As a result of the AHP analyses, the landslide susceptibility map was produced for Trabzon province (Fig. 4). In the study, lithology, slope, and aspect are found to be important parameters for the study area, whereas distance to streams and roads were of lesser importance.

4.3. Bivariate statistics method

In this study, landslide susceptibility analyses were implemented using statistical bivariate methods, namely, the statistical index (*Wi*) method (van Westen, 1997) and the weighting factor (*Wf*) method (Cevik and Topal, 2003). For this reason, geology, slope, aspect, elevation, land cover, distance to streams, and distance to roads layers were used in the analyses.

The Wi method is based on statistical correlation (map crossing) of the landslide inventory map with attributes of a different parameters map. The map crossing results in a cross-table, which can be used to calculate the density of landslides per parameter class. A standardization of these

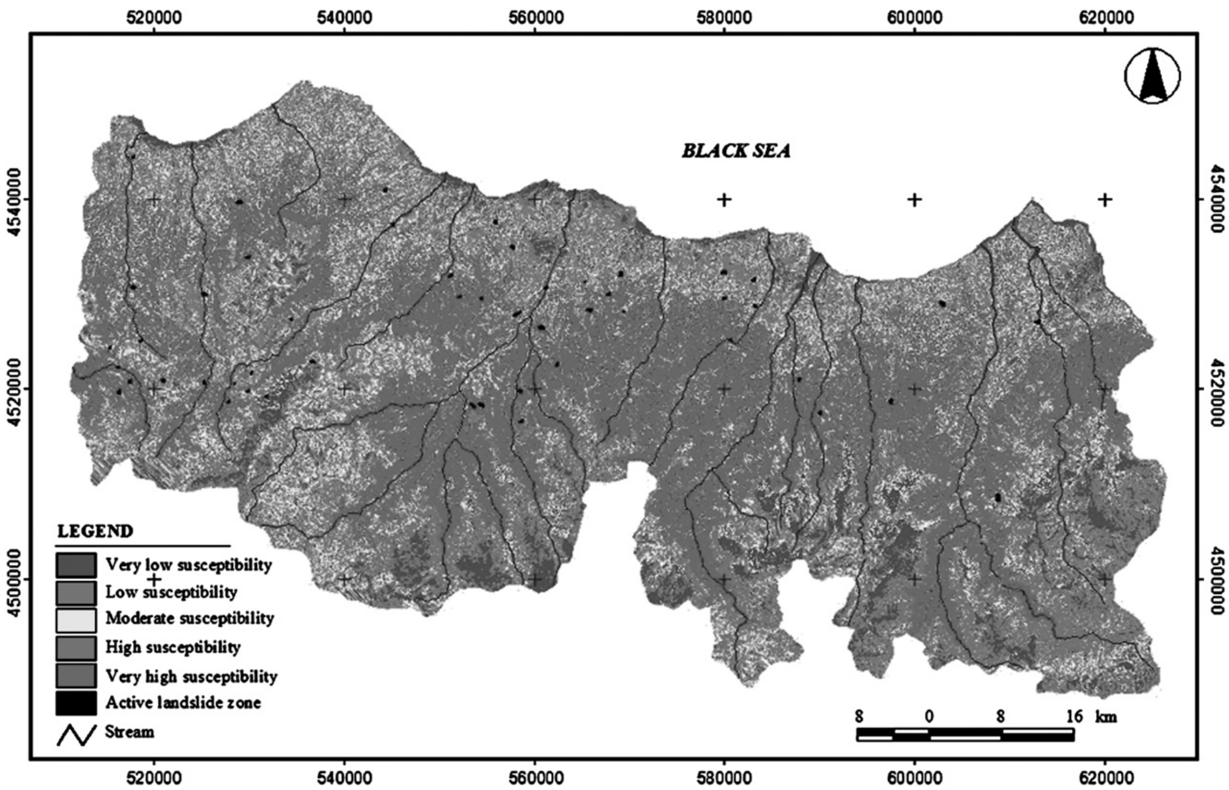

Fig. 4. The landslide susceptibility map produced by AHP.

Table 3
Distribution of landslide for various data layers, *Wi* and *Wf* values of each attribute.

Parameter	Classes	Landslide area (%)	Wi	Wf
Geology	Alv	1.54	−0.920	91.16
	Pl	2.23	−0.066	
	Ev	13.17	−1.023	
	Kru	80.02	0.381	
	Jkr	0.00	0.000	
	Jlh	0.00	0.000	
	γ2	3.04	0.625	
	Kk	0.00	0.000	
Slope (%)	0–10	2.41	−1.741	47.57
	10–20	5.71	−0.195	
	20–30	11.79	0.063	
	30–50	30.83	0.140	
	>50	49.26	0.173	
Aspect	Flat	0.72	−2.687	61.36
	North	8.74	−0.349	
	Northeast	12.65	−0.020	
	East	17.14	0.369	
	Southeast	11.17	0.190	
	South	8.49	−0.022	
	Southwest	11.46	0.084	
	West	16.36	0.333	
	Northwest	13.27	0.091	
Elevation (m)	0–500	25.33	0.064	100.00
	500–1000	29.67	0.289	
	1000–1500	34.28	0.546	
	1500–2000	6.36	−1.022	
	2000–2500	4.35	−1.165	
	2500–3000	0.00	0.000	
	3000–3500	0.00	0.000	
Land cover	Tea	1.69	0.445	37.41
	Hazelnut	23.15	0.408	
	Deciduous	42.85	0.120	
	Coniferous	1.65	−0.333	
	Mix wood	4.77	−0.080	
	Rocky	1.02	−0.115	
	Pasture	8.03	−0.840	
	Agriculture	16.48	−0.039	
	Settlement	0.35	−1.189	
The distance to stream (m)	0–25	28.21	−0.035	1.50
	25–50	9.62	−0.104	
	50–75	20.37	0.033	
	75–100	11.28	0.002	
	100–150	9.80	0.067	
	150–200	10.38	0.063	
	200–250	10.33	0.010	
The distance to road (m)	0–25	21.09	0.059	1.00
	25–50	20.20	0.010	
	50–75	19.52	−0.028	
	75–100	19.46	−0.029	
	100–125	19.72	−0.013	

density values can be obtained by relating them to the overall density in the entire area (Oztekin and Topal, 2005). In this study, the Wi values for each class of each parameter map were obtained quantitatively using the following formula suggested by van Westen (1997):

$$Wi = ln\frac{Densclass}{Densmap} = ln\frac{\frac{Npix(Si)}{Npix(Ni)}}{\frac{SNpix(Si)}{SNpix(Ni)}} \quad (4)$$

where

Wi Weight given to a certain parameter class
Densclass Landslide density within the parameter class
Densmap Landslide density within the entire map
Npix(Si) Number of pixels that contain landslide in a certain parameter class
Npix(Ni) Total number of pixels in certain parameter class.
SNpix(Si) Number of pixels all landslide
SNpix(Ni) Total number of all pixels

Then the *Wi* value of each attribute was calculated (Table 3). Finally, all layers were overlaid and a resulting susceptibility map was obtained (Fig. 5). The *Wi* susceptibility map was divided into equal classes according to the total number of elements. The classes are; very low, low, moderate, high, and very high susceptibility. However, in the statistical index method, it is considered that each parameter map has an equal effect on landslides, which may not be the case in reality (Oztekin and Topal, 2005). Therefore, a weighting factor (*Wf*) for each parameter map was produced. For this purpose, first the *Wi* value of each pixel was determined by the statistical index method, then, all pixel values within the landslide zones belonging to each layer were summed. By using the maximum and minimum of all layers, the results were stretched (Cevik and Topal, 2003). Finally, the weighting factor ranging from 1 to 100 for each layer was determined by the following formula:

$$Wf = \frac{(TWi_{value}) - (MinTWi_{value})}{(MaxTWi_{value}) - (MinTWi_{value})} * 100$$

where

Wf Weighting factor calculated for each layer
TWi_{value} Total weighting index value of cells within landslide bodies for each layer
$MinTWi_{value}$ Minimum total weighting index value within selected layers
$MaxTWi_{value}$ Maximum total weighting index value within selected layers

By executing this formula, the weighting factor (*Wf*) values of each layer were determined (Table 3). For the analyses, the *Wf* value for each layer was multiplied by the *Wi* value of each attribute, and finally, all parameter maps were summed up to yield the final landslide susceptibility map from the *Wf* method (Fig. 6). The association between pixel value and cumulative pixel count mainly yielded five susceptible zones namely—very low, low, moderate, high, and very high. According to the results of the *Wf* method, elevation is found to be the most important parameter for the landslides in the study area.

4.4. Logistic regression method

Logistic regression permits one to type a multivariate regression relationship between a dependent variable and several independent variables. Logistic regression, which is one of the multivariate analysis models, is helpful for forecasting the presence or absence of a characteristic or outcome based on the values of a set of predictor variables. The advantage of logistic regression is that, through the addition of a suitable 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 (Lee, 2005). In the present situation, the dependent variable is a binary variable representing presence (1) or absence (0) of a landslide. Where the dependent variable is binary, the logistic link function is applicable (Atkinson and Massari, 1998).

In the landslide susceptibility studies, logistic regression model is one the acceptable methods to characterize the association between the presence or absence of a landslide, the dependent variable, and a set of independent parameters including geology, slope, and land cover. (Ayalew and Yamagishi, 2005). Presence (1) and absence (0) coefficients can be utilized to calculate approximate ratios for each of the independent variables. Logistic regression analysis is generally used in earth sciences, and explained as a linear equation given below (Lee, 2005).

$$Y = Logit(p) = ln\left(\frac{p}{1-p}\right) \quad (5)$$

$$Y = C_0 + C_1.X_1 + C_2.X_2 + \ ..... + C_n.X_n \quad (6)$$

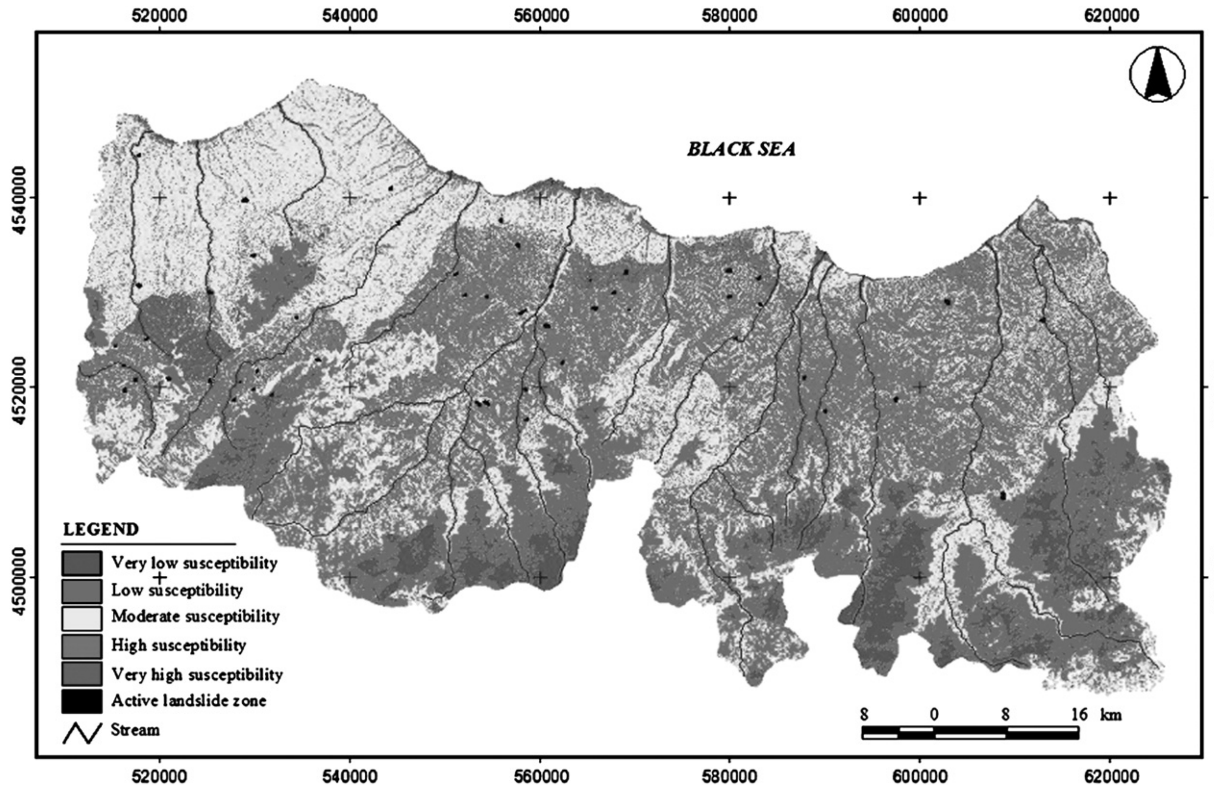

Fig. 5. The landslide susceptibility map developed using *Wi* method.

where p is the probability that the dependent variable (Y) is 1, $p/(1-p)$ is the so-called odd or frequency ratio, C_0 is the intercept, and $C_1, C_2,\ldots, C_n$ are coefficients, which measure the contribution of the independent factors ($X_1, X_2,\ldots, X_n$) to the variations in Y (Lee, 2005).

The spatial association between landslide inventory and the landslide factors maps (geology, slope, aspect, land use, elevation, distance to stream, and distance to road) was assessed using the logistic regression method. The statistical assessment was carried out

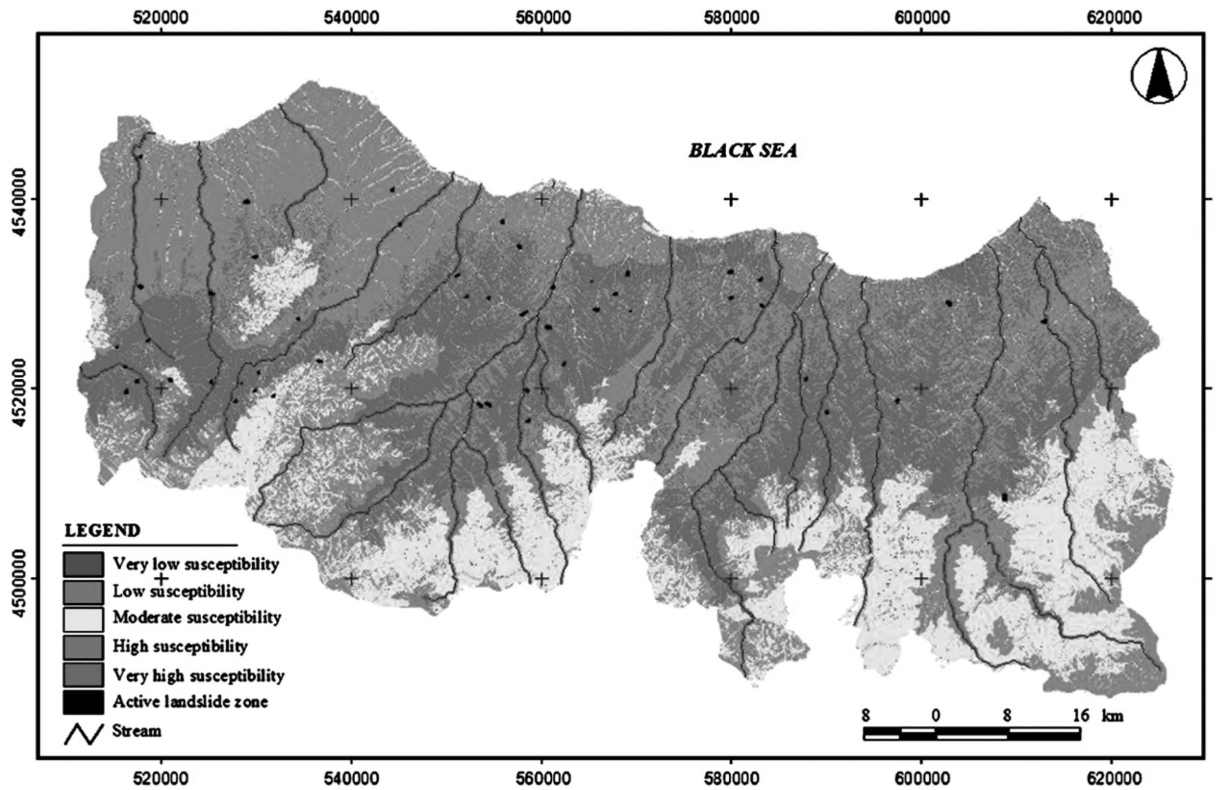

Fig. 6. The landslide susceptibility map developed using *Wf* method.

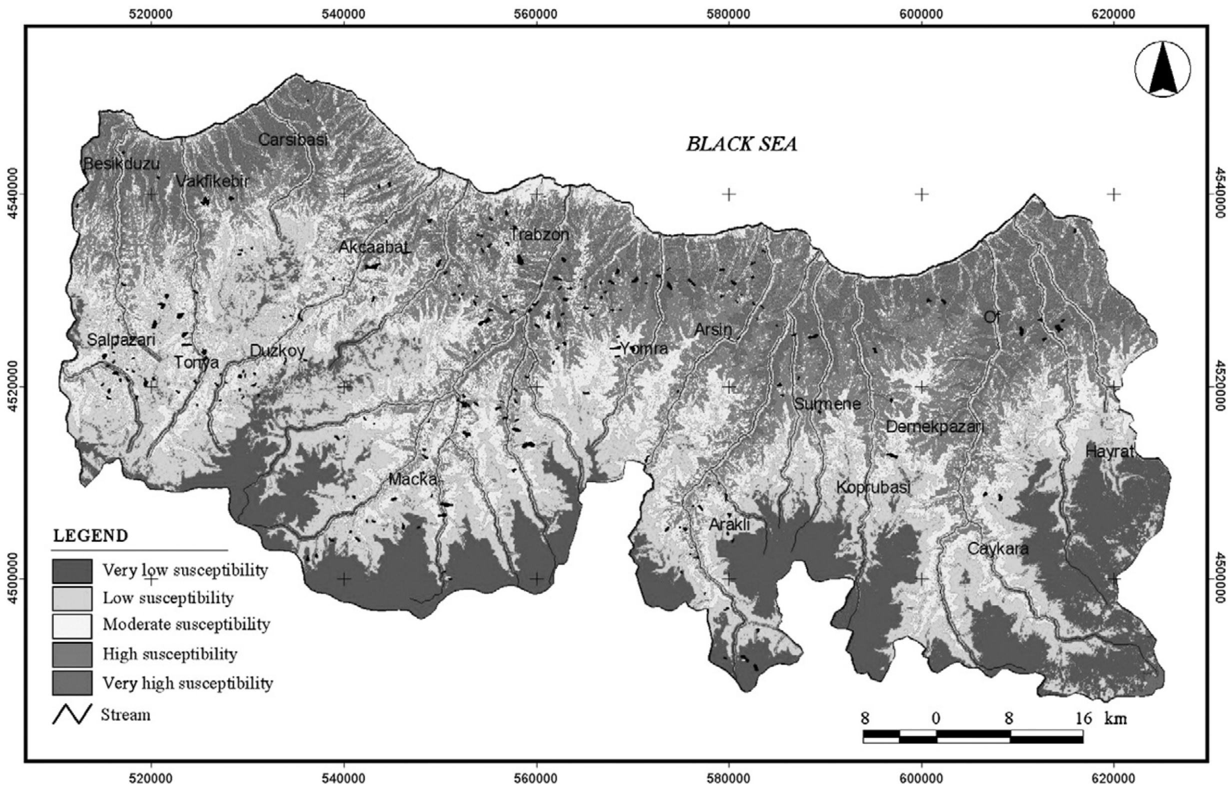

Fig. 7. The landslide susceptibility map produced by LR.

using an IDRISI GIS environment. In this assessment, a logistic regression equation was obtained as shown in Eq. (7) and the LR map was produced (Fig. 7).

$$\begin{aligned} Y = & -4.7485 + 0.000929 * Geology - 0.052129 * Landuse \\ & + 0.000503 * Aspect + 0.050838 * Slope - 0.006434 * Road \\ & - 0.239024 * Elevation - 0.098631 * Stream. \end{aligned} \quad (7)$$

The statistical results of the logistic regression method are abridged in Table 4. A key starting point could be the model chi-square value of which provides the usual significance test for logistic regression. It is a difference between $-2\ln L$ (L = likelihood) for the best-fitting model and $-2\ln L_0$ for the null hypothesis in which all the coefficients are set to 0, and measures the improvement in fit that the independent variables bring to the regression. The high value for the model chi-square indicates that the occurrence of landslides is far less likely under the null hypothesis (without landslide influencing parameters) than the full regression model (where the parameters are included). The goodness of fit is an alternative to the model chi-square for assessing the significance of LR models. The calculation is based on the difference between the observed and the predicted values of the dependent variable. The smaller this statistic, the better fit it indicates (Ayalew and Yamagishi, 2005).

Table 4
Summary statistics of the logistic regression model.

Statistics	Value
Number of sampled observations	471900[a]
2ln L	18859.687
2ln L_0	17353.213
Goodness of fit	285841.938
Pseudo R^2	0.0799
ROC	0.7502

[a] (Using 50 m cell size was used to LR analysis).

The pseudo R^2 equal to 1 indicates a perfect fit, whereas 0 shows no relationship. When a pseudo R^2 is greater than 0.2, it shows a relatively good fit (Clark and Hosking, 1986). The pseudo R^2 in this study is 0.0799. In addition, a disjunctive approach, which is much easier to interpret, is to look at how well the model actually predicts the dependent variable. In this case, IDRISI uses the so-called Relative Operating Characteristic (ROC) to compare a Boolean map of "reality" (the presence or absence of landslides) with the probability map. The ROC value ranges from 0.5 to 1, where 1 indicates a perfect fit and 0.5 represents a random fit (Ayalew and Yamagishi, 2005; Akgun and Bulut, 2007). A value of 0.7502 was obtained in this study, which can be taken as a sign of good correlation between the independent and dependent variables.

According to Eq. (7), the geology, slope, and aspect coefficients are positive, the land use, elevation, distance to road, and distance to stream coefficients are negative. This means that the geology, slope, and aspect are positively related to the occurrence of a landslide whereas land use, elevation, distance to road, and distance to stream indicate a negative relation with the landslide occurrence in the study area. In particular, the coefficient that belongs to the parameter "slope" strongly departs from 0 and led to the inference that the topographical slope has a higher effect on the development of landslides than any other parameter.

5. Results and comparative analysis

The landslide susceptibility maps were prepared using five different weighting procedures in a GIS-based approach. The area and percentage distribution of the susceptibility classes in the study area were determined as a result of the five different methods. To test the reliability of the landslide susceptibility maps produced by the frequency ratio, AHP, *Wi* and *Wf* methods, and logistic regression, a landslide activity map of fifty active zones of recent landslides and the susceptibility maps were compared. In these comparisons, the area on the landslide activity map that shows where the landslides occurred is matched with the landslide susceptibility maps. Then, the distribution

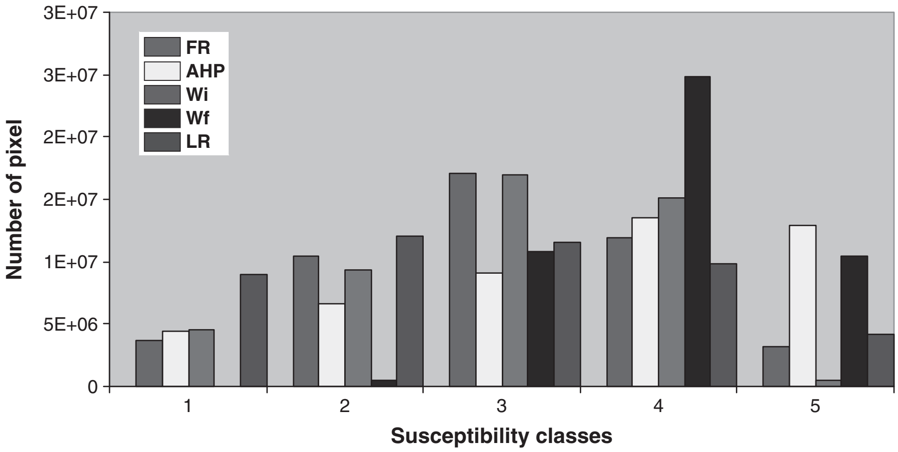

Fig. 8. Bar graphs showing the relative distribution of susceptibility levels when the susceptibility maps are classified on the basis of standard deviations.

of the actual landslide areas is determined according to the landslide susceptibility zones. The landslide susceptibility map has a continuous scale of numerical values and there is a need to separate these values into susceptibility classes. There are several mathematical methods for the classification susceptibility degrees (Ayalew et al., 2004; Suzen and Doyuran, 2004). The standard deviation classifier is proposed when the histogram of data values exhibits a normal distribution (Suzen and Doyuran, 2004). As a result, the standard deviation classifier was used since the data values in the landslide susceptibility maps obtained using the FRM, AHP, Wi, Wf, and LR show a normal distribution (Fig. 8).

According to the landslide susceptibility map produced from the frequency ratio method, 8.00% of the total area is found to be of very low landslide susceptibility. Low, moderate and high susceptible zones represent 22.38%, 36.93% and 25.79% of the total area, respectively. The very high landslide susceptibility area is 6.91% of the total study area.

The landslide susceptibility map generated with AHP which included 9.58% of total area is determined to be of very low landslide susceptibility. Low and moderate susceptible zones make up 14.22% and 19.46% of the total area, respectively. The high and very high susceptible zones values are close to each other, 29.00% and 27.74%, respectively.

The landslide susceptibility map created in accordance with the statistical index (*Wi*) contains 9.84% of the total area which is designated to be of very low landslide susceptibility. The value is near to the very low category in relation to the FR and AHP methods. Low, moderate and high susceptibility zones constitute 19.95%, 36.46% and 32.58% of the total area, respectively. At only 1.18%, the percentage of very high susceptibility area is very small.

The landslide susceptibility map produced through the weighting factor (*Wf*) method involves different values from the other methods. The very low and low susceptibility areas are very small percentages at 0.13% and 1.16%, respectively but the percentages of moderate, high, and very high susceptibility areas are 23.10%, 53.24%, and 22.38%, respectively.

The logistic regression method showed different results while containing high percentages values for the low susceptibility zone (21.88%) in the LR method, the low susceptibility zones percentage in the FR, AHP, *Wi*, and *Wf* methods show small values such as 5.18%, 13.54%, 3.21%, and 1.76%, respectively. The very low susceptible area is denoted at a value of 2.66%. The moderate, high, and very high susceptibility zones show 32.89%, 30.94%, and 11.64% of the whole areas, respectively (Fig. 8). According to the LR method, it is determined that the geology, slope, and aspect coefficients are positive, the land use, elevation, distance to road, and distance to stream coefficients are negative. This means that the geology, slope, and aspect are positively related to the occurrence of landslides whereas land use, elevation, distance to road, and distance to stream indicate a negative relationship with landslide occurrence in the study area.

For the verification procedure the five susceptibility maps were first divided into five classes based on standard deviations of the corresponding histograms (Fig. 9). Next, they were crossed with the landslide activity map containing fifty active landslide zones. Fig. 9 presents a histogram that summarizes the result of the entire process. The high and very high susceptibility zones (4 and 5) found by the FR, AHP, *Wi*, and *Wf*, LR methods contain 60.98%, 62.71%, 62.56%, 93.29%, and 42.58% of the active landslide zones, respectively. Fig. 9 shows that the extent of the active landslide zones located in the very high

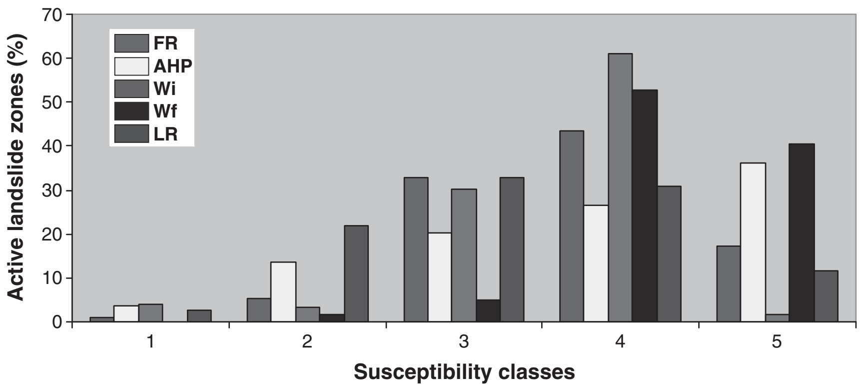

Fig. 9. A histogram showing the amount of active landslide zones that fall into the various classes of the FR, AHP, *Wi*, *Wf*, and LR susceptibility maps.

susceptibility class is higher in the map of the *Wf* than the FR, AHP, *Wi*, and LR maps. 40.59% of the active landslide zones fall into the very high susceptibility class on the *Wf* map. This value falls to 1.68% in the case of the susceptibility map produced by the *Wi* method. Besides, 60.88% of the active landslide zones coincide with the high susceptibility class on the *Wi* map. The moderate zones (3) of the FR, *Wi*, and LR methods include about 30% of the active landslide zones. In addition, while covering 20% of the moderate class from the AHP method, the *Wf* method includes only 5% approximately. The low (2) and very low susceptible (1) zones contain less than 7.5% of the active landslide zones in the FR, *Wi*, and *Wf* methods. The values are 17.11% and 24.53%, for AHP and LR, respectively. According to using analyses methods, the very low susceptible zones include less than 5% of the active landslide zones all of the methods (see Fig. 9). From the analysis in Fig. 9, it is easy to conclude that the very high and high susceptibility classes of the *Wf* map captured the locations of the active landslide zones (93.29%) better than the corresponding counterparts of the FR, AHP, *Wi* and LR maps, at 60.98%, 62.71%, 62.56%, and 42.58%, respectively. This might be due to the fact that the *Wf* method presents much more distinct and homogeneous values for wide study areas such as this application. Furthermore, this might be derived from the landslide inventory map, because this map was produced as a result of a very high sensitivity study and field check.

6. Discussion and conclusion

The reasons for landslides are many, complex, convoluted, and every so often unknown. Although the basic factors related to landslides can be observed during field studies, aerial photos, and satellite images interpretations, some factors remain closed. So as to determine whether there are closed parameters affecting the occurrence of landslides, several geomorphometrical parameters were entered into the analyses. Most geomorphometrical factors are subjective and hard to measure quantitatively in the field. Therefore, it may be difficult to understand their contributions to the landslide occurrence mechanism. Since landslides are among the most dangerous natural disasters, for many years research institutions worldwide have attempted to assess the landslide hazard, determine the risk and to show its spatial distribution. In this context, this study undertook comprehensive research on slope stability assessment and landslide susceptibility mapping in a part of Trabzon province, in Turkey. The region is continually at risk of landslides following precipitation since the topography and lithological materials are of the very best fit to create landslides. It is known that the role of precipitation as the triggering mechanisms of landslides is strongly influenced by the landscape dynamic and geology.

This is primarily because of the problems inherited from landslide inventory maps and the absence of universal guidelines to select causal factors. In this study, the landslide inventory map was prepared in such a way that it includes shallow landslides and in consideration of the fact that geology, slope and aspect of materials are important parameters for susceptibility mapping various methods. An attempt was made to differentiate the concepts of landslide susceptibility mapping. Five of the available approaches, for landslide susceptibility mapping, used in this study, were FR, AHP, statistical index (*Wi*), weighting factor (*Wf*), and LR with the *Wf* map gives the best results. To confirm the practicality of the results, the five susceptibility maps were compared with 50 active landslide zones. The result was that the active landslide zones coincided with a high percentage for the high and very high susceptibility class in the FR, AHP, *Wi*, and *Wf* maps, but the values of LR were not in agreement. 93.29% of these landslide zones fall into the high and very high susceptibility classes of the *Wf* map. The FR, AHP, *Wi* and LR maps contained 60.98%, 62.71%, 62.56%, and 42.58% of the landslide zones, respectively. In the FR and *Wi* methods, the geology parameter is positively associated with the occurrence of landslides. According to the AHP method, the geology, slope, and aspect parameters upwards of land use, elevation, distance to stream, and distance to road are implicated in the occurrence of landslide in the study area. The elevation and geology factors are positively associated with the occurrence of landslide in the *Wf* method. In addition, in the LR method, the geology, slope, and aspect are positively associated with the occurrence of landslide whereas land use, distance to stream, elevation, distance to road appear to have a negative relation with landslide occurrence in the study area. Thus it can be concluded, that when field conditions and characteristics are accurately determined by professional expertise, the *Wf* method gives better results over larger areas as in this study.

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