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GIS-based landslide susceptibility mapping using bivariate statistical analysis in Devrek (Zonguldak-Turkey)

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Abstract Devrek town with increasing population is located in a hillslope area where some landslides exist. Therefore, landslide susceptibility map of the area is required. The purpose of this study was to generate a landslide susceptibility map using a bivariate statistical index and evaluate and compare the results of the statistical analysis conducted with three different approaches in seed cell concept resulting in different data sets in Geographical Information Systems (GIS) based landslide susceptibility mapping applied to the Devrek region. The data sets are created from the seed cells of (a) crowns and flanks, (b) only crowns, and (c) only flanks of the landslides by using ten different causative parameters of the study area. To increase the data dependency of the analysis, all parameter maps are classified into equal frequency classes based directly on the percentile divisions of each corresponding seed cell data set. The resultant maps of the landslide susceptibility analysis indicate that all data sets produce fairly acceptable results. In each data set analysis, elevation, lithology, slope, aspect, and drainage density parameters are found to be the most contributing factors in landslide occurrences. The results of the three data sets are compared using Seed Cell Area Indexes (SCAI). This comparison shows that the crown data set produces the most accurate and successful landslide susceptibility map of the study area.

Keywords Bivariate analysis · GIS · Landslide susceptibility mapping - Seed cell - Devrek - Turkey

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Introduction

Landslide activity has an increasing trend worldwide, especially in developing countries. Unplanned urbanization and development in unstable hillside areas under the pressures of increasing populations, deforestation, and increased precipitation by changing climates are the main reasons for this increasing trend. Landslide susceptibility maps provide valuable information to planners, developers, and engineers who implement land use strategies not only in the design stages but also in hazard mitigation stages.

There are a number of methods to produce landslide susceptibility maps and several hundreds of paper published in the literature. They are divided into two main categories: qualitative and quantitative approaches (Soeters and Van Westen [1996](#page-16-0); Aleotti and Chowdhury [1999](#page-13-0); Guzzetti et al. [1999;](#page-15-0) Ercanoglu et al. [2008;](#page-14-0) Nandi and Shakoor [2010;](#page-16-0) Yilmaz [2009a](#page-17-0); Bai et al. [2010;](#page-14-0) Lara and Sepulveda [2010](#page-15-0)). The qualitative methods extensively used during 1970s and 1980s (Aleotti and Chowdhury [1999\)](#page-13-0) include field geomorphological analysis (Rupke et al. [1988](#page-16-0); Concha-Dimas et al. [2007;](#page-14-0) Kouli et al. [2010](#page-15-0)) and use of index or parameter maps (Soeters and Van Westen [1996](#page-16-0); Van Westen and Lulie [2003\)](#page-16-0), which are generally used by geomorphologists. Quantitative methods include geotechnical engineering approaches, statistical analysis, and soft computing techniques (Aleotti and Chowdhury [1999](#page-13-0); Rozos et al. [2008;](#page-16-0) [2011](#page-16-0)). The geotechnical approaches use deterministic and probabilistic methods (Gökceoglu and Aksoy [1996](#page-15-0); Van Westen and Terlien [1996;](#page-16-0) Zhou et al. [2003](#page-17-0); Wang and Lin [2010](#page-17-0)). Recently, a number of researchers have used statistical methods, which include bivariate and multivariate analysis. In the bivariate analysis (Fernandez et al. [2003](#page-15-0); He et al. [2003](#page-15-0); Lin and Tung [2003](#page-15-0); Remondo et al. [2003;](#page-16-0) Cevik and Topal [2003](#page-14-0), [2004;](#page-14-0) Süzen

and Dovuran [2004a](#page-16-0); Gökceoglu et al. [2005;](#page-15-0) Saha et al. [2005;](#page-16-0) Clerici et al. [2002](#page-14-0), [2006;](#page-14-0) Yilmaz and Yildirim [2006](#page-17-0); Mathew et al. [2007;](#page-15-0) Conoscenti et al. [2008](#page-14-0); Dahal et al. [2008a](#page-14-0), [b](#page-14-0); Magliulo et al. [2008](#page-15-0); Yalcin [2008\)](#page-17-0) each individual factor is combined with landslide distribution map and weight values based on landslide densities are calculated for each parameter class. In the multivariate analysis, many causative factors are sampled and for each of the sampling units, the presence or absence of landslides is also determined. This analysis allows the estimation of the relative weights of each contributing factor by means of statistical procedures (Baeza and Corominas [2001\)](#page-14-0). In the literature, there is a trend to use multivariate statistical analysis such as Discriminant Analysis (Carrara et al. [1991,](#page-14-0) [2003;](#page-14-0) Santacana et al. [2003](#page-16-0); Guzzetti et al. [2005,](#page-15-0) [2006a](#page-15-0), [b](#page-15-0); Baeza et al. [2010a](#page-14-0)), Factor Analysis (Ercanoglu and Gökceoglu [2002](#page-14-0); Ercanoglu et al. [2004\)](#page-14-0), Logistic Regression Analysis (Afifi and Clark [1998](#page-13-0); Atkinson and Massari [1998;](#page-13-0) Lee and Min [2001](#page-15-0); Dai et al. [2001](#page-14-0); Dai and Lee [2002,](#page-14-0) [2003;](#page-16-0) Ohlmacher and Davis 2003; Süzen and Doyuran [2004a](#page-16-0), [b;](#page-16-0) Ayalew and Yamagishi [2005](#page-14-0); Can et al. [2005](#page-14-0); Chau and Chan [2005](#page-14-0); Yesilnacar and Topal [2005;](#page-17-0) Wang and Sassa [2005](#page-16-0); Lee [2005](#page-15-0), [2007a](#page-15-0); Duman et al. [2006](#page-14-0); Lee and Sambath [2006](#page-15-0); Yesilnacar and Süzen [2006;](#page-17-0) Akgün and Bulut [2007;](#page-15-0) Chang et al. [2007](#page-14-0); Greco et al. 2007; Akgün et al. [2008](#page-13-0); Nefeslioglu et al. [2008a](#page-16-0), [b](#page-16-0); Garcia-Rodriguez et al. [2008](#page-15-0); Görum et al. 2008; Lamelas et al. 2008; Pradhan et al. [2008;](#page-16-0) Tunusluoglu et al. [2008](#page-16-0); Yao et al. [2008;](#page-17-0) Chang and Chiang [2009;](#page-14-0) Mathew et al. [2009](#page-15-0); Meusburger and Alewell [2009](#page-15-0); Miller et al. [2009;](#page-15-0) Baeza et al. [2010b](#page-14-0); Das et al. [2010](#page-16-0); Erener and Düzgün 2010; Oh et al. [2009](#page-16-0), 2010; Yilmaz [2010a\)](#page-17-0), and Conditional Analysis (Clerici et al. 2002 ; Duman et al. 2005 ; Özdemir 2009). In recent years, researchers frequently use soft computing approaches such as Fuzzy Logic, Artificial Neural Network (ANN), and Neuro-Fuzzy methods (Binaghi et al.[1998;](#page-14-0) Ercanoglu and Gökceoglu [2002](#page-14-0), [2004](#page-14-0); Lu and Rosembaum [2003](#page-15-0); Remondo et al. [2003;](#page-16-0) Lee et al. [2003a,](#page-15-0) [b,](#page-15-0) [2004;](#page-15-0) Tangestani [2004;](#page-16-0) Ercanoglu [2005](#page-14-0); Ermini et al. [2005;](#page-14-0) Gomez and Kavzoglu [2005;](#page-15-0) Yesilnacar and Topal [2005;](#page-17-0) Chang and Chao [2006;](#page-14-0) Lee et al. [2006](#page-15-0); Lee and Evangelista [2006](#page-15-0); Kanungo et al. [2006;](#page-15-0) Lee [2007b](#page-15-0); Lee and Pradhan [2007](#page-15-0); Chen et al. [2009](#page-14-0); Choi et al. [2010;](#page-14-0) Falaschi et al. [2009](#page-14-0); Kanungo et al. [2009;](#page-15-0) Miles and Keefer [2009](#page-15-0); Paliwal and Kumar [2009](#page-16-0); Pradhan et al. [2009](#page-16-0); Pradhan and Lee [2009,](#page-16-0) [2010a](#page-16-0), [b](#page-16-0); Yilmaz [2009a,](#page-17-0) [b,](#page-17-0) [2010b](#page-17-0); Akgün and Türk [2010](#page-13-0); Pradhan et al. [2010;](#page-16-0) Rossi et al. [2010\)](#page-16-0).

Black Sea Region, which comprises the northern part of Turkey, has a number of landslides recorded every year. Steep topography and high precipitation make the region very prone to landsliding. Devrek is a town with a population of 22,000 and is located approximately 30 km south of Zonguldak in the western part of the Black Sea Region of Turkey. The settlement area is established in a valley formed by the Devrek Stream. Increasing population causes to spread the urbanization in the hillside areas where some landslides exist. The preparation of landslide susceptibility map of Devrek may serve as useful information to determine the landslide-free areas for future growth and urbanization of the town. The study area is accessible by asphalt paved D750 highway connected to Zonguldak in north and to the Trans European Motorway (TEM) in south (Fig. 1). The study area covers approximately 54 km^2 . Devrek region has the climatic characteristics peculiar to the Black Sea region, where summers are chilly, and winters are temperate but cold with rain and snow in higher areas. Precipitation occurs in all four seasons. The annual average precipitation is approximately 170 mm throughout

Fig. 1 a Location map, and **b** outline of the study area

the region. The average temperature is highest in July with 22.1°C, whereas it is the coldest in January with 4.2 °C through the year. The average value of humidity is 71% (DMI [2007](#page-14-0)). The eastern hillside parts of the study area are partly vegetated with mainly pine and oak trees.

The main goal of this study was to generate a landslide susceptibility map for the Devrek area by using statistical index (Wi) method of Van Westen [\(1993\)](#page-16-0), which is a bivariate statistical technique utilizing GIS. This method is preferred due to the ease of its application and good performance to predict the susceptible zones. In harmony with this aim, the seed cells are determined and further grouped into three data sets as the data belonging to seed cells of (a) crown and flanks, (b) only crowns, and (c) only flanks. Ten different causative factors are evaluated by three different training sets of seed cells and for each data set a landslide susceptibility map is calculated. The maps are then compared to assess the best one by Seed Cell Area Index method.

Geology and seismicity of the study area

Five lithological units are exposed in the study area (Yergök et al. [1987\)](#page-17-0). From older to younger, they are Kazpınar formation (Early Cretaceous), Alaplı formation (Late Cretaceous), Yahyalar formation (Paleocene), Çaycuma formation (Eocene), and Quaternary alluvial deposits. The geological map and the generalized columnar section of the area are presented in Fig. 2.

The volcanic and volcanoclastic sequence of Kazpınar formation (Krkz) is the oldest geologic unit in the study area. It gives outcrops in the southeastern parts of the study area with pink, partly green to gray andesites with small amounts of tuffs and marls. Andesites dominantly consist of plagioclase crystals with small amounts of hornblendes and biotites.

The Alaplı formation (Kra) overlies the Kazpınar formation by an angular unconformity. The formation consists of an alternating sequence of sandstones, marls, and limestones. The sequence starts with yellow, thick to very thick bedded sandstones. Thin layers of light yellow and red marls overlie the sandstone beds. Above them, there are light yellow to green clayey limestones and limestone beds in moderate thickness. The beds are dipping towards northwest with an average amount of 25°.

The Yahyalar formation (Ty) overlies the Alaplı formation conformably. It consists of an alternating sequence of sandy limestones and sandstones. The sandy limestones are gray to white and thick bedded. The sandstones are gray and thin bedded. The beds dip toward northwest with an average amount of 30°.

The Caycuma formation (T_C) overlies the Yahyalar formation conformably. It consists of an alternating sequence of sandstones, siltstones, claystones, and volcanoclastic sandstones (Fig. [3](#page-3-0)). The sandstones are yellow to light green in

Fig. 2 Geological map and generalized columnar section of the study area (modified from Yergök et al. [1987](#page-17-0))

Fig. 3 The alternating sequence in the Caycuma formation

color and have moderately thick beds. The siltstones are light green to gray and observed as thin layers. The claystones are light to dark green in color and have very thin layers. The volcanoclastic sandstones include agglomerates and tuffs. It is unconsolidated, thin layered, and alternating with thin layers of marls. The beds are dipping towards northwest with an average amount of 35° (Fig. [2\)](#page-2-0).

The Quaternary alluvial deposits (Qal) crop out along the Devrek Stream in the study area. The alluvial fill covers a wide area where the city center of Devrek is located (Fig. [2](#page-2-0)). The alluvium includes unsorted sediments from mud to block sizes. The coarse components are subangular to round in shape

In the study area, there are no mappable geologic structures such as faults, folds, and lineaments. However, the area lies approximately at 55 km north of the North Anatolian Fault Zone (NAFZ) (Fig. [4a](#page-4-0)) (MTA [2007](#page-16-0)). The earthquake activity of this region is directly controlled by the presence and activity of NAFZ, and its associated fault segments. The study area is located within the first-degree earthquake zone of Turkey (GDDA 2007). The distribution of epicenters of past and recent earthquakes are presented in Fig. [4b](#page-4-0) (KOERI [2007\)](#page-15-0). The study area and its vicinity are seismically not very active, but earthquakes that may occur in the future may trigger landslides. Nevertheless, no information exists about the effect of past earthquakes on landsliding in the study area. Since the study area is relatively small, the effect of seismicity is considered to be equal throughout the area; hence, seismicity is not considered as a parameter in this study.

Methodology and data used

This study was carried out in three main stages; data acquisition, data production and manipulation, analysis

and construction of the product (susceptibility) maps. The data acquisition part of the study is based on gathering available geological and topographical maps, and conducting fieldworks to visually inspect the lithologic units and map the landslides in the study area. The geology and geologic map of the study area were gathered mainly from Yergök et al. (1987) (1987) . During the field investigations, geological map from the literature was checked, the lithologic units were identified, and the landslide inventory map was prepared.

The data production stage consists of data entry, creating the parameter maps, and constructing the databases for the analyses in the next stage. A total of ten parameter maps (elevation, slope, aspect, profile curvature, plan curvature, distance to streams, drainage density, distance to ridges, distance to road and power line network, lithology) were created by utilizing TNT Mips software. The preparation of the data was carried out by using seed cells of Süzen and Doyuran $(2004a)$ for defining the decision rules of slope instabilities, and percentile class divisions for transforming the continuous variables into categorical variables. Seed cells were considered as the best undisturbed morphological conditions before landslide occurs. They were extracted by adding a buffer zone to the crown and flanks of a landslide. In this study, three different sets of seed cell databases were prepared for the analysis as decision rule generators. These seed cells were extracted from the crowns and flanks, only from the crowns, and only from the flanks from the buffer zones added to the landslides in the study area. Then, the continuous data sets extracted from the parameter maps were classified into categories based on percentile divisions of seed cells. The percentile divisions and distributions of seed cells were calculated using SPSS software resulting in reclassification of original parameter maps into percentile maps by using the percentile limits.

For creating the landslide susceptibility maps, statistical index (Wi) method of Van Westen [\(1993](#page-16-0)) was used. According to the landslide susceptibility analysis, landslide occurrences in each percentile class for each parameter map were calculated separately. Then, weight values were calculated by comparing the landslide occurrences in each percentile class with the overall landslide occurrence in the parameter map of the study area. The weight values estimate the influence of each causative parameter map. To build the final product maps, the parameter maps were spatially summed up according to their weight values.

Last, the final product maps created using three different seed cell data (from the crowns and flanks, only from the crowns, and only from the flanks) were compared. The results were discussed on the basis of field observations.

Production of parameter maps

Landslide inventory map

A landslide inventory map is the simplest output of direct landslide mapping. It shows the location of discernible landslides (Hansen [1984](#page-15-0); Wieczorek [1984;](#page-17-0) Einstein [1988](#page-14-0); Van Westen [1994](#page-16-0); Parise [2001](#page-16-0); Griffiths et al. [2002](#page-15-0); Yalcin and Bulut [2007](#page-17-0)). It is essential for landslide susceptibility mapping since any analysis require a discrete knowledge of which causative factor is effective under what magnitude, which would eventually be derived by overlaying an inventory map with the selected causative factors. A total of 26 active landslides were identified during field work in the study area (Fig. [5](#page-5-0)). These landslides are classified as slides (Fig. [6\)](#page-5-0). The sliding mechanism of the landslides is rotational, and turns into translational when the sliding mass intersects with the bedding surface of the rock units. The depth of the landslides is generally shallow. They are generally observed at gentle slopes of the Caycuma formation.

Digital Elevation Model (DEM) and its derivatives

The parameter maps including elevation, slope, aspect, curvature, distance to streams, drainage density and Fig. 5 Landslide inventory map of the study area (grey polygons are landslide bodies)

Fig. 6 A landslide occurred near the settlement area. Arrow in the figure indicates direction of movement of the landslide

distance to ridges were extracted from the DEM of the study area. The DEM of the study area was constructed from 1:25,000 scale topographical maps with a resolution of 12.5 m.

Elevation map

Elevation is another very frequently used parameter in landslide susceptibility studies (Pachauri and Pant [1992](#page-16-0); Ercanoglu et al. [2008](#page-14-0)). An elevation map portrays areas with different relative relief. Landslides may form in certain relief ranges (Dai et al. [2001](#page-14-0)). The relief map of the study area with x3 vertical exaggeration generated from the DEM is shown in Fig. [7](#page-6-0)a.

Slope map

Slope is the measure of surface steepness and measured in degrees. It has a range between 0° and 90° , where 0 represents the flat and 90 represents the vertical areas. Slope angle is very frequently used in landslide susceptibility studies since landsliding is directly related to slope angle (Anbalagan [1992;](#page-13-0) Pachauri et al. [1998;](#page-16-0) Saha et al. [2002](#page-16-0); Clerici et al. [2002\)](#page-14-0). Landslides mostly occur at certain critical slope angles (Dai et al. [2001;](#page-14-0) Gökceoglu and Aksoy [1996](#page-15-0); Uromeihy and Mahdavifar [2000;](#page-16-0) Lee and Min [2001](#page-15-0); Cevik and Topal [2003\)](#page-14-0). The slope values in the study area (Fig [7](#page-6-0)b) range between 0° and 63° . However, the mean value of the slope is 17° with a standard deviation of 10° .

Aspect

Aspect is a measure of slope orientation and measured in degrees. Aspect-related parameters such as exposure to sunlight, drying winds, rainfall (degree of saturation), and

Fig. 7 a Relief, b slope, and c aspect map of the study area

discontinuities may control the occurrence of landslides (Gökceoglu and Aksoy [1996;](#page-15-0) Dai et al. [2001](#page-14-0)). The aspect values of the study area vary between -1° and 360° where

 -1 represents the flat lying areas (Fig. 7c). The mean value of the aspect data is 200 with a standard deviation of 112.

Curvature

Surface curvature is the curvature of a line formed by intersecting a plane (in some chosen orientation) with the terrain surface. The curvature value is the reciprocal of the radius of curvature of the line, so a broad curve has a small curvature and a tight curve has a high curvature value. The curvature is measured in radians per meter.

Profile curvature is the curvature in the vertical plane parallel to the slope direction. It measures the rate of change of slope and therefore influences the flow velocity of water draining the surface and thus erosion and the resulting downslope movement of sediment. Plan curvature (also called contour curvature) is the curvature of a contour line formed by intersecting a horizontal plane with the surface. Plan curvature influences the convergence or divergence of water during downhill flow (MicroImages [2007](#page-15-0)). Profile curvature raster produced is presented in Fig. [8](#page-7-0)a. Positive values indicate convex upward surfaces. The values for the study area vary between -0.04 and 0.03. The mean value of the profile curvature data is 0 with a standard deviation of 0.003.

Plan (contour) curvature raster produced for the study is presented in Fig. [8b](#page-7-0). Positive values indicate convex outward surfaces. The values vary between -1.8 and 1.5. The mean value of the plan curvature data is 0 with a standard deviation of 0.02.

Derivatives of watershed analysis

The watershed process provides comprehensive processing and evaluation of raster DEMs to define watersheds, flow paths, and basins. The process begins by evaluating the elevation raster for depressions and constructs watershed polygons based on the depressions recognized. The drainage network and ridgelines generated by the watershed analysis are used to produce the parameter maps such as distance to streams, drainage density, and distance to ridges.

The distances of every pixel regarding the streams are calculated and presented in Fig. [9](#page-8-0)a. The minimum distance of pixels is 0 and the maximum is 545 m. The mean value of the distance to streams data is 107 with a standard deviation of 82.

The streams are also used to calculate the density of streams within every square kilometer in the whole study area. In order to maintain the 1 km^2 search distance, 564 m search radius is used. The vectors of the streams are converted to point data with a distance of 12.5 m and put into point density analysis. The drainage density values of the

Fig. 8 a Profile and b plan curvature map of the study area

410 000 411 000 412 000 413 000 414 000 415 000 416 000 417 000 418 000

Fig. 9 a Distance to streams, b drainage density, and c distance to ridge map of the study area

study area (Fig. 9b) range from 19 to 638. The mean value of the drainage density data is 293 with a standard deviation of 99.

The ridgelines output of the watershed analysis is used to calculate the nearest distances to the ridges of each pixel. The distance to ridge map is shown in Fig. 9c. The minimum value for the distance to ridges is 6 m and the maximum is 728 m. The distribution has a mean of 168 m with a standard deviation of 110.

Distance to road and power line network

Building the infrastructure elements such as roads (Karslı et al. [2009\)](#page-15-0) and power lines are considered as the manmade activities affecting slope instabilities. For the construction of power line poles, the forest under and in the vicinity of the pylon is cut, so land cover changes, whereas for the road construction both the slopes are cut, the land cover is changed and the economic activity near the roads due to highway tourism attract people that increases the interventions with natural slope.

The roads and power lines in the study area are digitized from the topographical base maps. The vector data of roads and power lines are merged together and the distances of every pixel regarding the roads and power lines are calculated. Distance to road and power line network map of the study area is presented in Fig. [10](#page-9-0). The minimum distance of pixels is 0 and the maximum is 746 m. The distribution has a mean of 100 with a standard deviation of 99.

Lithology

The geological map of the study area is compiled from existing geological maps and publications from the literature. The existing maps contain information with some inadequacies and mismatches. So, they were checked and refined during the field study. The compiled map was digitized. Five lithologic units were identified in the study area (Fig. [11](#page-9-0)). The Caycuma formation has the greatest areal coverage with almost the half (47.65%) of the study area. Majority of the landslides have occurred in this formation.

Landslide susceptibility analysis

In this study, landslide susceptibility analysis was carried out using the statistical index method (Wi) of Van Westen [\(1993](#page-16-0)), which is a bivariate method. For this purpose, landslide inventory, elevation, slope, aspect, profile curvature, plan curvature, distance to streams, drainage density, distance to ridge, distance to road and power line network, and lithology layers were used. Three different Fig. 10 Distance to road and power line network map of the study area

databases of seed cells were constructed for the bivariate statistical analysis. For the crown and flank database 3,931 seed cell nodes, for the only crowns database 2,289 seed cell nodes, and for the only flanks database 1,642 seed cell nodes were introduced. All seed cell nodes contain data from the ten parameter maps. All parameters except the categorical one (i.e., lithology) were analyzed and reclassified for each seed cell database

In the landslide susceptibility analysis, the occurrence of mass movements is considered as dependent, and parameters are independent variables. Each parameter map (as independent variable) is crossed with landslide distribution map, and weight values, which demonstrate the relative effect of each parameter or variable to instability, are calculated. Weight value for landslide susceptibility is calculated from the landslide density of each class of each parameter map. The landslide density of each class is calculated from following equation:

$$
D_{\text{area}} = 1000 \frac{Npix(SX_i)}{Npix(X_i)}
$$

Table 1 Weight values of all parameter classes of the crown and flank database

The weight value of each control factor class for landslide is defined as the difference between the landslide density of each class and the average landslide density in the study area. The formula for the weight value is

$$
W_{\text{area}} = 1000 \frac{Npix(SX_i)}{Npix(X_i)} - 1000 \frac{\sum Npix(SX_i)}{\sum Npix(X_i)}
$$

iable class X_i .

The calculated weight values are the equal to the degree of susceptibility to landslides of each parameter class. In the presence of a negative weight value, all weights are normalized by adding the absolute value of greatest negative weight to all of the weights of each percentile class. The calculated weights for each percentile class of each parameter for the three different databases, namely crowns and flanks, only crowns, and only flanks, are given in Tables 1, 2, and [3.](#page-11-0) Based on its categorical nature the

Parameter class	Parameter										
	Elevation	Slope	Aspect	Profile curv.	Plan curv.	Dist. to streams	Drain. dens.	Dist. to ridges	Dist. to road		
10	10.09	5.12	$\overline{0}$	$\overline{0}$	θ	$\mathbf{0}$	$\mathbf{0}$	1.12	$\boldsymbol{0}$		
20	28.41	12.61	1.93	4.78	3.53	1.54	4.99	$\overline{0}$	0.79		
30	36.83	13.28	18.80	5.87	3.17	5.23	11.10	2.88	1.53		
40	29.39	15.71	20.85	4.64	2.87	5.81	16.55	2.98	0.19		
50	24.44	15.22	29.69	4.38	1.35	5.95	5.23	2.67	0.11		
60	32.72	8.87	20.79	6.43	2.16	4.91	4.71	1.67	3.25		
70	19.49	8.69	17.88	5.02	3.39	4.70	13.41	3.55	4.09		
80	4.26	6.35	14.46	5.07	4.55	3.79	9.59	3.91	8.56		
90	8.53	3.98	6.87	8.14	3.56	4.03	21.20	3.93	9.28		
100	$\mathbf{0}$	$\mathbf{0}$	4.66	8.71	7.38	0.51	10.93	26.10	8.12		

Table 2 Weight values of all parameter classes of the only crowns database

Parameter class	Parameter										
	Elevation	Slope	Aspect	Profile curv.	Plan curv.	Dist. to streams	Drain. dens.	Dist. to ridges	Dist. to road		
10	8.89	2.07	$\overline{0}$	θ	0.03	0.94	$\mathbf{0}$	$\mathbf{0}$	0.86		
20	18.62	4.64	0.42	2.27	$\overline{0}$	1.69	1.92	3.76	0.61		
30	13.29	5.83	8.45	3.31	0.73	2.69	3.74	3.65	$\overline{0}$		
40	14.77	5.57	9.32	2.54	1.12	4.52	5.86	2.32	0.31		
50	16.77	5.45	11.49	1.81	0.57	4.26	2.36	2.29	1.79		
60	12.18	3.56	8.54	1.16	0.59	4.19	2.40	3.10	3.32		
70	8.99	3.93	5.91	2.39	1.20	3.12	6.44	4.00	7.66		
80	3.83	3.12	29.87	1.89	1.08	1.29	4.73	2.71	10.12		
90	5.47	2.22	1.60	0.81	0.15	0.33	7.50	4.53	10.24		
100	$\mathbf{0}$	$\overline{0}$	1.62	0.38	1.59	$\mathbf{0}$	4.81	14.99	3.39		

Table 3 Weight values of all parameter classes of the only flanks database

weights of the Caycuma formation within lithology layer is calculated separately, where the Caycuma formation has a weight value of 17.71 for crowns and flanks, of 10.02 for only crowns, and of 7.69 for only flanks.

After calculation of the weights, the weights are assigned to the parameter classes of parameter maps and all ten parameter maps are spatially summed up to create the susceptibility map. The resultant map is then reclassified into four susceptibility classes (very low, low, high, very high) using the susceptibility map distribution parameters. The mean value of the susceptibility map is taken as the pivot point, and classes are assigned to the plus and minus one standard deviations of the distribution.

The distribution of the susceptibility map of crowns and flanks data set results in a mean value of 45.72 and a standard deviation of 21.95. The resultant susceptibility map classified according to these values is presented in Fig. [12](#page-12-0)a. The ranges and the area covered of the susceptibility classes, and the percentage of seed cells in each susceptibility class for crowns and flanks case are presented in Table [4.](#page-13-0) According to these results, 44.77% of the study area is classified as high and very high susceptibility, whereas 93.39% of the seed cells are covered within the high and very high susceptibility classes. On the other hand, 55.23% of the study area is classified as low and very low susceptibility with 6.61% of the seed.

The distribution of the susceptibility map of crowns data set results in a mean value of 27.60 and a standard deviation of 12.65. The resultant susceptibility map classified according to these values is presented in Fig. [12](#page-12-0)b. Table [4](#page-13-0) presents the ranges and the area covered of the susceptibility classes, and the percentage of seed cells in each susceptibility class. According to these results, 46.47% of the study area is classified as high and very high susceptibility, while covering 94.71% of the seed cells. On the other hand, 53.53% of the study area is classified as low

and very low susceptibility. 5.29% of the seed cells are encountered in these classes.

The distribution of the susceptibility map of flanks data set results in a mean value of 21.21 and a standard deviation of 11.05. The resultant susceptibility map classified according to these values is presented in Fig [12c](#page-12-0). Table [4](#page-13-0) presents the ranges and the area covered of the susceptibility classes and the percentage of seed cells in each susceptibility class. According to these results, 44.18% of the study area is classified as high and very high susceptibility. 94.15% of the seed cells are in the high and very high susceptibility classes. On the other hand, 55.82% of the study area is classified as low and very low susceptibility. 5.85% of the seed cells are encountered in these classes.

In order to compare the results of the three seed cell databases, Seed Cell Area Index (SCAI) of the susceptibility classes of the maps is calculated (Table [5](#page-13-0)). SCAI is simply the density of landslides among the classes and is calculated by dividing the susceptibility class area percent values by the landslide seed cell percent values. The logic behind SCAI lies in the correct classification of seed cells within a very conservative areal extent. As a result, it was desired that the high and very high susceptibility classes should have very small SCAI values and low and very low susceptibility classes to have higher SCAI values (Süzen and Doyuran [2004b](#page-16-0)).

When the SCAI values of the three seed cell data sets are compared, it is seen that the crowns database has the most desirable SCAI values in the very low, low, and very high susceptibility classes. For the high-susceptibility class, the SCAI values are very close to each other, but flanks database has the best result. When the crowns and flanks data sets are compared in terms of the high-susceptibility class, it is found that the crowns database produces a 2.43% greater areal extent than the flanks database with only 1.31% decreases in the landslide seed cells, which could be

Fig. 12 Landslide susceptibility map of the study area produced from the seed cells of a crowns and flanks, b only crowns, and c only flanks presented with landslides (grey polygons)

accepted. As a result of the SCAI analysis, the most accurate and successful map of the study area is produced by the seed cells of crowns.

Discussion

The landslide susceptibility assessment of the Devrek area was carried out using ten different parameters which are generally accepted as landslide contributing factors and widely used in landslide susceptibility assessment studies in the literature. These are lithology, elevation, slope, aspect, profile curvature, plan curvature, distance to streams, drainage density, distance to ridges, and distance to road, and power line network.

The landslide susceptibility assessment was carried out using bivariate statistical method. Besides the scale of the work, statistical method was chosen because of its objectivity and data dependency. However, some procedures in bivariate statistical method are still subjective. Questions arise in the classification of parameter classes and the division of the final susceptibility map into susceptibility classes. To overcome the problem in the classification of parameter classes, percentile method (Süzen and Doyuran [2004a\)](#page-16-0) was applied. Using the percentile method, the parameters were directly classified according to the data itself. On the other hand, the final susceptibility map was divided into susceptibility classes using the susceptibility map distribution. As a result, the objectivity and data dependency of the study were secured.

The analyses of the three data sets resulted in acceptable susceptibility maps since majority of the seed cells falls in high and very high susceptibility classes in each data set. All of the weight values calculated are consistent and reflect no significant extremes which could lead to inconsistencies in the production of susceptibility maps. If the weight values of each parameter class of every attribute are sorted from the highest to the lowest value, elevation, lithology, slope, aspect, and drainage density are found to be the highest contributing factors of landslide occurrence in the study area in all data sets.

The analysis carried out with the crowns and flanks data set indicates that the slopes in the Caycuma formation with angles from 5° to 17° having altitude values of 139–225 m, and facing to southwest, west and northwest are identified as unstable. Drainage density affects the instability where the drainage density values are from 270 to 300 km^2 and from 357 to 566 km². Distance to ridges is the least contributing factor since landslides occurred mostly in the lower parts of hills. In the case of crowns data set, landslide susceptibility accumulates on the slopes of Çaycuma formation with angles from 5° to 16° , which are facing to southwest, west, and northwest at elevations from 150 to

Susceptibility class	Crown and flanks			Only crown			Only flanks		
	Range	Area covered $(\%)$	Seed cells Range (%)		Area covered $(\%)$	Seed cells Range (%)		Area covered $(\%)$	Seed cells (%)
Very low	$0 - 23.76$	17.22	0.10	$0 - 14.94$	16.25	0.09	$0 - 10.16$	16.58	0.30
Low	23.76-45.72	38.01	6.51	14.94–27.60	37.28	5.20	$10.16 - 21.21$	39.24	5.54
High	45.72–67.67	26.78	18.29	27.60–40.25	29.37	19.09	21.21-32.27	26.94	20.40
Very high	67.67–137.40	17.99	75.10	$40.25 - 80.02$	17.10	75.62	32.27-89.56 17.24		73.75

Table 4 The range and areal coverage of the susceptibility classes in the map produced from crowns and flanks, only crown, and only flanks database

Table 5 The densities of landslides among susceptibility classes of the three data sets

Data set	Susceptibility class	Area covered $(\%)$	Seed cell $(\%)$	SCAI
Crowns and	Very low	17.22	0.10	172.20
flanks	Low	38.01	6.51	5.84
	High	26.78	18.29	1.46
	Very high	17.99	75.10	0.24
Crowns	Very low	16.25	0.09	180.56
	Low	37.28	5.20	7.17
	High	29.37	19.09	1.54
	Very high	17.10	75.62	0.23
Flanks	Very low	16.58	0.30	55.27
	Low	39.24	5.54	7.08
	High	26.94	20.40	1.32
	Very high	17.24	73.75	0.23

218 m. Drainage density values range between 268 to 296 and 417 to 566 per square kilometers. Distance to road and power line network parameter has the least effect on the landslide occurrences in the analysis of crowns data set. The results of the flanks data set are also similar to the crowns data set. Instabilities are on the slopes of the Caycuma formation with angles from 5° to 13° at elevations of 110–210 m, facing to southwest, west and northwest. Drainage density values are from 273 to 307 and from 360 to 537 per square kilometers. Plan curvature parameter has the least effect on the slope instabilities in the case of flanks data set.

All three susceptibility maps are consistent with the field observations. Additionally, in all susceptibility maps, the alluvial deposits of the Devrek Stream are classified as low and very low susceptible. These parts of the area are flat and there is no possibility of landslide occurrence.

Conclusions and recommendations

The field investigation reveal that a total of 26 landslides exist were identified in the Devrek area. They are generally

shallow slides, and observed in the Caycuma formation. The landslide susceptibility analysis using the statistical index method (Wi) of Van Westen [\(1993](#page-16-0)) was carried out for seed cells of crowns and flanks, only crowns, and only flanks. The final maps indicate that all data sets produced acceptable results. In all data sets, elevation, lithology, slope, aspect and drainage density were found as the most effective parameters on landslide occurrence of the study area.

Based on the comparison of the susceptibility maps by using the Seed Cell Area Index (SCAI), the map produced from the crowns data set was found as the most accurate and successful landslide susceptibility map of the study area. Seed cells reflect the conditions before landslide occurs and used as decision rules generators for landslide occurrences. Since a landslide starts to be formed at the crown part, choosing only crowns for seed cells might be enough according to the results of this study.

This landslide susceptibility assessment study of the Devrek region may serve as useful information for land use planning. The areas of site-specific studies can be identified and prioritized for detailed geotechnical investigations.

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