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ORIGINAL ARTICLE

Landslide susceptibility mapping for a landslide-prone area (Findikli, NE of Turkey) by likelihood-frequency ratio and weighted linear combination models

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Abstract Landslides are very common natural problems in the Black Sea Region of Turkey due to the steep topography, improper use of land cover and adverse climatic conditions for landslides. In the western part of region, many studies have been carried out especially in the last decade for landslide susceptibility mapping using different evaluation methods such as deterministic approach, landslide distribution, qualitative, statistical and distribution-free analyses. The purpose of this study is to produce landslide susceptibility maps of a landslide-prone area (Findikli district, Rize) located at the eastern part of the Black Sea Region of Turkey by likelihood frequency ratio (LRM) model and weighted linear combination (WLC) model and to compare the results obtained. For this purpose, landslide inventory map of the area were prepared for the years of 1983 and 1995 by detailed field surveys and aerial-photography studies. Slope angle, slope aspect, lithology, distance from drainage lines, distance from roads and the land-cover of the study area are considered as the landslide-conditioning parameters. The differences between the susceptibility maps derived by the LRM and the WLC models are relatively minor when broad-based classifications are taken into account. However, the WLC map showed more details but the other map produced by LRM model produced weak results. The reason for this result is considered to be the fact that the majority of pixels in the LRM map have high values than the WLC-derived susceptibility map. In order to validate the two susceptibility maps, both of them were compared with the landslide inventory map. Although the landslides do not exist in the very high susceptibility class of the both maps, 79% of the landslides fall into the high and very high susceptibility zones of the WLC map while this is 49% for the LRM map. This shows that the WLC model exhibited higher performance than the LRM model.

Keywords Landslide · Likelihood frequency ratio · Multicriteria decision analysis · GIS · Findikli (Turkey)

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Introduction

Landslides are dangerous natural hazards that occur suddenly and cause considerable damage. Over the last two decades, many governments and international research institutes in the world have investigated considerable resources in assessing landslide hazards and in attempting to construct maps portraying their spatial distribution (Guzetti et al. 1999).

In Turkey, earthquakes and landslides are foremost and the second most important natural hazards (Ildır 1995). Especially the Black Sea Region of Turkey is the most susceptible area to landsliding. This region exhibits mountainous topographical features, and is commonly subjected to heavy precipitation. Because of these adverse effects, the region is prone to extensive and severe landslides (Ercanoglu and Gokceoglu 2002). For these reasons, in the last decades, several studies on landslide susceptibility mapping have been carried out in the region. However, the investigation areas of these studies accumulate in the western part of the Black Sea region (Gokceoglu and Aksoy 1996; Suzen and Doyuran 2004a, b; Yesilnacar and Topal 2005; Ercanoglu and Gokceoglu 2004; Cevik and Topal 2003) except one study (Akgun and Bulut 2007), and in these studies, several different methods and techniques for landslide susceptibility mapping have been proposed and applied. Researchers used quantitative assessment models such as logistic regression, landslide information value, multicriteria-decision analysis, neural networks and fuzzy logic, to produce landslide susceptibility maps in the Black Sea Region.

Throughout the world, it is possible to find many studies on landslide susceptibility assessment. The basic concept of landslide susceptibility assessment was first introduced by Radbruch (1970), Dobrovolny (1971) and Brabb and Pampeyan (1972) as the spatial distribution of factors related to the instability processes in order to determine zones of landslide-prone areas without any temporal implication. Guzetti et al. (1999) and Chacon et al. (2006) summarized most of the landslide susceptibility mapping studies. More recently, probabilistic models have been proposed (Jibson et al. 2000; Lee and Min 2001; Donati and Turrini 2002; Lee et al. 2004a, b; Lee and Dan 2005; Gokceoglu et al. 2005; Lee and Sambath 2006). Logistic regression model, one of the statistical models, has also been employed for the purpose of landslide susceptibility mapping (Atkinson and Massari 1998; Dai and Lee 2001; Ohlmacher and Davis 2003; Lee 2004; Can et al. 2005; Gorsevski et al. 2006). Gokceoglu et al. (2000), Shou and Wang (2003) and Zhou et al. (2003) have used the geotechnical and factor of safety parameter models to investigate the slope failure of the studied areas. Data mining using fuzzy logic and artificial neural network models have also been applied by Geographical information system (GIS) as a new landslide susceptibility assessment approach (Ercanoglu and Gokceoglu 2002; Lee et al. 2003, 2006; Ermini et al. 2005; Gomez and Kavzoglu 2005).

Landslides in the study area, which occur frequently, often result in significant damages to people and property (Bulut et al. 2000). The landslides, which occurred in 1983, caused considerable damage to study area, Findikli in Turkey. Due to little effort to assess the landslides triggered by heavy rainfall, damage was extensive. Through scientific analysis of landslides, we can evaluate landslide-susceptibility areas, prediction of landslide prone areas, and thus decrease landslide-damage employing suitable mitigation measures. To carry out this, landslide susceptibility mapping were carried out and verified in the study area because landslide susceptibility maps are the first stage of the landslide hazard mitigation measures. GIS softwares (Map Info 7.0 and Idrisi Kilimanjaro) were used as a basic analytical tool for space management and data manipulation.

Following an extremely heavy rainfall in 1983, 109 landslides were recorded in the east of Findikli, Rize, northeast Turkey, and the area was selected as a proper case in which to assess the frequency and distribution of landslides. For this purpose, detailed landslide inventory maps of the study area were prepared by extensive field surveys conducted in the period of 1983 and 1995, including 109 and 10 landslide locations, respectively. Landslide-conditioning parameter maps are produced from Digital Elevation Model (DEM) and from existing thematic maps such as lithology and land-cover of the study area.

Likelihood ratio and weighted linear combination (WLC) models were used to prepare the landslide susceptibility maps of the study area and the results were compared within the scope of both effectiveness of the methods used and effectiveness of the environmental casual parameters governing the landslides.

The study area

The area locates at the East Black Sea Region (Fig. 1) which is known as the one of the most landslide-prone areas in Turkey. The western border of the study area starts from Findikli town, at a ~65-km distance from Rize city and extends in NE direction towards Guzelyali district. The study area covers an area of 43 km^2. A simplified lithological map of the area is shown in Fig. 2. Upper Cretaceous volcanic units, namely Hemsindere Formation (Korkmaz and Gedik 1988), are the oldest rocks in the region and cover 24.60 km^2 surface area of the study region. These units are mainly composed of andesite, dacite and their pyroclastic units. Andesite and its pyroclastic units cover a great area in the region (16.59 km^2), while dacite and its pyroclastic units cover 8.01 km^2. The Upper Cretaceous volcanics are highly susceptible to landsliding due to its susceptibility to weathering and most of the landslides occurred in the area are observed in these units. Hemsindere Formation is intruded by microgabro–gabro (0.49 km^2) and granodiorite–quartz microdiorite (0.96 km^2) intrusion rocks of Paleocene. Quaternary slope debris and alluvium are the youngest units in the area and their areal extents are 11.69 and 5.24 km^2, respectively. In the study area, no major well-developed structural elements such as faults and folds are observed.

The main streams in the study area are Abu and Sumer Rivers (Fig. 1). These rivers and their tributaries form a dentritic drainage pattern due to topographical and

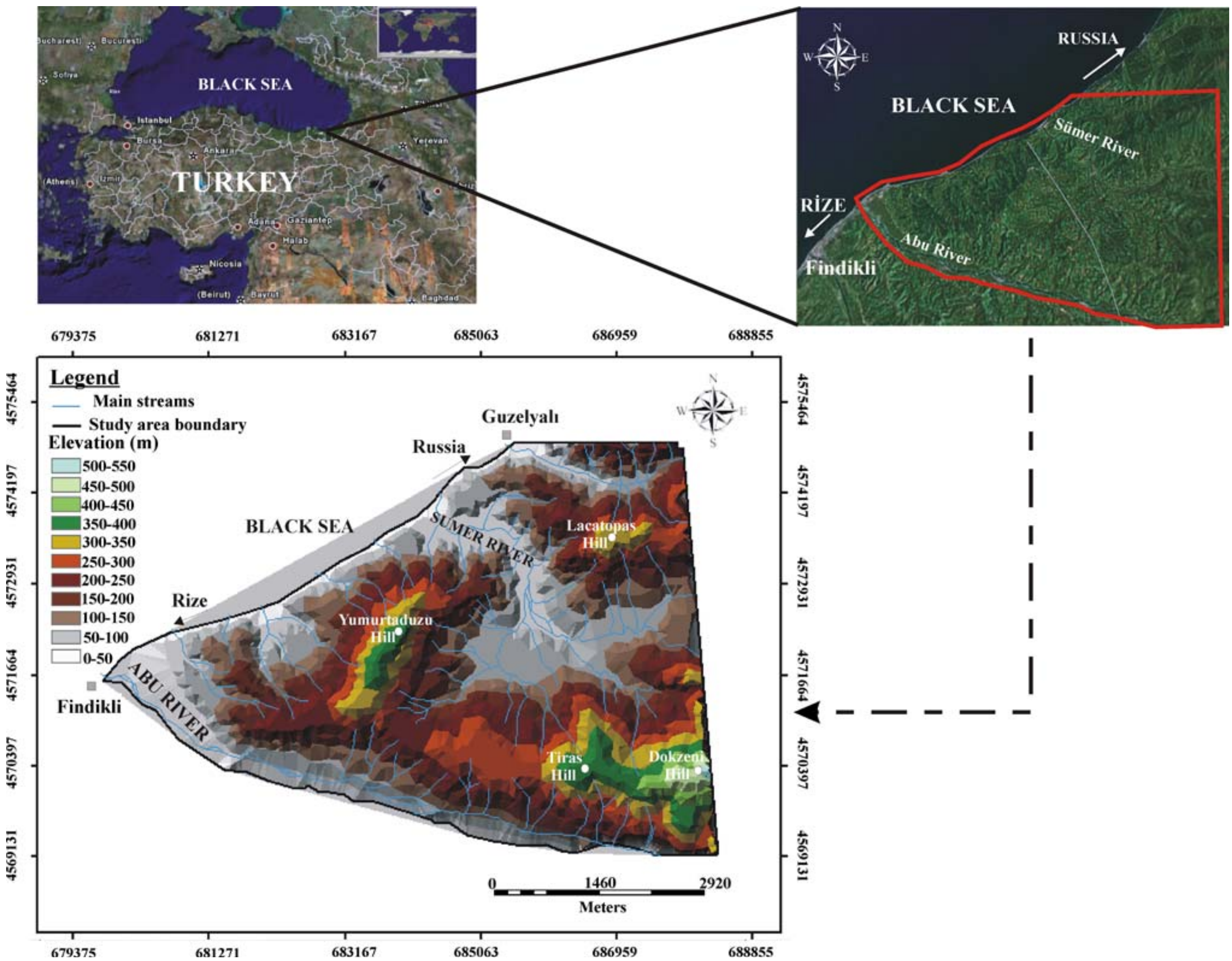

Fig. 1 Location map of the study area

geological features of the area. Elevations in the area range between 34 and 550 m, and the highest point in the study area is Dokzeni Hill. There are also other important hills such as Tiras, Yumurtaduzu and Lacatopas (Fig. 1). Slope angles range between 0° and 88° with an average of 35°. Slope aspects in the area generally trend toward NE–SW direction. Dense vegetation and extensive tea-plantation fields cover the lower and gentle slopes, while sparse vegetation is dominant at steeper slopes and higher elevations. Findikli is the main settlement area and there are also many scattered villages throughout the study area. The climate of the study area is very humid and temperate. Precipitation is very heavy (Fig. 3) and occurs frequently in the form of rain and snow throughout the winter. According to the data obtained from General Directory of Meteorological Services of Turkey (2006), the annual mean precipitation at a station located at Findikli town over the period of 1960–2000 is 2,200 mm (www.meteor.gov.tr).

Data

The first stage in all the landslide susceptibility assessment studies consists in the collecting of existing information and data for the investigation area (Aleotti and Chowdhury 1999). This stage is accepted to be the most important part of the landslide hazard mitigation studies (Guzetti et al. 2000; Ercanoglu and Gokceoglu 2004). The reliability and accuracy of the collected data also affect the success of the applied method. Therefore, the relation between the landslide occurrence and the conditioning parameters employed has also crucial importance for the landslide susceptibility mapping.

For landslide susceptibility assessment, several spatial data controlling the landslide occurrence are necessary, together with the landslide inventory data. When applying a method to landslide susceptibility assessment, definition of the criteria controlling the degrees of susceptibility is very important. Despite any parameter being important

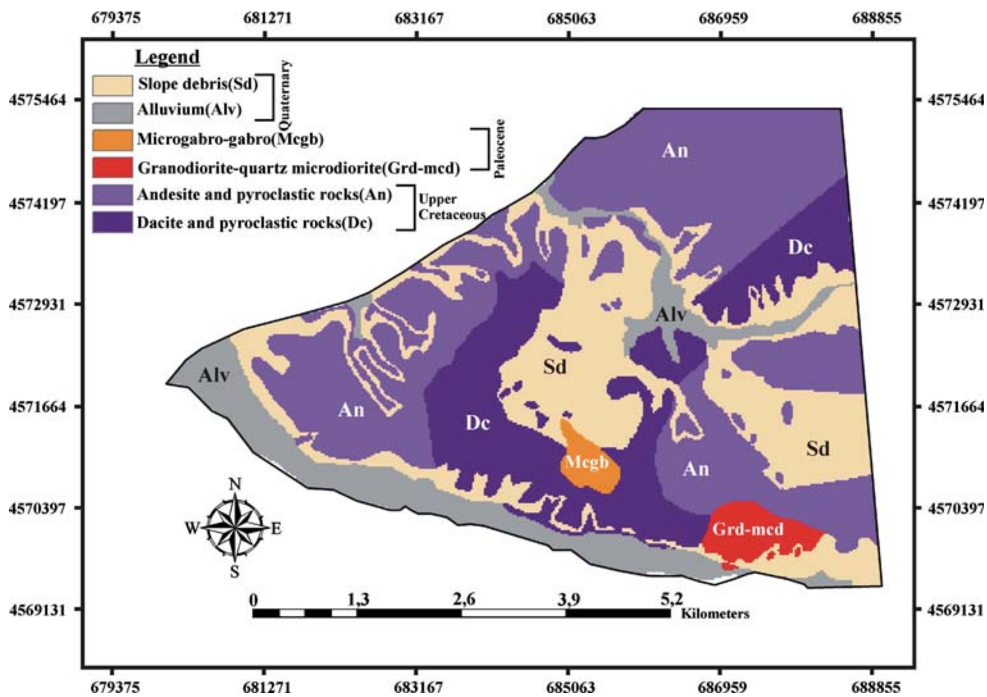

Fig. 2 Simplified lithological map of the study area (Bulut et al. 1995)

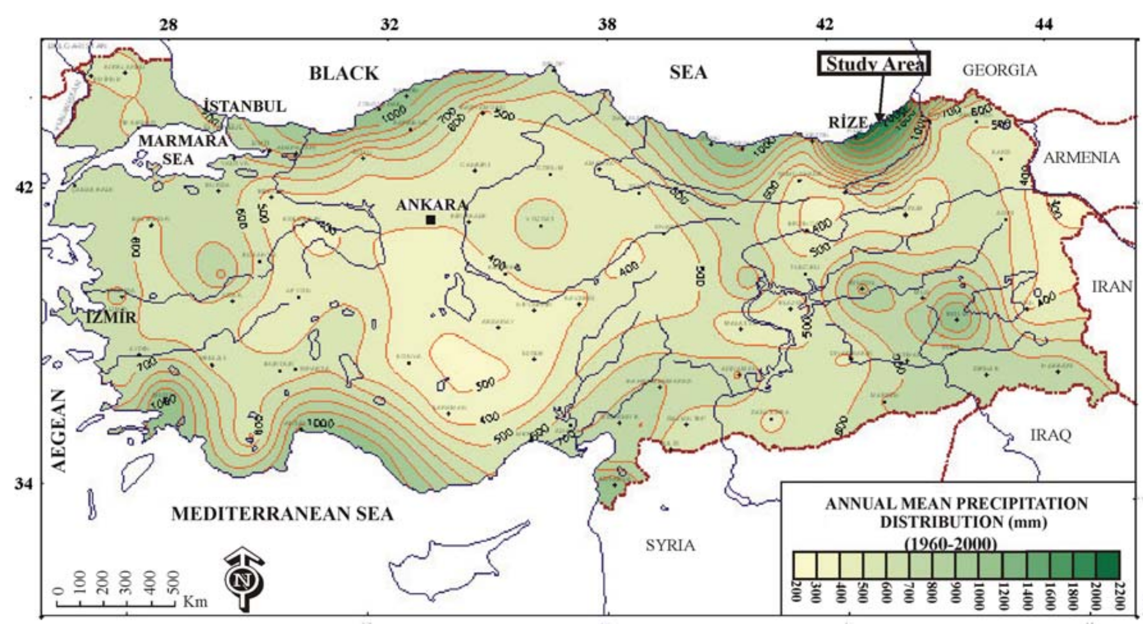

Fig. 3 Annual mean precipitation distribution map of Turkey between 1960 and 2000 years (http://www.meteor.gov.tr/2006/zirai/zirai-calismalar)

with respect to the landslide occurrence for a given area, the same parameter may not be important for another area (Ercanoglu and Gokceoglu 2004). That is why, different parameters can be used and ranked subjectively or objectively to construct a landslide susceptibility map.

In order to produce a detailed and reliable landslide inventory map, extensive field surveys and observations were performed in the study area. A total of 109 landslides were identified and mapped in the area in 1983 and the mode of failure was determined as rotational slide for all the slided masses according to the landslide classification proposed by Varnes (1978). The areal extent of the smallest observable slide is 200 m^2 and the largest is 22,400 m^2 approximately. In addition to this data, a second inventory map was prepared in 1995, and ten additional slides were mapped in the study area. These landslides were also classified as rotational slides according to Varnes (1978). All the landslides mapped are presented in Fig. 4.

In the study, six parameters were considered during the landslide susceptibility zoning of the study area (Table 1). These parameters can be divided into three categories such as geological, topographical and environmental conditioning parameters. The working scale was chosen as 1:25,000. Since the positional accuracy needed for 1:25,000 scale maps must be ±12.5 (USGS 1993), the pixel size of landslide inventory and all parameter maps was 25 m. The study area includes 689.525 pixels and the landslides include 5,428 pixels.

Since various lithological units have different susceptibilities to active geomorphologic processes like landslides, lithology plays an important role on the landslide occurrence (Carrara et al. 1991; Anbalagan 1992; Pachauri et al. 1998; Dai et al. 2001). Therefore, lithology was considered as the geological parameter in this study.

Many of the topographical parameters such as slope gradient, slope aspect, drainage network, etc., are commonly used in the literature in different works (Pachauri et al. 1998; Guzetti et al. 1999; Dai and Lee 2002; Suzen and Doyuran 2004a, b; Ercanoglu and Gokceoglu 2004). In this study, slope gradient, slope aspect and distance from drainage path parameters were considered as topographical parameters in the landslide susceptibility analysis and were constructed by using Idrisi Kilimanjaro GIS and image processing package (Eastman 2003). The elevation (Z) attribute-bearing vector data such as slope gradient and slope aspect maps were calculated using the DEM of the study area, which was produced by triangulation irregular networks (TIN) interpolation method. On the other hand, if the vector data such as drainage and road vectors have no elevation (Z) attributes, which are quantified by presence or absence of the spatial object, a non-interpolative method should have to be applied (Bonham-Carter 1996). This non-interpolative method is either the density (number of line/point elements of fixed length in a fixed area) of the object within a specified area, or the nearest distance between the pixels and that object (Suzen and Doyuran 2004b). For this reason, distance from drainage data was derived from the 1:25,000 scale topographical vector map and the aerial orthogonal distance between the pixels and drainage lines was calculated. Since there is no consensus in literature about the distances to drainage classes, the researchers have used different distances with respect to the closeness of the topographical element (Van Westen and Bonilla 1990; Anbalagan 1992; Pachauri and Pant 1992; Donati and Turrini 2002, Ercanoglu and Gokceoglu 2004; Suzen and Doyuran 2004a, b; Lee 2005; Akgun and Bulut 2007). In this study, the distances of 0, 50, 100, 150, 200 and higher than 200 m, to the drainage path are considered.

Land-cover and road distance were considered as the environmental conditioning parameters. Land-cover map (Fig. 5) was initially prepared by field studies, and then converted to digital format by digitizing the map produced in the field. Distance to road map was produced using the same procedure that was carried out to create the distance from drainage map and the distances of 0, 50, 100, 150, 200 and longer than 200 m, to the road were considered.

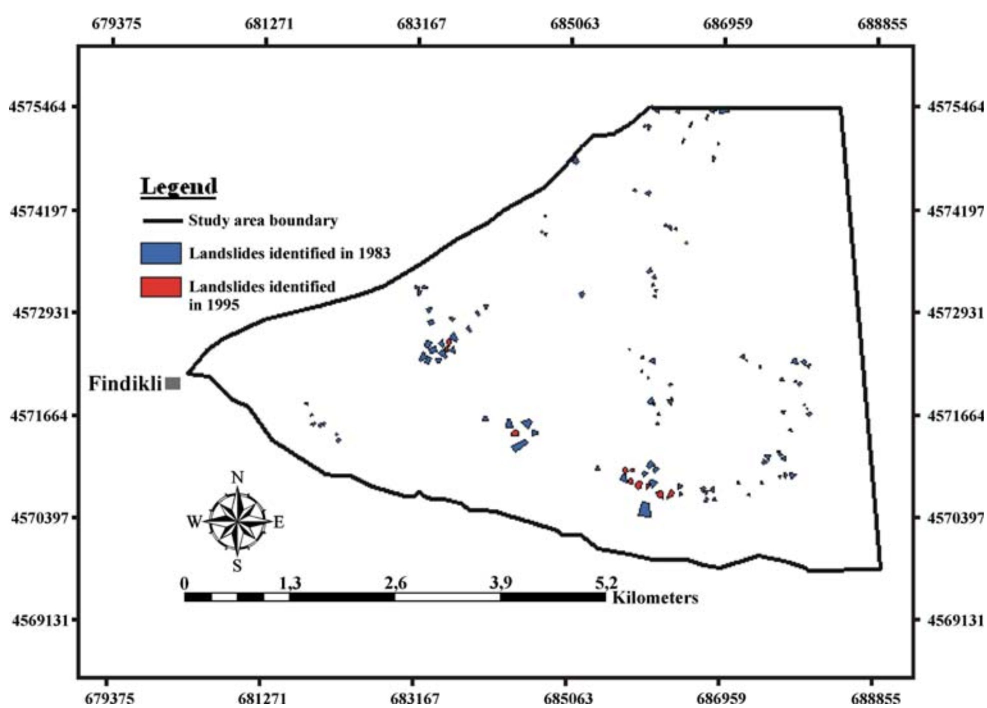

Fig. 4 The landslide inventory map of the study area, prepared in 1983 and 1995 by field observations

Table 1 Data layer of the study area

Classification	Sub-classification	GIS data type	Scale
Geological hazard	Landslide	Polygon vector	1:25,000
Damageable objects	Road	Line vector	1:25,000
Basic map	Topographical map	Line vector	1:25,000
	Geological map	Polygon vector	1:25,000
	Land-cover map	Polygon vector	1:25,000
Hydrologic data	Drainage path	Line vector	1:25,000

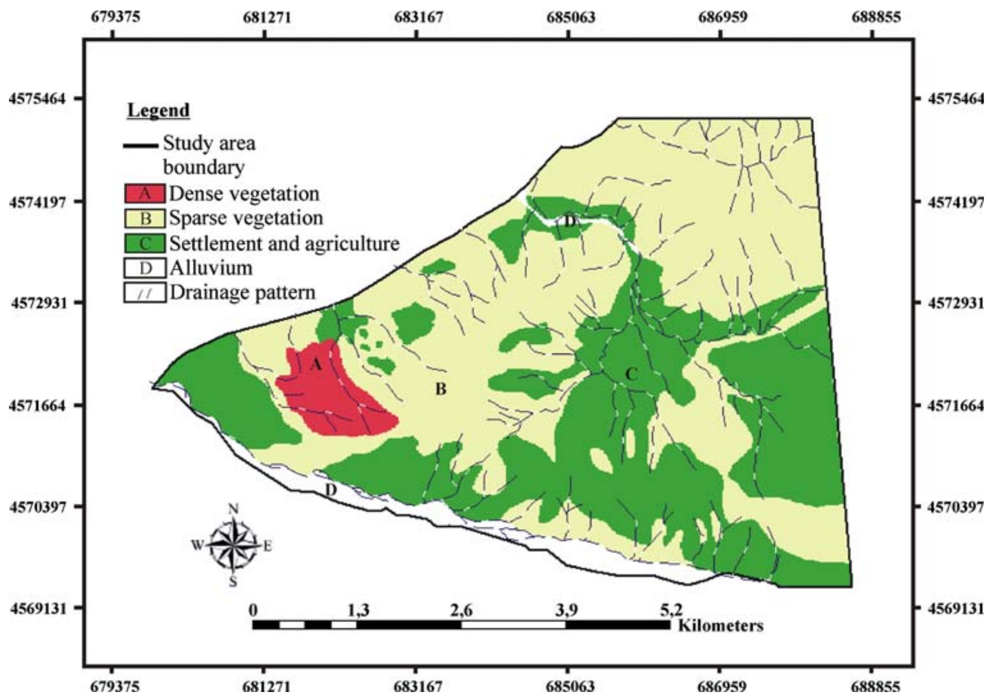

Fig. 5 Land-cover map of the study area

Methodology

In literature, there are numerous methods to assess the probability of landsliding. Generally, these methods can be sub-divided into two groups as statistical and geomorphologic (based on expert knowledge and experience) approaches (Soeters and van Westen 1996; Suzen and Doyuran 2004b).

Among the statistical methods, two important groups arose in the literature, bivariate and multivariate methods. In bivariate statistical method, each parameter map conditioning to landslide is overlaid with the landslide inventory map, and weighting values based on landslide densities are calculated for each parameter class. In order to calculate the weight values, there are many methods such as landslide susceptibility (Brabb 1984; Suzen and Doyuran 2004b), information value (Kobashi and Suzuki 1988), weights of evidence (Bonham-Carter 1996; Lee and Sambath 2006) and statistical index (van Westen 1997) methods. In conventional multivariate statistical methods such as multiple regression and discriminant analysis, the weights of parameters governing landslide occurrence indicate the relative contribution of each of these parameters to the degree of hazard within a given area. With the geomorphologic approaches, expert opinions are used to predict landslide susceptibility using data on conditioning parameters to landsliding. They are based on the assumption that the relationships between landslide susceptibility and the conditioning parameters to landsliding are known and are specified in the models (Dai et al. 2001). However, there are some limitations on these approaches. First is that long-term information on the landslides and their casual parameters for the same site or for sites with similar environmental conditions are essential. The second is the subjectivity of weightings and ratings of the variables.

In this study, a statistical method (likelihood-ratio model) and a multicriteria decision making approach (WLC model) were used and compared with respect to their accuracy and validity in classification of susceptibility classes. There are some differences between these models.

The most important distinction between the models used is that the likelihood ratio model (LRM) is based on bivariate statistics and the WLC model is based on expert knowledge. The ratio values obtained from landslide-conditioning parameters using LRM can be used as weight values for each of the parameters considered and using these weight values can be assigned to relevant parameters to produce a landslide susceptibility map (Lee and Min 2001). However, the weight values for the same purpose can be obtained using multicriteria decision model such as analytical hierarchy process (AHP) that is so-called a semi-quantitative method (Ayalew et al. 2004) and applied using subjective judgments with some mathematical processes. Although there are some discrepancies about the method's meaningfulness of responses to the underlying questions, it has been tested theoretically and empirically for a variety of decision applications, including spatial decision making and landslide susceptibility mapping (Siddiqui et al. 1996; Malczewski 1999; Barredo et al. 2000; Ayalew et al. 2005; Komac 2006; Akgun and Bulut 2007).

Likelihood ratio model

Likelihood ratio model is based on the observed relationships between distribution of landslides and each conditioning parameter of landslide occurrence, to exhibit the correlation between landslide locations and the parameters controlling landslide occurrence in the study area (Lee 2005). The spatial relationship between landslide location and each parameter's conditioning landslide occurrence were obtained using the LRM. In this model, the ratio is that of the area where landslide occurred, to the total area, so that a value of 1 is an average value. If the value is >1, it means percentage of the landslide is higher than the area and refers to a higher correlation, whereas the values lower than 1 means lower correlation.

Relationship between landslides and topography

The slope gradient is a basic topographical feature for landslide susceptibility mapping. Gentle slopes are expected to have a low frequency for shallow-seated landslides due to the generally lower shear stresses associated with low gradients. At a slope of 10° or less, the likelihood ratio is 1.05 (Table 2). This value indicates a moderate to high probability of a landslide occurring. From 10° to 20°, the ratio is lower than 1, indicating low probability. If the slope angle is between 20° and 30°, a landslide may occur and the ratio is 1.19 indicating a high probability. The remained slope angles, higher than 30°, also exhibit low probability relatively because their ratio values are lower than 1. The reason for this circumstance is that the resistant lithologic units exist in the steep slopes and they are not covered by highly and completely weathered lithologic units, which are susceptible to landsliding.

In the case of aspect, landslides were most common on from southwest to west-facing slopes. Hence, hill slopes facing from the southwest to west are highly susceptible to landsliding. The slopes aspecting from northeast to east have also high susceptibility to landsliding but they are relatively less susceptible than the southwest-west slopes. The reason for this situation depends on both the geological and topographical features because the southwest to west facing hill slopes are common on completely weathered dacite, andesite and pyroclastic rocks, whereas the northeast to east facing hill slopes are covered commonly by slope debris. In addition to this, the southwest to west-facing hill slopes have 20 to 30° slope gradients, whereas the northeast to east slopes have 10° to 20° slopes. The frequency of landslides was lowest on east-southeast facing hill slopes (Table 2).

Relationship between landslide and lithology

With respect to relationship between landslides and lithology, the landslide-occurrence value is the highest in the areas where dacite, andesite and their pyroclastic units are completely weathered and the slope gradients differ from 20 to 30°. The andesite and its pyroclastic rocks, which are completely weathered, are also susceptible to landsliding than the others in the study area because the slope gradient in these units ranges between 10° and 20°. This situation depends on the presence of fracture density on dacite, andesite and pyroclastic rocks. The landslide-occurrence values are the lowest in granodiorite and quartz microdiorite (Table 2). Additionally, the probability of landslide is lower in slopes formed by debris material covering a considerable area in the study district. Since the slope gradient is equal to zero in alluvium, no landslide susceptibility in this unit is expected (Table 2).

Relationship between landslide and land-cover

The landslide occurrence value is higher in settlement and agricultural areas such as tea plantation fields and lower in sparsely vegetated areas (Table 2). Since the topography in the area is steep and there is no proper enough flat morphology for agriculture and settlement, inclined and mountainous areas are needed to use for these purposes. However, the reasons of high landslide probability in these areas are human activities such as cultivation of the hill slopes for agricultural purposes and slope excavation for both road cutting and settlement foundations (Fig. 6).

Table 2 Likelihood ratio values of the landslide-conditioning parameters

Parameter	Class	Pixels with landslide	Landslide density[a] (%)	Numbers of pixels in domain	Percentage of domain[b] (%)	Likelihood ratio[c]
Slope gradient	0–10	1,025	18.88	124,261	18.02	1.05
	10–20	1,901	35.02	267,775	38.83	0.90
	20–30	2,053	37.82	219,276	31.80	1.19
	30–40	399	7.35	64,470	9.35	0.79
	40–50	50	0.92	7,075	1.03	0.90
	>50	0	0.00	6,668	0.97	0.00
Slope aspect	Flat	0	0.00	4,718	0.68	0.00
	0–45	761	14.02	97,573	14.15	0.99
	45–90	423	7.79	52,358	7.59	1.03
	90–135	219	4.03	48,267	7.00	0.58
	135–180	476	8.77	76,231	11.06	0.79
	180–225	1,087	20.03	139,467	20.23	0.99
	225–270	1,216	22.40	92,657	13.44	1.67
	270–315	574	10.57	78,764	11.42	0.93
	315–359	672	12.38	99,490	14.43	0.86
Lithology	Slope debris	815	15.02	187,257	27.16	0.55
	Alluvium	0	0	84,915	12.31	0.00
	Microgabro–Gabro	33	0.61	7,925	1.15	0.53
	Granodiorite–quartz microdiorite	17	0.31	15,497	2.25	0.14
	Andesite and pyroclast	2,598	47.89	265,717	38.54	1.24
	Dacite and pyroclast	1,962	36.17	128,214	18.60	1.95
Land-cover	Dense vegetation	0	0	22,271	3.39	0
	Sparse vegetation	2,780	51.22	359,310	54.66	0.94
	Settlement and agriculture	2,648	48.78	275,789	41.95	1.16
Distance from road (m)	0–50	1,771	32.63	154,683	22.43	1.45
	50–100	1,337	24.63	121,868	17.67	1.39
	100–150	1,034	19.05	90,246	13.09	1.46
	150–200	427	7.87	60,089	8.71	0.90
	>200	859	15.83	262,639	38.09	0.42
Distance from drainage (m)	0–50	1,069	19.69	175,088	25.39	0.78
	50–100	1,091	20.10	144,356	20.94	0.96
	100–150	828	15.25	116,491	16.89	0.90
	150–200	1,041	19.18	86,156	12.49	1.53
	>200	1,399	25.77	167,434	24.28	1.06

[a] Ratio of landslides occurred

[b] Ratio of landslides not occurred

[c] Ratio of landslides occurred divided by ratio of landslides not occurred

Relationship between landslide and road distance

Since improper excavations of the slopes were carried out for road cutting to connect the tea plantations and houses in the study area, landslides occurred mainly in the areas close to the roads. Therefore, proximity to a road can be accepted as one of the most influencing parameters for landsliding in the study area. The closer the road, the greater is the landslide probability (Table 2). At a distance of <50 m, the ratio is 1.45, showing a high probability of a landslide. The ratio is lower than 1 at a distance >150 m and this indicates a low probability.

Relationship between landslide and drainage distance

In order to assess the influence of drainage on landslide occurrence, a statistical analysis was carried out. For this purpose, the distance to drainage was identified by buf-

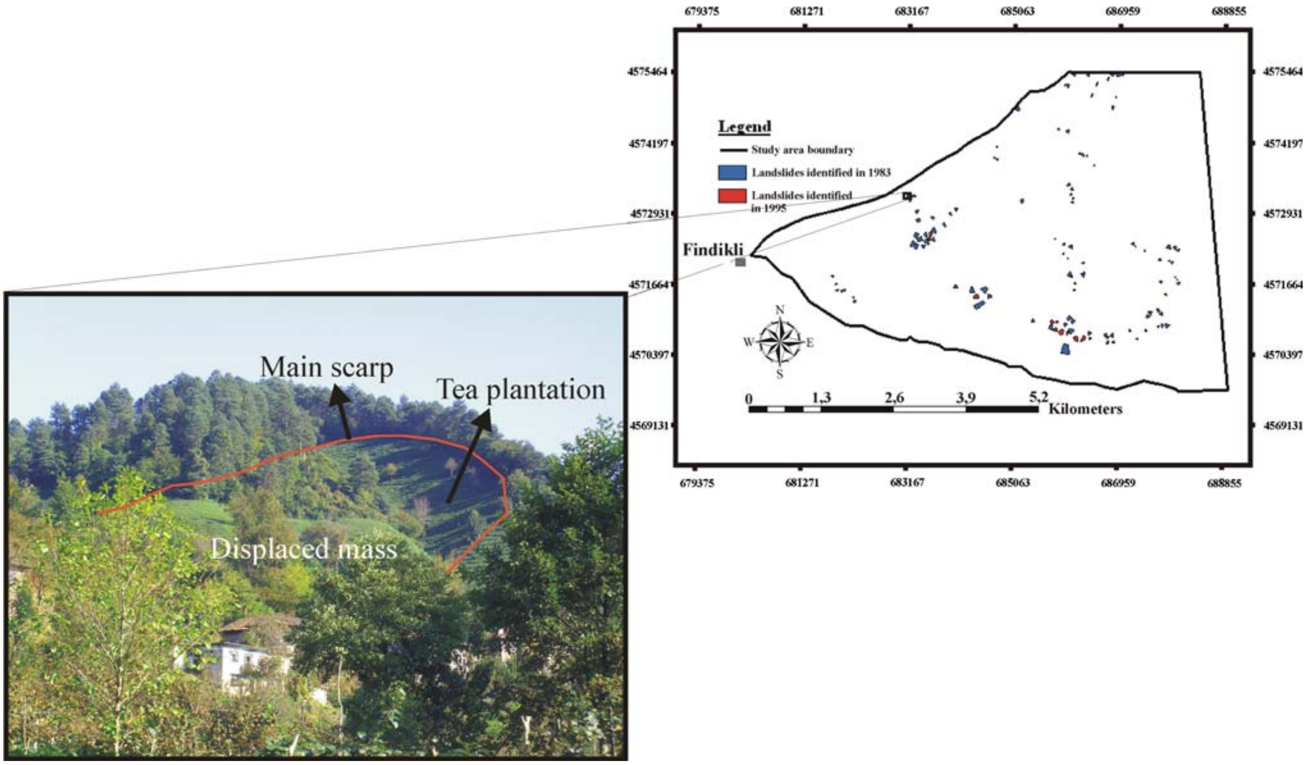

Fig. 6 A general view showing the relationship between the hill slopes and land-cover in the study area

fering. In the case of the relationship between landslide occurrence and distance from drainage, as the distance from drainage increases, the landslide occurrence probability increases (Table 2). At a distance of higher than 150 m, the ratio was >1, showing a high probability of landslide occurrence and at distances <150 m, the ratio was lower than 1, indicating a low probability. In general, this is contrary to what is expected. The landslides occurred predominantly on the slope faces generally 150 and 200 m away from the drainage lines. This is considered to be due to the terrain modification caused by undercutting of the slopes in the study area.

Susceptibility mapping by likelihood ratio model

In order to calculate the likelihood ratio, the area ratio for landslide occurrence was determined for the class of each parameter contributing to landslide occurrence. For this purpose, the landslide inventory map, produced in 1983, was overlaid with thematic layers, and an area ratio for the class of each parameter to the total area was calculated. Therefore, likelihood ratios (*a*/*b*) for the class of each parameter were calculated by dividing the landslide occurrence ratio (*a*) by the area ratio (*b*). Then, the likelihood ratios of each parameter's class were summed and the total values of the likelihood ratios obtained were assigned to each relevant parameter map as a weight value.

The parameter maps weighted were combined to determine the landslide susceptibility index (LSI), as presented in Eq. 1.

$$\mathrm{LSI} = \mathrm{Wr}_1 + \mathrm{Wr}_2 + \ldots \mathrm{Wr}_n, \qquad (1)$$

where, Wr is the parameter map weighted.

The higher the LSI value, the higher the landslide susceptibility whereas lower value means a lower susceptibility of landslide. The calculated likelihood ratios of each parameter's classes are shown in Table 2. Using these likelihood ratios, a landslide susceptibility map (Fig. 7) was obtained by the LSI map. Since the LSI map obtained has a continuous scale of numerical values, a necessity of dividing these values into susceptibility classes has appeared. For this purpose, there are some mathematical methods proposed by Scott (1979) and Friedman and Diaconis (1981), which was based on the optimum bin width classification of the histogram. According to Suzen and Doyuran (2004a), both the methods cited are ineffective to multimodel distributions, and they proposed a new method based on percentile divisions of seed cells to classify the continuous data sets into categories. Ayalew et al. (2004) took into consideration four systems of classifier that use the natural breaks, quantiles, equal intervals and standard deviation to choose the best method. The quantile-based classification system takes into consideration widely

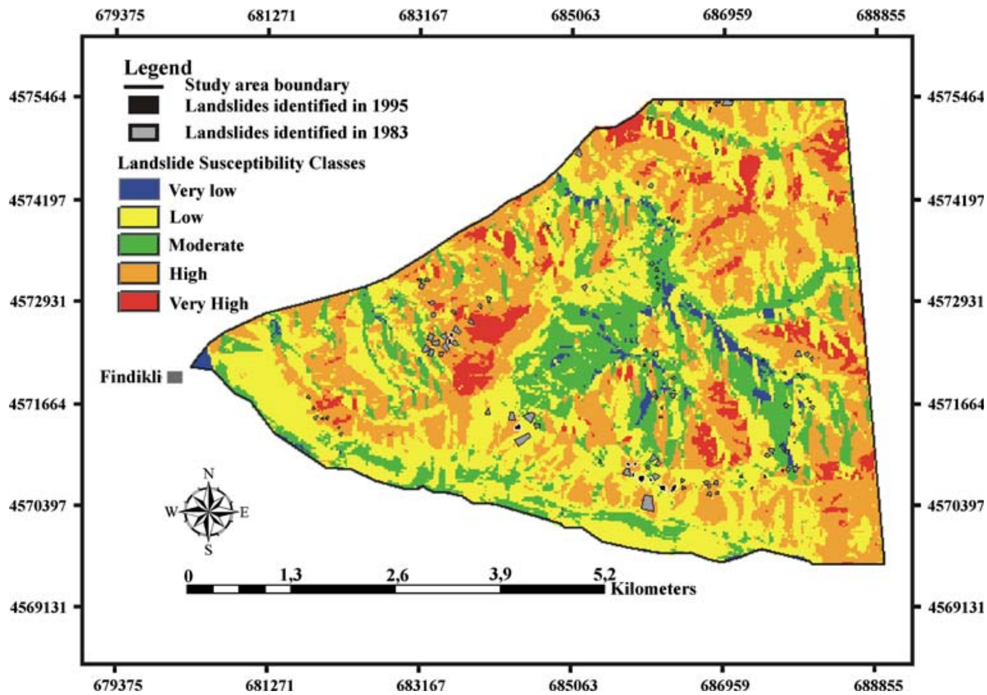

Fig. 7 Landslide susceptibility map produced by the likelihood ratio model

different values into the same class, the equal intervals emphasizes one class of susceptibility relative to others and the natural breaks set the boundaries where relatively big jumps exist in data values, they found the standard deviation method as the best method, as it uses the mean value of the data obtained to create the classbreaks. The standard deviation classifier is also proposed in case the histogram of data values exhibits a normal distribution (Suzen and Doyuran 2004a). Therefore, the standard deviation classifier was used as well because the data values in the LSI map obtained using the LRM show a normal distribution (Fig. 8).

According to this susceptibility map, 2.96% of the total area is found to be very low susceptible. Low, moderate and high susceptible zones constitute 31.09, 39.74 and 23.3% of the area, respectively. The very high susceptible area is 2.88% of the total study area.

Weighted linear combination model

Weighted linear combination is likely the best known and commonly used multicriteria-GIS method (Eastman 1999; Jiang and Eastman 2000; Sener et al. 2006). WLC is a method in which triggered parameters affecting a landslide can be combined by applying weights. In this method, a primary issue is to assign weights to each parameter separately. There are many techniques such as the statistical index method (Wi) (Van Westen 1997), weighting parameter (WF) (Cevik and Topal 2003; Oztekin and Topal 2005) and AHP (Saaty 1980; Saaty and Vargas 2001; Ayalew et al. 2004, 2005; Sener et al. 2006) to find weights. In this regard, the AHP, a theory for dealing with complex technological, economical and socio-political problems, is an appropriate method for deriving the weight assigned to each parameter (Saaty 1980).

Basically, AHP is a multiobjective, multicriteria decision making approach that employs a pair-wise comparison procedure to arrive at a scale of preference among a set of alternatives (Malczewski 1999). Specifically, the weights are determined by normalizing the eigenvector associated with the maximum eigenvalue of the (reciprocal) ratio matrix. In this method, the pair-wise matrix is used and ranking of all parameters is made by a continuous scale ranging from 1/9 to 9 (Table 3). When the parameter on the vertical axis is more important than the parameter on the horizontal axis, this value varies between 1 and 9. Contrary to this, the value varies between the reciprocals 1/2 and 1/9.Weight values are calculated by taking the main eigenvector of the matrix (Malczewski 1999). In AHP, the consistency utilized in constructing a matrix is checked by a consistency ratio (CR). CR is used to show the probability that the matrix judgements were randomly generated (Saaty 1980).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \qquad (2)$$

where RI is the average of resulting consistency index depending on the order of the matrix given by Saaty (1980) and CI is the consistency index and can be expressed as

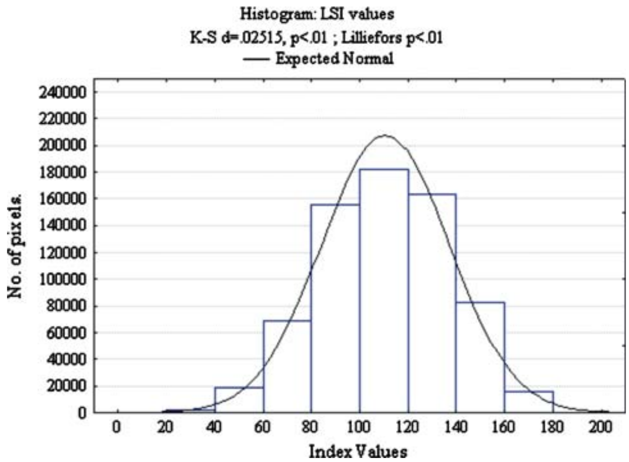

Fig. 8 Relative distribution of the susceptibility classes produced by two susceptibility assessment model

Table 3 Scale of preference between the parameters in AHP (Saaty 2000)

Scale	Degree of preferences
1	Equally
3	Moderately
5	Strongly
7	Very Strongly
9	Extremely
2, 4, 6, 8	Intermediate
Reciprocals	Opposites

$$\mathrm{CI} = \frac{(\lambda_{\max} - n)}{(n - 1)}, \tag{3}$$

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

In order to be acceptable of the computed weights, the consistency ratio must be <0.1 (Malczewski 1999; Saaty 2000). A consistency ratio above 0.1 requires revisions of the judgements in the matrix because of an inconsistent treatment of particular parameter ratings.

Susceptibility mapping by weighted linear combination model

In order to produce a landslide susceptibility map using WLC model, initially, the parameter weights which are rule based in the ratings giving to each class of a parameter on the basis of a certain criterion were determined using the AHP method. In order to realize this stage, a pair-wise comparison matrix with score given in Table 4 was constructed. The appropriate scores used in this study were chosen based on the detailed field observations, and using these observations, a criterion was constituted. This criterion is the landslide density, a ratio between the area affected by landslide pixels on a class of a certain parameter and the total area of that class, changed into percentage. These landslide density percentages used were also calculated for the LRM, therefore they are given in Table 2. Using six parameters, the comparison matrix was constructed. The diagonal boxes of a pair-wise comparison matrix always take a value of 1. The boxes in the upper and lower halves are symmetrical with one another and the corresponding values are reciprocal with each other. When the matrix is generated, the weights will be gained using the parameter layers as input. Then, the weights are taken into account as the average of all possible ways of comparing the casual parameters (Malczewski 1999; Ayalew and Yamagishi 2005).

In this study, the weight value of the land-cover is the highest. The lithology, slope gradients, road distance, drainage distance and slope aspect are arranged in order of the their weights (Table 4).

The consistency ratio is found to be 0.05 and this value expresses the proper degree of consistency ratio utilized to produce the comparison matrix because it is <0.1. In order to produce a landslide susceptibility map by WLC model, the weights corresponding to parameters were multiplied by the relevant parameter maps and then, all the weighted parameter maps were overlaid. The flow chart of the method is presented in Fig. 9. In this way, an index map showing the spatial distribution of the landslide susceptibility was obtained. To provide visual interpretation, the produced susceptibility index map was divided into equal areas. Thus, the landslide susceptibility classes were clearly identified. Based on this method, five susceptibility classes were distinguished such as very low, low, moderate, high and very high (Fig. 10). According to this susceptibility map, 0.71% of the study area is very low susceptible and the low, moderate and high susceptible zones form 26.91, 14.81 and 42.15% of the study area, respectively. About 15.14% of the total area is estimated to be very high susceptible.

Comparision of the results

Two susceptibility maps were produced using the LRM and WLC model. Looking at the both maps obtained, some similarities and also differences are perceived. In order to make a comparison between the two maps, two different comparison methods were employed. They are basic linear correlation and cross-correlation methods. The basic linear correlation process was carried out using statistical package, Statistica 6.0, and the cross-correlation was completed

Table 4 The pair-wise comparison matrix, parameter weights and consistency ratio value

Parameter	Slope aspect	Drainage distance	Lithology	Land-cover	Slope gradient	Road distance	Weights
Slope aspect	1						0.0466
Drainage distance	2	1					0.0668
Lithology	5	3	1				0.2501
Land-cover	5	5	2	1			0.3668
Slope gradient	3	3	1/2	1/2	1		0.1859
Road distance	3	2	1/4	1/6	1/4	1	0.0838

Consistency ratio: 0.05 < 0.1 (acceptable)

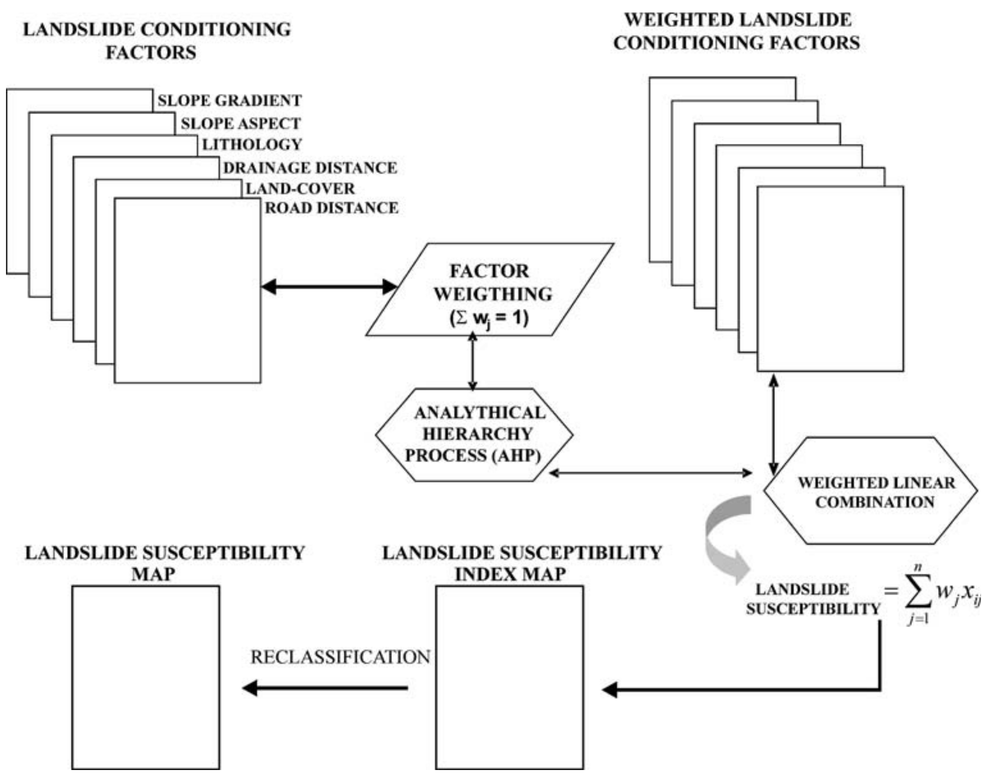

Fig. 9 Flow chart of the used model

using Idrisi Kilimanjaro software. The purpose of the two comparison methods applied was to exhibit the similarities between the two landslide susceptibility maps obtained.

In order to carry out the basic linear correlation, both maps were converted to ASCII file and then imported into the statistical package. With the basic linear correlation process, a correlation coefficent (r) was found to be 0.64 that is significant at 0.95 confidence level. This value shows a considerable similarity between both susceptibility maps. In addition to this process, cross-correlation was applied to both the maps. In this method, two operations were performed. The first was image cross-tabulation in which the categories of one image are compared with those of a second image and a tabulation is kept of the number of cells in each combination (Eastman 2003). With this operation, some measures of association between the images were obtained. The first of these measures was Cramer's V, a correlation coefficient that ranges from 0.0 indicating no correlation with 1.0 indicating perfect correlation (Ott et al. 1983). In addition to this, a chi-square value was also determined so that the significance of Cramer's V could be tested. The results showing the cross-correlation between the two landslide susceptibility maps are given in Table 5. The second measure obtained from cross-correlation was Kappa index value and it is shown in Table 5. The Kappa index (also called Khat or the Kappa Index of Agreement, KIA) is used if the two images have completely the same number of classes (Carstensen 1987) and ranges from 0.0 to 1.0 with the same interpretation. It only has meaning if the categories on the two maps depict the same kind of data with the same data classes (Eastman 2003). Because of these reasons, the Kappa index value was also considered to

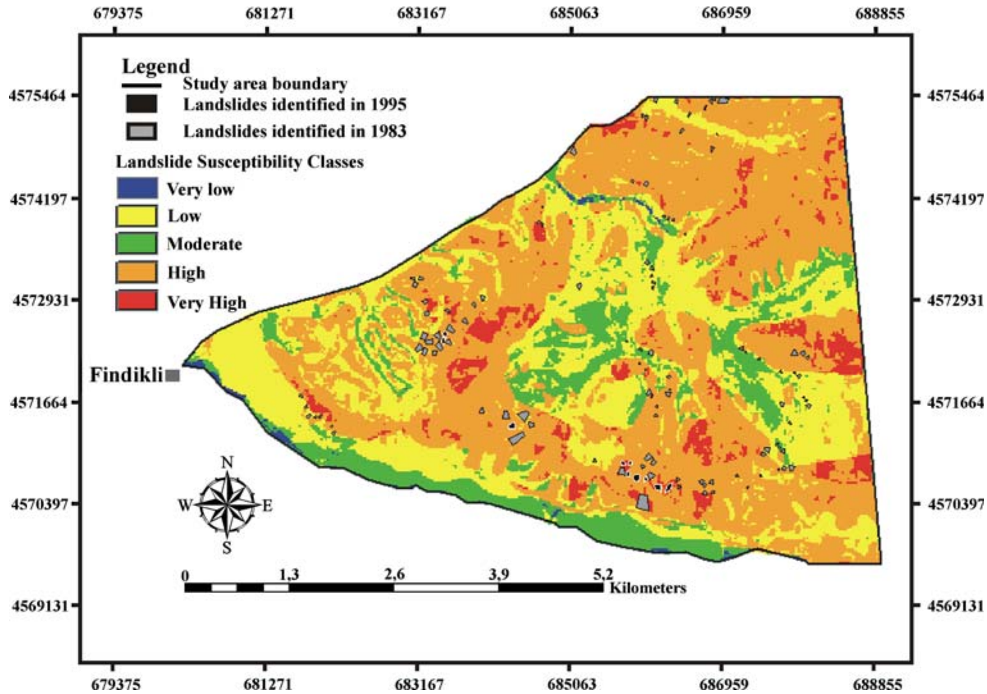

Fig. 10 Landslide susceptibility map produced by the weighted linear combination model

Table 5 Cross-correlation of the WLC (columns) against LRM (rows) landslide susceptibility maps and the statistical data obtained

Susceptibility classes	1	2	3	4	5	Total	KIA	Statistical data
1	0.0035	0.0131	0.0026	0.0000	0.0000	0.0192	0.5501	Cramer's V = 0.4185
2	0.0024	0.0631	0.0932	0.0236	0.0000	0.1824	0.4201	χ^2 = 483,162.31
3	0.0003	0.0434	0.1567	0.1973	0.0025	0.4002	0.1734	
4	0.0000	0.0005	0.0582	0.2550	0.0206	0.3342	0.2506	
5	0.0000	0.0000	0.0001	0.0330	0.0309	0.0640	0.5435	
Total	0.0063	0.1201	0.3108	0.5089	0.0540	1.0000	Overall κ = 0.2784	

be an evidence to show the similarity between the two susceptibility maps. At the end of the cross-correlation process, the Cramer's V and overall KIA values were determined to be 0.4185 and 0.2784, respectively. The Cramer's V value shows a favorable similarity between the both susceptibility maps, whereas the overall KIA value indicates less similarity. However, on making a close inspection of the KIA values for each of the susceptibility classes, very low, low, moderate, high and very high classes having 0.55, 0.42, 0.17, 0.25 and 0.54 KIA values indicate very low, low and very high susceptibility classes of both maps that are similar, but there is an evident dissimilarity between the low and moderate susceptibility classes, and this situation decreases the overall KIA value.

As shown in Fig. 11, the histogram of the susceptibility map constructed by LRM exhibits a near normal distribution after re-classification of the likelihood ratio index map into five classes of susceptibility, whereas the histogram of the susceptibility map produced by WLC model is negatively skewed showing that high and very high susceptibility classes constitute more areas in the WLC map than LRM map. The reason for this situation may be based on the theoretical natures of the approaches employed herein. Due to the subjectivity in constructing the pair-wise comparison matrix, the result obtained by WLC model at a specific place is more or less dominated by the contribution of a single or a few numbers of landslide-conditioning parameters. Contrary to this, the likelihood ratio at any points perceives the casual parameters to landsliding that maximize the likelihood of the observed sample values. Therefore, it is concluded that the more the method is objectively constructed, the more the accurate results can be obtained.

Verification of the susceptibility maps

Three basic methods can be applied to obtain an independent sample of landslide in order to verify a landslide

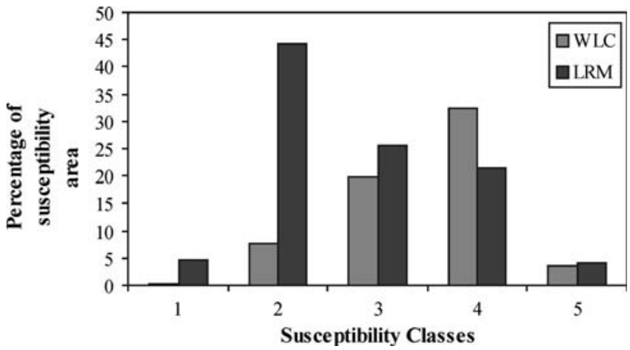

Fig. 11 Relative distribution of the susceptibility classes produced by two susceptibility assessment models (1: very low, 2: low, 3: moderate, 4: high and 5: very high)

susceptibility map as applied by Remondo et al. (2003). In the first method, the original landslide inventory is randomly split into two groups, one for the susceptibility analysis and one for verification process. In the second method, the susceptibility analysis is carried out in a part of the study area and the susceptibility map thus obtained is tested in another part with different landslides. In the last method, the susceptibility analysis employed using landslides generated in a certain period and verification is carried out by means of landslides that occurred in a different period. The latter is accepted as the most reliable method to perform the verification process of the susceptibility map obtained (Irigaray et al. 1999, 2006; Remondo et al. 2003). Therefore, the last method proposed was applied to carry out the verification process in this study.

In order to verify both landslide susceptibility maps, the maps were matched with the landslide locations observed and mapped both in 1983 and 1995 in the study area. For this purpose, the two maps were separately overlaid with the landslide inventory map and the landslide occurrence percentage in all susceptibility classes for both maps were determined. Using this approach, landslide occurrence percentages falling to all the susceptibility classes of each maps were determined. The verification result is presented

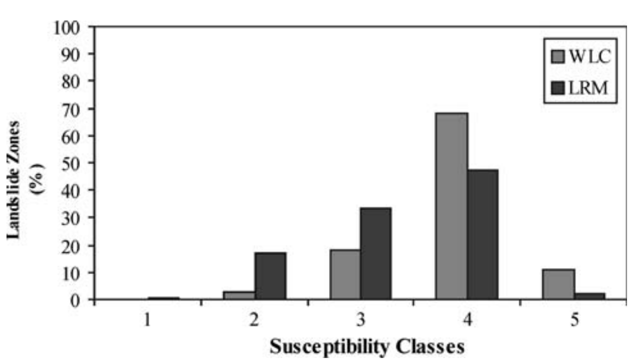

Fig. 12 A histogram exhibiting the percentage of the recent landslide zones falling into the susceptibility classes of the LRM and WLC susceptibility maps

as a graph in Fig. 12. In this graph, it is clearly seen that no landslide fall into the very low susceptibility classes in both the LRM and WLC maps. In the LRM map, 16.78, 33.30, 47.41 and 1.97% of the recent landslides fall into the low, moderate, high and very high susceptibility classes, respectively, 2.54, 18.21, 68.09 and 11.14% recent landslides fall into the low, moderate, high and very high susceptibility classes in the WLC map. In this regard, it is easy to say that many of landslide zones in the study area are more compatible with the susceptibility classes in the WLC map than the LRM map.

Conclusions and discussion

In this study, two landslide susceptibility mapping models, the LRM and the WLC model, were applied to Findikli district, Rize, Northeast Turkey, as the study area, using a GIS for estimating the susceptible areas of the study area. The produced susceptibility maps were compared with the landslide zone map of the area and the effectiveness of the used methods was tested.

A landslide inventory map of the study area was compiled in 1983 by detailed data from field surveys and aerial-photography studies. In the study area, a total of 109 landslides were identified, and the common failure mode was determined as rotational slides. In addition to this map, a second inventory map was prepared in 1995 and ten additional landslides in type of rotational slide were recorded. The main triggering parameter for the landslides in the area is heavy rainfall since the area receives heavy precipitation frequently.

Two statistical methods are used for landslide susceptibility mapping. The first one is LRM, which uses the frequency relations between the occurred landslides and the parameters conditioning landslide occurrence in the area. The second model is WLC which is a well-known multicriteria decision analysis model. The two landslide susceptibility maps are obtained using the LRM and WLC models, and five susceptibility classes are distinguished in the two maps. According to both the maps, the northern and eastern parts of the study area are more prone to landslide occurrence. In the WLC map, high susceptibility class covers widespread areas than in the LRM map. The least susceptible zones of the study area are in the central parts, and these areas are very similar in both the susceptibility maps. Although the two maps show a similarity, some distinctions are also observed. These distinctions depend on the methodological approach used in the two models. The LRM map results are inferred from the actual landslide data, whereas the WLC model is based on the expert judgment to choose the effectiveness of the parameters for landslide susceptibility mapping. However, much of the WLC model uses the subjective decisions; the parameters considered are analysed by reliable mathematical approach such as AHP.

Up to recent years, there has been no attempt to the preparation of the landslide inventory maps in Turkey. However, especially in the last decade, many researchers and governmental research institutions such as the General Directorate of Mineral Resources have spent considerable efforts to prepare a national landslide inventory database. For this purpose, the Turkey Landslide Inventory Project has been initiated in 1997 by the General Directorate of Mineral Resources and it will be finished by the next year (Duman et al. 2005). With the help of this project, preparation of the landslide susceptibility maps in Turkey by the previously mentioned methods will be made easier.

The obtained landslide susceptibility maps are expected to be utilized by the local governmental authority because the data will help them in their decision-making and policy planning efforts in the near future.

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References

Akgun A, Bulut F (2007) GIS-based landslide susceptibility for Arsin-Yomra (Trabzon, North Turkey) region. Environ Geol 51(8):1377–1387

Aleotti P, Chowdhury R (1999) Landslide hazard assessment: summary review and new perspectives. Bull Eng Geol Environ 58:21–44

Anbalagan R (1992) Landslide hazard evaluation and zonation mapping in mountainous terrain. Eng Geol 32:269–277

Atkinson PM, Massari R (1998) Generalized linear modelling of susceptibility to landsliding in the central Appennines, Italy. Comput Geosci 24(4):373–385

Ayalew L, Yamagishi H (2005) The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. Geomorphology 65:15–31

Ayalew L, Yamagishi H, Ugawa N (2004) Landslide susceptibility mapping using GIS-based weighted linear combination, the case in Tsugawa area of Agano River, Niigata Prefecture, Japan. Landslides 1:73–81

Ayalew L, Yamagishi H, Marui H, Kanno T (2005) Landslide in Sado Island of Japan: Part II. GIS-based susceptibility mapping with comparision of results from two methods and verifications. Eng Geol 81:432–445

Barredo JI, Benavides A, Hervas J, van Westen CJ (2000) Comparing heuristic landslide hazard assessment techniques using GIS in the Trijana basin. Gran Canaria Island, Spain. Int J Appl Earth Obser Geoinf 2:9–23

Bonham-Carter GF (1996) Geographical information systems for geoscientist, modeling with GIS. Pergamon Press, Oxford

Brabb EE (1984) Innovative approaches to landslide hazard and risk mapping. In: Proceedings of the 4th international symposium on landslides, vol 1. Canadian Geotechnical Society, Toronto, pp 307–324

Brabb EE, Pampeyan EH (1972) Preliminary map of landslide deposits in San Mateo County, California. US Geological Survey Miscellaneous Field Studies, Map MF-360, scale 1:62.500 (reprinted in 1978)

Bulut F, Boynukalin S, Tarhan F, Ataoglu E (1995) The reasons of the landslides occurred in the east of the Findikli (Rize) district. In: Proceedings of the 2nd national landslide symposium, Adapazarı, pp 143–152

Bulut F, Boynukalın S, Tarhan F, Ataoğlu E (2000) Reliability of landslide isopleth maps. Bull Eng Geol Environ 58:95–98

Can T, Nefeslioglu HA, Gokceoglu C, Sonmez H, Duman TY (2005) Susceptibility assessment of shallow earthflows triggered by heavy rainfall at three subcatchments by logistic regression analyses. Geomorphology 72:250–271

Carrara A, Cardinalli M, Detti R, Guzetti F, Pasqui V, Reichenbach P (1991) GIS techniques and statistical models in evaluating landslide hazard. Earth Surf Proc Land 16(5):427–445

Carstensen LW (1987) A measure of similarity for cellular maps. Am Cartogr 14(4):345–358

Cevik E, Topal T (2003) GIS-based landslide susceptibility mapping for a problematic segment of the natural gas pipeline, Hendek (Turkey). Environ Geol 44:949–962

Chacon J, Irigaray C, Fernandez T, El Hamdouni R (2006) Engineering geology maps: landslides and geographical information systems. Bull Eng Geol Environ 65:341–411

Dai FC, Lee CF (2001) Terrain-based mapping of landslide susceptibility using a geographical information systems: a case study. Can Geotech J 38:911–923

Dai FC, Lee CF (2002) Landslide characteristics and slope instability modelling using GIS, Lantau Island, Hong Kong. Geomorphology 42:213–228

Dai FC, Lee CF, Xu ZW (2001) Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong. Environ Geol 40(3):381–391

Dobrovolny E (1971) Landslide susceptibility in and near anchorage as interpreted from topographic and geologic maps, in the great Alaska earthquake of 1964-Geology volume. Publication 1603. U.S. Geological Survey Open File Report 86-329, National Research Council, Committee on the Alaska Earthquake, National Academy of Sciences, USA, pp 735–745

Donati L, Turrini MC (2002) An objective method to rank the importance of the parameters predisposing to landslides with the GIS methodology: application to an area of the Appennines (Valnerina; Perugia, Italy). Eng Geol 63:277–289

Duman TY, Can T, Emre O, Kecer M, Dogan A, Ates S, Durmaz S (2005) Landslide inventory of Northwestern Anatolia. Eng Geol 77:99–114

Eastman R (1999) Multi-criteria evaluation and GIS. In: Longley PA, Goodchild MF, Maguire DJ, Rhind DW (eds) Geographical information systems, Chap 35. Wiley, New York

Eastman R (2003) IDRISI Kilimanjaro: guide to GIS and image processing. Clark Labs, Clark University, Worcester, USA

Ercanoglu M, Gokceoglu C (2002) Assessment of landslide susceptibility for a landslide-prone area (north of Yenice, NW Turkey) by fuzzy approach. Environ Geol 41:720–730

Ercanoglu M, Gokceoglu C (2004) Use of fuzzy relations to produce landslide susceptibility map of a landslide prone area (West Black Sea Region, Turkey). Eng Geol 75:229–250

Ermini L, Filippo C, Casagli N (2005) Artificial Neural Networks applied to landslide susceptibility assessment. Geomorphology 66:327–343

Friedman D, Diaconis P (1981) On the histograms a density estimator L_2 theory. Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete 57:453–476
General Directory of Meteorological Services of Turkey (2006) www.meteor.gov.tr/2006/zirai/zirai-calismalar (connected:18.10.2006)
Gokceoglu C, Aksoy H (1996) Landslide susceptibility mapping of the slopes in the residual soils of the Mengen region (Turkey) by deterministic stability analyses and image processing techniques. Eng Geol 44:147–161
Gokceoglu C, Sonmez H, Ercanoglu M (2000) Discontinuity controlled probabilistic slope failure risk maps of the Altındağ (settlement) region in Turkey. Eng Geol 55:277–296
Gokceoglu C, Sonmez H, Nefeslioglu HA, Duman TY, Can T (2005) The 17 March 2005 Kuzulu landslide (Sivas, Turkey) and landslide-susceptibility map of its near vicinity. Eng Geol 81:65–83
Gomez H, Kavzoglu T (2005) Assessment of shallow landslide susceptibility using artificial neural networks in Jabanosa River Basin, Venezuela. Eng Geol 78:11–27
Gorsevski PV, Gessler PE, Foltz RB, Elliot WJ (2006) Spatial prediction of landslide hazard using logistic regression and ROC analysis. Trans GIS 10(3):395–415
Guzetti F, Cardinali M, Reichenbach P, Carrara A (2000) Comparing landslides maps: a case study in the Upper Tiber basin, Central Italy. Environ Manage 25(3):247–263
Guzetti F, Carrarra A, Cardinali M, Reichenbach P (1999) Landslide hazard evaluation: a review of current techniques and their application in a multiscale study, Central Italy. Geomorphology 31:181–216
Ildir B (1995) Türkiyede heyelanlarin dagilimi ve afetler yasası ile ilgili uygulamalar. In: Onalp A (ed) Proceedings of the 2nd national landslide symposium, Turkey, Sakarya University, pp 1–9
Irigaray C, Fernandez T, El Hamdouni R, Chacon J (1999) Verification of landslide susceptibility mapping. A case study. Earth Surf Proc Land 24:537–544
Irigaray C, Fernandez T, El Hamdouni R, Chacon J (2006) Evaluation and validation of landslide-susceptibility obtained by GIS matrix method: examples from the Betic Cordillera (southern Spain). Nat Hazards. doi:10.1007/s11069-006-9027-8
Jiang H, Eastman JR (2000) Application of fuzzy measures in multicriteria evaluation in GIS. Int J Geog Inform Sci 14:173–184
Jibson WR, Edwin LH, John AM (2000) A method for producing digital probabilitic seismic landslide hazard maps. Eng Geol 58:271–289
Kobashi S, Suzuki M (1988) Hazard index for the judgment of slope stability in the Rokko Mountain region. In: Proceedings of the interpraevent, vol 1. Grazz, Austria, pp 223–233
Komac M (2006) A landslide susceptibility model using analytical hierarchy process method and multivariate statistics in perialpine Slovenia. Geomorphology 74:17–28
Korkmaz S, Gedik A (1988) Geology of the region between Rize-Findikli-Camlihemsin districts and petroleum occurrences. Geol Eng J 32:5–15 (in Turkish)
Lee S (2004) Application of likelihood ratio and logistic regression model for landslide susceptibility mapping using GIS. Environ Manage 34:223–232
Lee S (2005) Application of logistic regression model and its validation for landslide susceptibility mapping using GIS and remote sensing data. Int J Remote Sens 26:1477–1491
Lee S, Choi J, Min K (2004a) Probabilistic landslide hazard mapping using GIS and remote sensing data at Boun, Korea. Int J Remote Sens 25:2037–2052
Lee S, Dan NT (2005) Probabilistic landslide susceptibility mapping in the Lai Chau province of Vietnam: focus on the relationship between tectonic fractures and landslides. Environ Geol 48:778–787
Lee S, Min K (2001) Statistical analysis of landslide susceptibility at Yongin, Korea. Environ Geol 40:1095–1113
Lee S, Ryu JH, Lee MJ, Won JS (2003) Landslide susceptibility analysis using artificial neural network at Boun, Korea. Environ Geol 44:820–833
Lee S, Ryu JH, Lee MJ, Won JS (2006) The application of artificial neural networks to landslide susceptibility mapping at Janghung, Korea. Math Geol 38(2):199–219
Lee S, Ryu JH, Won JS, Park H (2004b) Determination and application of the weights for landslide susceptibility mapping using an artificial neural network. Eng Geol 71:289–302
Lee S, Sambath T (2006) Landslide susceptibility mapping in the Damrei Romel area, Cambodia using frequency ratio and logistic regression models. Environ Geol 50(6):847–855
Malczewski J (1999) GIS and multicriteria decision analysis. Wiley, New York
Ohlmacher CG, Davis CJ (2003) Using multiple regression and GIS technology to predict landslide hazard in northeast Kansas, USA. Eng Geol 69:331–343
Ott L, Larson RF, Mendenhall W (1983) Statistics: a tool for the social sciences. Duxbury Press, Boston
Oztekin B, Topal T (2005) GIS-based detachment susceptibility analyses of a cut slope in limestone, Ankara, Turkey. Environ Geol 49:124–132
Pachauri AK, Pant M (1992) Landslide hazard mapping based on geological attributes. Eng Geol 32:81–100
Pachauri AK, Gupta PV, Chander R (1998) Landslide zoning in a part of the Garhwal Himalayas. Environ Geol 36(3–4):325–334
Radbruch DH (1970) Map of relative amounts of landslides in California. US Geological Survey Open-File Report 70-1485, 36 pp, map scale 1:500.000. US Geological Survey Open-File Report, 85-585
Remondo J, Gonzalez A, Diaz de Teran JR, Cendrero A, Fabbri A, Cheng CF (2003) Validation of landslide susceptibility maps: examplesand applications from a case study in Northern Spain. Nat Hazards 30(3):437–449
Saaty TL (1980) The analytical hierarchy process. McGraw Hill, New York
Saaty TL (2000) The fundamentals of decision making and priority theory with the analytic hierarchy process, vol VI, 2nd edn. RWS Publications, Pitsburg
Saaty TL, Vargas GL (2001) Models, methods, concepts and applications of the analytic hierarchy process. Kluwer, Boston
Scott DW (1979) On optimal and data-base histograms. Biomeditrika 66(3):605–610
Sener B, Suzen ML, Doyuran V (2006) Landfill site selection by using geographic information systems. Environ Geol 49:376–388
Shou KJ, Wang CF (2003) Analysis of the Chiufengershan landslide triggered by the 1999 Chi-Chi earthquake in Taiwan. Eng Geol 68:237–250
Siddiqui MZ, Everett JW, Vieux BE (1996) Landfill sitting using geographic information systems: a demonstration. J Environ Eng 122(6):515–523
Soeters R, Van Westen CJ (1996) Slope instability recognition analysis and zonation. In: Turner KT, Schuster RL (eds) Landslides: investigation and mitigation. Transportation Research Board National Research Council, Special Report No: 247, Washington, DC, pp 129–177
Suzen ML, Doyuran V (2004a) Data driven bivariate landslide susceptibility assessment using geographical information sys-

tems: a method and application to Asarsuyu Catchment, Turkey. Eng Geol 71:303–321
Suzen ML, Doyuran V (2004b) A comparison of the GIS based landslide susceptibility assessment methods: multivariate versus bivariate. Environ Geol 45:665–679
USGS (1993) USCS data user guide 5 for DEM's, ftp:// mapping.usgs.gov /pub /ti /DEM/demguide (connected: 12.05.2006)
Van Westen CJ (1997) Statistical landslide analysis. ILWIS 2.1. for windows application quide. ITC Publication, Enschede
Van Westen CJ, Bonilla JBA (1990) Mountain hazard analysis using PC-based GIS. 6th IAEG Congress, vol 1. Balkema, Rotterdam, pp 265–271
Varnes DJ (1978) Slope movement types and processes. In: Schuster RL, Krizek RJ (eds) Landslides analysis and control. Special Report, vol 176. Trasportation Research Board, National Academy of Sciences, New York, pp 12–33
Yesilnacar E, Topal T (2005) Landslide susceptibility mapping: a comparision of logistic regression and neural networks methods in a moderate scale study, Hendek region (Turkey). Eng Geol 79:251–266
Zhou G, Esaki T, Mitani Y, Xie M, Mori J (2003) Spatial probabilistic modeling of slope failure using an integrated GIS Monte Carlo simulation approach. Eng Geol 68:373–386