Theoretical and Applied Climatology (2020) 140:1233–1246
https://doi.org/10.1007/s00704-020-03126-2

ORIGINAL PAPER

Landslide susceptibility mapping for the Black Sea Region with spatial fuzzy multi-criteria decision analysis under semi-humid and humid terrestrial ecosystems

İ. Demirağ Turan[1] · B. Özkan[2] · M. Türkeş[3] · O. Dengiz[4]

Received: 14 December 2019 / Accepted: 31 January 2020 / Published online: 4 March 2020

Abstract
Landslide, which is a process experienced not only at the local and catchment scales but also the regional and national scales, adversely affects the natural environment, including the flora and fauna, and the socio-economic well-being of human communities. The main aim of the present study was to generate a landslide susceptibility mapping model for the semi-humid and humid terrestrial ecosystems of the Black Sea Region. The modelling was done by using a spatial multi-criterion analysis (SMCA) method based on the integration of fuzzy environment and geographical information system (GIS) techniques and also the use of the AHP approach by incorporating 9 environmental indicators and 27 sub-indicators. In order to allocate a weighting value for each indicator, the fuzzy-AHP approach was applied to determine efficiently sensitive levels of importance for the indicator. In addition, precipitation climatology was included in detail with respect to the temporal and spatial distribution of rainfall in the study area. It was determined that approximately 33% of the research area includes high or very high susceptibility to landslide, whereas about 37% of the research area is in the low or very low susceptibility classes. Most highly or very highly susceptibility areas were located in the western and central Black Sea regions. In conclusion, this study provides an alternative perspective a useful alternative method for landslide susceptibility mapping through the incorporation of fuzzy sets through AHP in conjunction with the Buckley approach in modelling.

1 Introduction

Landslide can be defined as denotational process which causes soil and rock to be displaced by mostly gravity forces and also the landform resulting from such movement. This phenomenon occurs throughout the world, under all climatic environmental conditions and in all regions, and is responsible for hundreds of deaths and injuries each year and billions of dollars of damage. In addition, happening of landslides often are characterized as local concerns or problems but their effects and costs frequently cross local jurisdictions and may become state, provincial or national problems. Therefore, landslide susceptibility mapping (LSM) is a vital tool in avoidance of disaster, or mitigation, as it can show the landslide potential of an area (Dai et al. 2002). Moreover, LSM provides important information for the prediction of landslides that includes an indication of the time scale within which a particular landslide is likely to occur (Atkinson and Massari 2011). Also, Xu et al. (2012) stated that effective LSM can also support a convenient understanding of 'susceptible areas'. In this sense, Wu et al. (2016) indicated that a variety of GIS-based susceptibility mapping techniques have been employed to better assist planners to understand landslide damage.

To date, many LSM studies have been performed by numerous investigators and various methods were recommended. These approaches can be separated into qualitative and quantitative approaches (Ferentinou and Chalkias 2013; Zhou et al. 2016). Qualitative approaches mostly involve probability analysis procedures that depend on expert opinion (Meng et al. 2016; Mandal and Mandal 2018). On the other hand, the quantitative methods used by measures Generali and Pizziolo (2013), Meng et al. (2016), Sharma et al. (2015),

✉ O. Dengiz
odengiz@omu.edu.tr

1 Department of Geography, The Faculty of Economic, Administrative and Social Sciences, Samsun University, Samsun, Turkey

2 Department of Industrial Engineering, Faculty of Engineering, Ondokuz Mayıs University, Samsun, Turkey

3 Center for Climate Change and Policy Studies, Boğaziçi University, İstanbul, Turkey

4 Department of Soil Science and Plant Nutrition, Faculty of Agriculture, Ondokuz Mayıs University, Samsun, Turkey

Hong et al. 2017, and Yan et al. (2019) have mainly employed data-based, mathematical assessment models; deterministic approaches based on physical mechanics; or probability models based on reliability. In both the qualitative and quantitative approaches, it is necessary to process large amounts of information quickly and effectively in order to develop a model or to generate LSM, particularly for large areas or regions. In the last few decades, technological advances in LSM have facilitated the production of higher precision maps. In particular, GIS technique has made it possible to generate various thematic maps relevant to the parameters or indicators responsible for the happening of this phenomenon. In LSM, GIS technique has greatly advanced the efficiency and accuracy of the process. There are many criteria that should be incorporated in LSM, including slope, land use-land cover and soil texture when conducting GIS-based landslide sensitivity analysis. Each of these criteria has a different level of importance in landslide sensitivity assessment. Therefore, the relative importance of the indicator applicable to a particular environment should be determined. The determination of the relative importance levels of the criteria can be achieved by employing multi-criteria decision analysis (MCDA) methods. The analytic hierarchy process (AHP) is one of the MCDA methods frequently cited in the literature (Skilodimou et al. 2019a, b; Turan Demirağ et al. 2019). However, it is insufficient in cases where there is no certainty and it cannot fully reflect human intuition in the MCDA process. In response, the Fuzzy-AHP (FAHP) process has been adopted to overcome these deficiencies. In this current research, the FAHP approach was used to determine the relative importance of the criteria used in landslide susceptibility analysis.

The creation of maps showing landslide risk in the Black Sea region is difficult. The region is highly trendy to landslide but the use of field studies is ineffective due to environmental conditions such as steep topography and the obscuring of landslides by dense vegetation. Therefore, it is necessary to generate landslide mapping models in order to detect landslide 'hot spot' areas. Consequently, the main objective of the current research was to generate LSM modelling of the Black Sea Region of Turkey, which includes semi-humid and humid terrestrial ecosystems. Furthermore, that aim was to be achieved by using the SMCA method, which is based on 'fuzzy environment' incorporation with GIS and the AHP approach, which integrated nine environmental indicators and twenty seven sub-indicators.

2 Materials and methods

2.1 General characteristics of the research area

The area of the current study, which incorporates the entire Black Sea region of Turkey, covers the area from the Demirköy district located in Kırklareli Province in the western Turkish coastal zone of the Black Sea to the Hopa district in Artvin Province in the coastal zone of the Eastern Black Sea sub-region. This study area, situated between 0 m and 3827 m amsl, encompasses about 84,843.5 km^2. The Black Sea Region of Turkey can be defined as a somewhat narrow zone running across almost the entire north of the country and bordered by the Black Sea itself in the north and high northern Anatolian mountains in the south. The Turkish Black Sea coastline is about 1400 km in length and is administered as 16 provinces. The main rivers in the Black Sea Region are the Kızılırmak, Sakarya and Yeşilırmak (Fig. 1.).

The climate of this area is characterised by heavy precipitation in both winter and summer (except for August) and moderate temperatures. The average annual humidity is 76.2%, the average annual precipitation is 1200 mm (varying from 392.7 mm in Yusufeli to 2374.7 mm in Kemalpaşa, Artvin) and the average annual temperature is 8.8 °C. The present study emphasizes the general climatology, but especially the precipitation climatology of the study area, because the rainfall regime, including its variability, is one of the important and/or triggering factors for landslides (Erginal et al. 2009). The rainfall regime of the study area in terms of seasonality was classified as an 'ever-rainy' Black Sea rainfall regime characterized mainly by low annual and inter-annual variability and a low drought probability (Türkeş 2017). However, according to the Köppen-Geiger climate classification system, a temperate rainy or humid temperate west coast climate without dry season termed humid mesothermal predominates in the coastal Black Sea region of Turkey, whereas this region includes a very humid climate, based on the Thornthwaite climate classification system (Türkeş 2010).

Görür (1988) and Sosson et al. (2016) reported that the Black Sea in the north is an oceanic back-arc basin. This area formed during the Cretaceous Period behind and north of the Pontide magmatic extrusive in consequence of the subduction of the northern Neo-Tethys Ocean. In pre-Cretaceous times, the Pontides were adjacent to Dobrugea and Crimea. The Black Sea region has a rough, irregular and very heterogeneous morphology that includes steep slopes which were shaped by tectonic plate movements manifested as mostly North East-South West and North West-South East directed folding and fault systems. In general, the flat delta plains of the Kizilirmak River at Bafra and the Yesilirmak River at Çarşamba are under intensive, irrigated agriculture (e.g. rice, fruits, vegetables), whereas the steep mountain slopes and hilly areas generally receive more regular precipitation. These steep slopes have a substantial role in hazelnut and tea production (Miháliková et al. 2016), especially in the eastern Black Sea region.

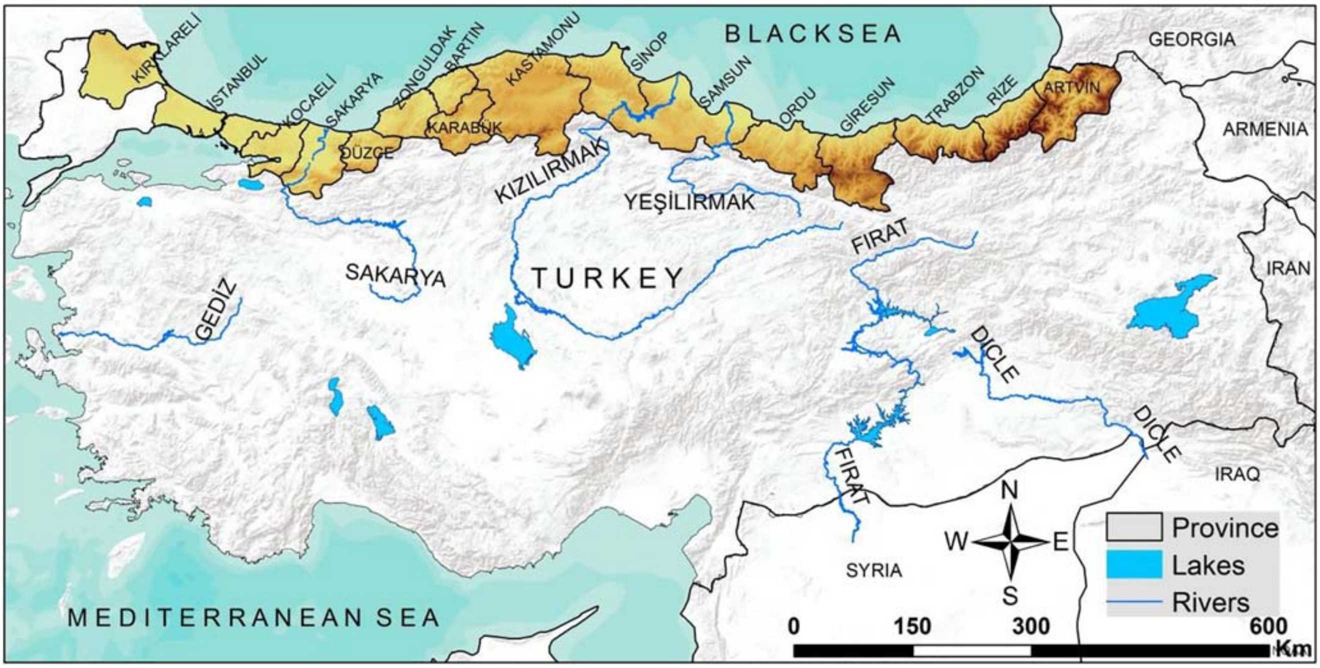

Fig. 1 Provinces included in the study of landslide susceptibility in the Black Sea Region of Turkey

2.2 Data sources

The current study employed a modified methodology for the implementation of different data sources to landslide susceptibility assessment. It is principal to know the induced and triggering elements and to generate the required thematic maps. Consequently, 27 main thematic layers were produced. The necessary data for the conduct of the study, which had been collected in different formats and at different scales, was stored in the geographic database organized for this research. The obtained raw data were arranged by means of the GIS program to increase their sensitivity for application to landslide susceptibility modelling. The point data (such as soil texture and climate data) employed for this purpose were prepared with geo-statistical and interpolation methods in a raster shape at 90 m × 90 m resolution. In the same way, 90 m × 90 m transformation was applied to the raster data format, according to the attribute data to be performed in the data model provided for the vector data shape. The data obtained at higher resolution was brought to the standard working scale. Data in .txt and .xls format from 118 meteorological stations was obtained from the Turkish Meteorological Service (TMS). These data were interpolated across the study area by using the Kriging geo-statistics method. In order to create geological layer, General Directorate of Mineral Research and Exploration (MTA) geological data base index in the .shp style was used. In addition, the soil database of the General Directorate of Agricultural Reform (TRGM) and the .shp style were used in the construction of soil depth map, and 4742 soil samples were used to determine soil textural distribution. CORINE databases from 2000, 2006 and 2012 from the Ministry of Forestry and Water Affairs (OSIB) of Turkey have been included in the .mdb format. LCLU were prepared by using the CORINE 2012 database received from OSIB. Digital elevation model (DEM) raster data shape at a resolution of 10 m produced by the General Command of Mapping was used for aspect and slope layers.

2.3 Fuzzy sets

The fuzzy set theory was firstly performed by Zadeh (1965). Its application enables decision makers to effectively deal with uncertainty. In conventional set theory, a factor either belongs or does not belong to the set. The factors in fuzzy sets have degrees of membership. The method for determination of the membership function of a triangular fuzzy number (TFN) (Laarhoven and Pedrycz 1983) is as follows:

A fuzzy number $\widetilde{A}$ on $\mathbb{R}$ can be a TFN if its membership function $x \in \widetilde{A}$, $\mu_{\widetilde{A}}(x) : \mathbb{R} \rightarrow [0, 1]$ is equal to:

$$\mu_{\widetilde{A}}(x) = \begin{cases} (x-l)/(m-l), & l \leq x \leq m, \\ (u-x)/(u-m), & m \leq x \leq u, \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

In here, l and u represent the lowest and the highest boundaries, respectively, of the fuzzy number $\widetilde{A}$, and m is the modal value. The TFN can be denoted by $\widetilde{A} = (l, m, u)$ and the following are the operational principles for two TFNs, $\widetilde{A}_1 = (l_1, m_1, u_1)$ and $\widetilde{A}_2 = (l_2, m_2, u_2)$.

Plussage of a fuzzy number ⊕

$$\widetilde{A}_1 \oplus \widetilde{A}_2 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (2)$$

Multiplication of a fuzzy number ⊗

$$\widetilde{A}_1 \otimes \widetilde{A}_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (3)$$

for $l_1 l_2 > 0$; $m_1 m_2 > 0$; $u_1 u_2 > 0$

Subtraction of a fuzzy number⊖

$$\widetilde{A}_1 \ominus \widetilde{A}_2 = (l_1, m_1, u_1) \ominus (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \quad (4)$$

Division of a fuzzy number ⊘

$$\widetilde{A}_1 \oslash \widetilde{A}_2 = (l_1, m_1, u_1) \oslash (l_2, m_2, u_2) = (l_1 / u_2, m_1 / m_2, u_1 / l_2) \quad (5)$$

for $l_1 l_2 > 0$; $m_1 m_2 > 0$; $u_1 u_2 > 0$

Reciprocal of a fuzzy number

$$\widetilde{A}_1^{-1} = (l_1, m_1, u_1)^{-1} = (1/u_1, 1/m_1, 1/l_1) \quad (6)$$

for $l_1 l_2 > 0$; $m_1 m_2 > 0$; $u_1 u_2 > 0$

2.4 Fuzzy AHP

AHP is one of the mostly favoured problem solving methods in multi-criteria decision-making. AHP is a mathematical approach that incorporates qualitative and quantitative variables in decision-making by prioritizing the group or individual. However, the method is deficient, especially in the case of pairwise comparisons where there is no certainty (Huang et al. 2008). In addition, the AHP method does not reflect human intuition, even if it incorporates the knowledge of the expert. The FAHP method has been proposed as a means of overcoming these deficiencies. The method has been used for different problems, including tourism management (Wang et al. 2014), supply chain management (Jakhar and Barua 2014), site selection (Ertuğrul and Karakaşoğlu 2008), weapon selection (Dağdeviren et al. 2009), work safety (Zheng et al. 2012), machine-tool selection (Durán and Aguilo 2008) and energy systems management (Heo et al. 2010).

There have been many FAHP approaches adopted (Laarhoven and Pedrycz 1983; Buckley 1985; Chang 1996; Cheng 1997; Deng 1999), with a limited number of studies reporting the application of the method in LSA (Feizizadeh et al. 2014; Roodposhti et al. 2014). The present investigation is different from other studies conducted in the field of landslide susceptibility analysis in that Buckley's FAHP way (1985) was used to detect the weightings of the indicators.

The process for determining the weightings of the assessment criteria with FAHP can be summed up briefly as follows:

Step 1:

Pairwise comparison matrices are constructed between all criteria in the hierarchical structure. Allocated linguistic terms to the pairwise comparisons by asking which the more important of each two dimension is such as:

$$\widetilde{A} = \begin{bmatrix} 1 & \widetilde{a}_{12} & \cdots & \widetilde{a}_{1n} \\ \widetilde{a}_{21} & 1 & \cdots & \widetilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{a}_{n1} & \widetilde{a}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \widetilde{a}_{12} & \cdots & \widetilde{a}_{1n} \\ 1/\widetilde{a}_{21} & 1 & \cdots & \widetilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\widetilde{a}_{n1} & \widetilde{a}_{n2} & \cdots & 1 \end{bmatrix} \quad (7)$$

where $\widetilde{a}_{ij}$ measure denotes, let $\widetilde{1}$ be (1,1,1) when i equal j (i.e. $i=j$); if $\widetilde{1}, \widetilde{2}, \widetilde{3}, \widetilde{4}, \widetilde{5}, \widetilde{6}, \widetilde{7}, \widetilde{8}, \widetilde{9}$ measure the importance of criterion i relative to criterion j then $\widetilde{1}^{-1}, \widetilde{2}^{-1}, \widetilde{3}^{-1}, \widetilde{4}^{-1}, \widetilde{5}^{-1}, 6^{-1}, \widetilde{7}^{-1}, \widetilde{8}^{-1}, \widetilde{9}^{-1}$ measure how relatively important criterion j is to criterion i.

Step 2:

The use of the geometric mean technique to define the fuzzy geometric mean and the fuzzy weighting of each criterion was described by Buckley (1985) as follows:

$$\widetilde{r}_i = \left(\widetilde{a}_{i1} \otimes \widetilde{a}_{i2} \otimes \ldots \otimes \widetilde{a}_{in}\right)^{1/n} \quad (8)$$

and then, $\widetilde{w}_i = \widetilde{r}_i \otimes \left(\widetilde{r}_1 \otimes \ldots \otimes \widetilde{r}_n\right)^{-1}$ (9)

where $\widetilde{a}_{in}$ is the fuzzy value of criterion i compared to criterion n; thus, $\widetilde{r}_i$ is the geometric mean of the fuzzy comparison values of criterion i for each criterion; and $\widetilde{w}_i$ is the fuzzy weighting of the ith criterion and can be indicated by a TFN, $\widetilde{w}_i = (lw_i, mw_i, uw_i)$, with lw_i, mw_i and uw_i representing the lower, middle and upper values, respectively, of the fuzzy weighting of the ith criterion.

Step 3:

The result of the fuzzy synthetic decision reached for each alternative is a fuzzy number. Defuzzification is a mathematical process performed to convert fuzzy output into a crisp value. The three most common defuzzification methods are the means of maxima, Center of Area (COA) and the 'a-cut' methods (Yang et al. 2008). The COA method is a simple and practical method and there is no need to introduce the preferences of any evaluators (Sun 2010). The best non-fuzzy performance (BNP) value of the fuzzy number, $\widetilde{w}_i$, which is equal to (lw_i, mw_i, uw_i), can be determined as follows:

$$BNP_i = lw_i + \frac{(uw_i - lw_i) + (mw_i - lw_i)}{3}, \quad \forall i. \tag{10}$$

These calculation processes are really hard and difficult, if they are made manually. In this process, Microsoft Excel software was used to create pairwise comparison matrices and perform progressive calculations of the FAHP method. In this study, the scale provided in Table 1 was used to create the pairwise comparison matrix in the FAHP model.

2.5 Multiple-criteria analysis approach

The objective of the application of SMCA approach is to provide solutions to decision-making problems described by multiple alternatives which can be assessed in the context of criteria used for decision-making. The landslide susceptibility indicators (criteria), namely topography (slope and aspect), geological pattern, vegetation (land use and land cover, vegetation coverage ratio), soil (depth and texture) and climate (maximum precipitation, number of rainy days, coefficient of variation and average total precipitation over the long term), and their features and weighting rates that are normally employed in landslide susceptibility assessment, were used to integrate information on the research land. To perform SMCA, a weighted linear combination approach was carried out by using the following formula:

$$\mathrm{LSI} = \sum_{i=1}^{n} (\mathrm{W}i.\mathrm{X}i) \tag{11}$$

where LSI is the landslide susceptibility index, *Wi* is the weighting of criteria *i* and the *Xi* sub-criteria score is, *i*.

2.6 Interpolation analyses

In this study, different interpolation methods (inverse distance weighing—IDW with the weights of 1, 2, 3 and radial basis function-RBF with thin plate spline (TPS), simple kriging (OK) with spherical, exponential and Gaussian variograms, ordinary kriging (OK) with spherical, exponential and Gaussian variograms, universal kriging (OK) with spherical, exponential and Gaussian variograms) were applied for predicting the spatial distribution of soil quality index criteria with ArcGIS 10.2.2. In the current study in order to find the most convenient interpolation approach, the root mean square error (RMSE) was used because the lowest RMSE value facilitates the most accurate prediction. The calculations of interpolation models for the spatial distribution of soil textural and climatic data were determined with the following formula:

$$\mathrm{RMSE} = \sqrt{\frac{\sum (z_{i^*} - z_i)^2}{n}} \tag{12}$$

where RMSE is the root mean square error, Z_i is the estimated value, Z_{i*} is the observed value and n is the number of observations. In addition, in order to best allocate values to the different landslide susceptibility classes, the natural break method developed by Jenks (1967) and cited by many researchers (Margarint et al. 2013; Jaafari et al. 2014; Ba et al. 2017), was employed in this study. In addition, the LSI classes are presented in Table 2.

3 Results and discussion

3.1 Parameters used in landslide susceptibility analysis

Landslide, which is a mass movement of the earth's surface material, is triggered by either geo-physical or climatic factors or a combination of both. However, many researchers have reported that there are no universal guidelines regarding the selection of indicators for LSM. According to these researchers, one factor may be important to the occurrence of landslides in a particular land but not in another area. The identification of causal indicators therefore requires including the nature of the study area and accommodating the available data (Acar et al. 2019; Shahabi et al. 2015). In order to describe the susceptibility of an area to landslide, layers of data

Table 1 Triangular fuzzy conversion scale employed in the modelling of landslide susceptibility in the Black Sea Region of Turkey

Fuzzy number	Linguistic scales for importance	Triangular fuzzy number	Triangular fuzzy reciprocal number
$\tilde{1}$	Equally important	(1,1,1)	(1,1,1)
$\tilde{2}$	Intermediate	(1,2,3)	(1/3,1/2,1)
$\tilde{3}$	Weak	(2,3,4)	(1/4,1/3,1/2)
$\tilde{4}$	Intermediate	(3,4,5)	(1/5,1/4,1/3)
$\tilde{5}$	Strong	(4,5,6)	(1/6,1/5,1/4)
$\tilde{6}$	Intermediate	(5,6,7)	(1/7,1/6,1/5)
$\tilde{7}$	Very strong	(6,7,8)	(1/8,1/7,1/6)
$\tilde{8}$	Intermediate	(7,8,9)	(1/9,1/8,1/7)
$\tilde{9}$	Essential	(8,9,10)	(1/10,1/9,1/8)

Table 2 Landslide susceptibility index classes used for landslide susceptibility assessment of the Black Sea Region of Turkey

Definition	Class	Index value
Very high	1	3.33–4.02
High	2	3.00–3.32
Moderate	3	2.72–2.99
Low	4	2.43–2.71
Very low	5	1.69–2.42

describing different characteristics of the earth should be assessed simultaneously. In landslide susceptibility modelling, the main factors considered necessary for incorporation in a robust model are lithology; topography, including slope and aspect; land use-land cover (LULC); soil, including texture and depth; and precipitation climatology, including maximum precipitation at various standard times, number of rainy days with various precipitation totals, coefficient of variation for precipitation and long-term average precipitation.

The classifications for the larger coastal Black Sea region's long-term average precipitation amounts, maximum precipitation totals at standard times, inter-annual variability and number of rainy days used in the current study are summarised as follows, in terms of their significance for land-slide occurrence as a whole and within each factor:

– Precipitation amounts (mm): long-term mean of summer, autumn and annual precipitation totals (mm);
– Long-term averages of the number of rainy days:

• Long-term average number of rainy days with an amount more than 50 mm: summer, autumn and annually;
• Long-term average number of rainy days with an amount more than 10 mm: annually, summer and autumn;
• Long-term average number of rainy days with an amount more than 0.1 mm: summer, autumn and annually;

– Coefficient of variation (CV, %): winter, summer and autumn.
– Maximum precipitation amounts (mm) at the standard times of 30 min and 1, 3, 6 and 12 h.

The selection of the aforementioned main factors was based on studies by Bathrellos et al. (2017), Skilodimou et al. (2019a, b) and Acar et al. (2019). Spatial and proportional distributions of landslide susceptibility classes are provided (Table 3, Fig. 2).

Landslide is strongly linked to topographic features; slope and aspect have been commonly used in LSM across many countries (Yan et al. 2018; Skilodimou et al. 2019a, b; Bera et al. 2019). In this study, the slope and aspect thematic maps were created by using a DEM which had been created from the topographic map of the study area at 10 m contour intervals. Half of the total area of the Black Sea Region had a slope of more than 10%, with 75.3% of that land found in the eastern part of the study area, whereas low slope land (< 10%), which constitutes about one-fourth of the total area, is situated mostly in the western part. Shahabi et al. (2014) noted that aspect and slope have a major role in the frequency of landslide events and their severity. Furthermore, Dehnavi et al. (2015) reported that aspect can influence landslide susceptibility my means of the effects of elements such as soil moisture, exposure to sunlight, precipitation and wind direction. Thus, this study recognizes slope-aspect as a factor impacting landslide susceptibility; the aspect layer produced in this study was produced from DEM, with most of the aspect (87.3%) north or south facing.

Vegetation can indirectly indicate the stability of a slope through its coverage density, type and LULC, and it also has an essential role in preventing or at least reducing the extent of a particular landslide. Lahaoi et al. (2017) reported that vegetation tends a dual target by restraining rain with its foliage and by retaining soil in place with its widespread root systems. Moreover, Mallick et al. (2018) reported that branches with foliage assist in slowing down the rate at which water flows over the soil surface, and that they also help retain the soil in place, whereas in the extinction of foliated branches and the root structure of trees, bushes and other part of plants, the land is quite likely to slide away because of the loss of internal cohesion after saturation. In the current study, the vegetation density of more than half of the Black Sea Region was more than 40%, which was mostly located at the eastern end of the study area, whereas only 17% was in the low density vegetation category (Fig. 2, Table 3). Moreover, the LULC of an area is a significant factor in the assessment of the frequency and occurrence of landslides. Dai et al. (2002) stated that the complex physical mechanism acting on the earth surface can be detected from the land use-land cover pattern. The area covered by the current study has about 56.5% vegetation cover, with thick evergreen (mostly coniferous) and broadleaf forest cover situated mostly in the mountainous areas of the middle and eastern parts of the Black Sea Region (Türkeş 2015). The remaining area is covered by crop and pasture lands at 21.5% and 19.7%, respectively, and artificial areas (particularly settlement areas of human habitation) are in the most vulnerable class, which implies that the increasing intensity of human interference with the land and natural processes, including its vegetation cover, increases the occurrence of landslide. It should be noted that the artificial areas and bare lands are not common (2.3% of the study area) and generally lie at lower altitudes.

Many soil properties related to landslide potential are most often not included with indicators such as lithology, land-use potential, slope and vegetation cover-land use that are used for landslide susceptibility assessment. For example, soil factors such as texture and/or its depth have been ignored by most

Table 3 Spatial and proportional distribution of some landslide susceptibility factors for the Black Sea Region of Turkey

Slope			Aspect		
Class (%)	ha	%	Class	ha	%
1: 0–10	2,096,350	24.7	1: Flat	25,682	0.3
2: 10–25	2,695,892	31.8	2: East	1,047,360	12.3
3: 25–45	2,292,390	27.0	3: South	2,948,290	34.7
4: 45+	1,399,720	16.5	4: North	4,463,020	52.6
Vegetation density (%)			Land use-land cover		
1: 0–10	1,453,890	17.1	1: Forest, irrigated farm, water surface	4,794,527	56.5
2: 10–40	2,290,970	27,0	2: Pasture lands	1,670,848	19.7
3: 40–70	1,781,830	21.0	3: Crop lands	1,824,023	21.5
4: 70+	2,957,662	34.9	4: Artificial area, bare land	194,954	2.3
Soil depth (cm)			Soil texture		
1: 0–20	2,360,915	27.8	1: coarse: S, SL	1,422,340	16.8
2: 20–50	4,061,284	47.9	2: medium: CL, SiCL, SCL, L, SiL, Si, SL	6,500,932	76.6
3: 50–90	1,168,710	13.8	3: fine: C, SiC, SC	561,080	6.6
4: 90+	893,443	10.5			
Lithology					
1: Alluvial sediments and deposits				534,070	6.3
2: Sandstone, granite, agglomerate, andesite, trachyte, gabbro, basaltic vulcanite, ultra-basic magmatic and eruptive rocks, melange, ophiolitic, serpentine, metamorphic rocks such as shale, schist, phyllite				3,282,940	38.7
3: Marine coastal strip dune, old alluvial sediments, travertine, conglomerate, limestone, dolomite, marble				217,721	2.6
4: Terrestrial dune, volcanic ash, tuff, marl, claystone, mudstone and siltstone, gypsum, evaporates				4,449,621	52.4

S sand, *LS* loamy sand, *CL* clay loam, *SiCL* silty clay loam, *SCL* sandy clay loam, *L* loam, *SiL* silty loam, *Si* silt, *SL* sandy loam, *C* clay, *SiC* silty clay, *SC* sandy clay

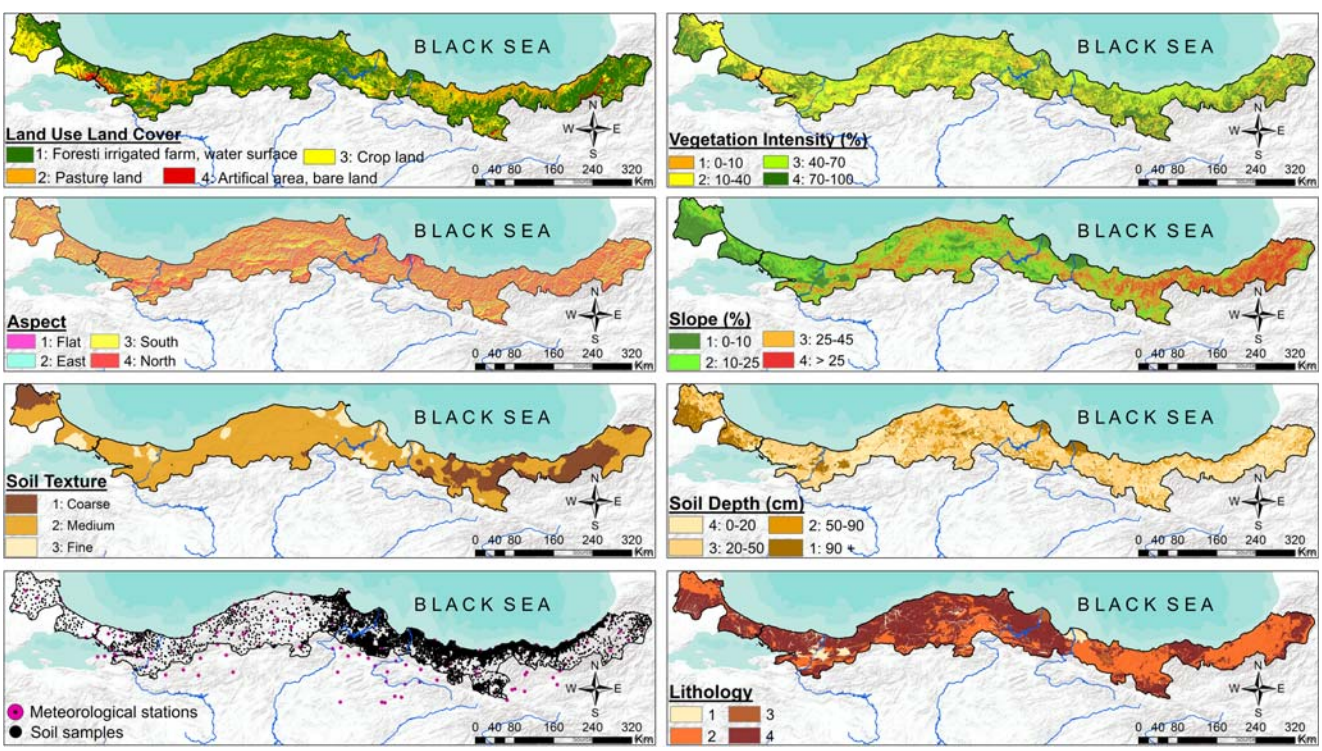

Fig. 2 Spatial distribution of some landslide susceptibility factors, soil characteristics and meteorological station pattern maps in the Black Sea Region of Turkey

researchers during the identification of landslide prone areas. Sharam et al. (2012) attempted an assessment of landslide vulnerability by incorporating the effects of the different factors that influence soil parameters. Their comparison between the actual zone of landslide occurrence and the zones of increasing vulnerability revealed a 90% concurrence of landslides with the most vulnerable zone, demonstrating the efficacy of soil properties as potential factors of landslide.

Soil texture and soil depth, which significantly affect water storage capacity and dynamic pedogenic behaviour through the effects of shrinking and swelling, were incorporated in the present study. A total of 4742 soil samples were used in the application of the exponential semivariogram of ordinary kriging to determine the most suitable model (according to RMSE values) for the production of maps showing the spatial distribution of soil texture (Fig. 2). The results showed that about 77% of the study area has medium textured soils (mostly clay loam, loam and sandy clay loam), about 7.0% has fine soil texture (clay, silty clay and sandy clay) and the remainder (about 17%) has sandy and sandy loam textured soil. In addition, the soil depth of about 48% of the study area is in the range of 20–50 cm. Furthermore, the depth of the soil in nearly 28% of the research area is less than 20 cm and the soil is therefore described as shallow, whereas the soil of only 10.5% is more than 90 cm.

Lithology is also an important phenomenon in that it provides material for the occurrence of landslides and constitutes the base for landslide occurrence. Many researchers consider lithological properties to be important indicators for LSM (Mondal and Maiti 2013; Chen et al. 2013). The Black Sea Region was influenced by extensive tectonic activity during the Early Cretaceous Period (Tüysüz et al. 2012), resulting in the development of the Western and Eastern Black Sea basins and on its southern continental margin has other sedimentary basins. Structural and lithological differences in the study area are evidenced by the wide exposure of Pre-Late Cretaceous sedimentary rocks in the Southern area, whereas the Northern area is shaped by Late Cretaceous and Middle Eocene volcanic rocks (Ersoy et al. 2016). The study area therefore includes different kinds of geological strata reflected in the classification of lithological units (Fig. 2). The 1/25,000 scale, geological data base of MTA was used in the present study. It shows that about half of the study area is in class 4, which includes sedimentary rocks such as volcanic ash, tuff, marl, clay stone, mud stone and silt stone, which are located mostly in the central and western parts of the Black Sea Region, whereas most of the eastern part consists of volcanic material classed as 2. Alluvial sediments and deposits from the Quaternary Period are mostly situated on the Bafra and Çarşamba plains which correspond with the deltas of the Kızılırmak and Yeşilırmak Rivers, respectively, and some narrow coastal plains.

Precipitation and precipitation-related variables and factors are some of the most critical climatic variables and are therefore precondition for different applications, encapsulating LSM (Xu 2015). That is why, for natural hazard related research, this factor is also crucial to understand the temporal and spatial phenomena related to precipitation. For that purpose, precipitation data for a 30-year period (1976–2016) from the TSM were utilised.

Generally, the larger Black Sea region is characterised by high and consistent precipitation, with the exception of the inner areas bordering the northern-central Anatolia and north-eastern Anatolia sub-regions. The area between the eastern Black Sea sub-region and the northern part of eastern Anatolia is also characterised by rain-shadow conditions in the deep river valleys. Consequently, there is medium to high level landslide vulnerability overall in the coastal belt with steep areas and exposure to north-westerly and northerly circulation and weather systems. The current study reports that summer is the season for most landslide activity in the study region. Another important climate related factor is the number of rainy days, with various thresholds for precipitation totals included. In this respect, rainy days can be defined as the number of days with precipitation greater than a certain threshold within a month or a year, e.g. greater than 0.1 mm, 10.0 mm, 20.0 mm and 50 mm. The precipitation total is one of the most important weather and climatic indicators for the triggering of landslides or mud flows, particularly if there is a combination of high number of rainy days and high amounts of rainfall in a place vulnerable to mass wasting. The seasonal and annual average number of rainy days with a minimum of 0.1 mm precipitation has a similar distribution pattern over the larger Black Sea coastal region (winter and spring are not given here). Except for the coastal Black Sea zone of the Marmara Region (i.e. northern Thrace of the northern Marmara sub-region bordering the western Black Sea basin) and the somewhat continental inner parts of the Central Black Sea sub-region, almost the whole coastal Black Sea region is rated in the medium to high susceptibility classes for landslide in autumn and annually. On the other side, almost all of the eastern Black Sea sub-region is highly vulnerable to landslide occurrence. In autumn, the number of days with 10 mm of rain is generally indicative of a medium degree of susceptibility to landslide development over almost all of the study region. The annual number of rainy days is associated with an evident mix-pattern, and for the summer season almost the entire study region shows mostly a low to low-medium degree of vulnerability. Because of the hydro-climatological importance of the amounts of autumn, winter and summer precipitation and their variability across the whole coastal Black Sea Region, the coefficients of variation (CV %) were calculated and classified for these seasons. In terms of the long-term mean of the year to year variability of precipitation characterised here with the CV as a percentage, the largest area susceptible to landslide occurrence is in summer over much of the study region, with the exception of the Eastern Black Sea

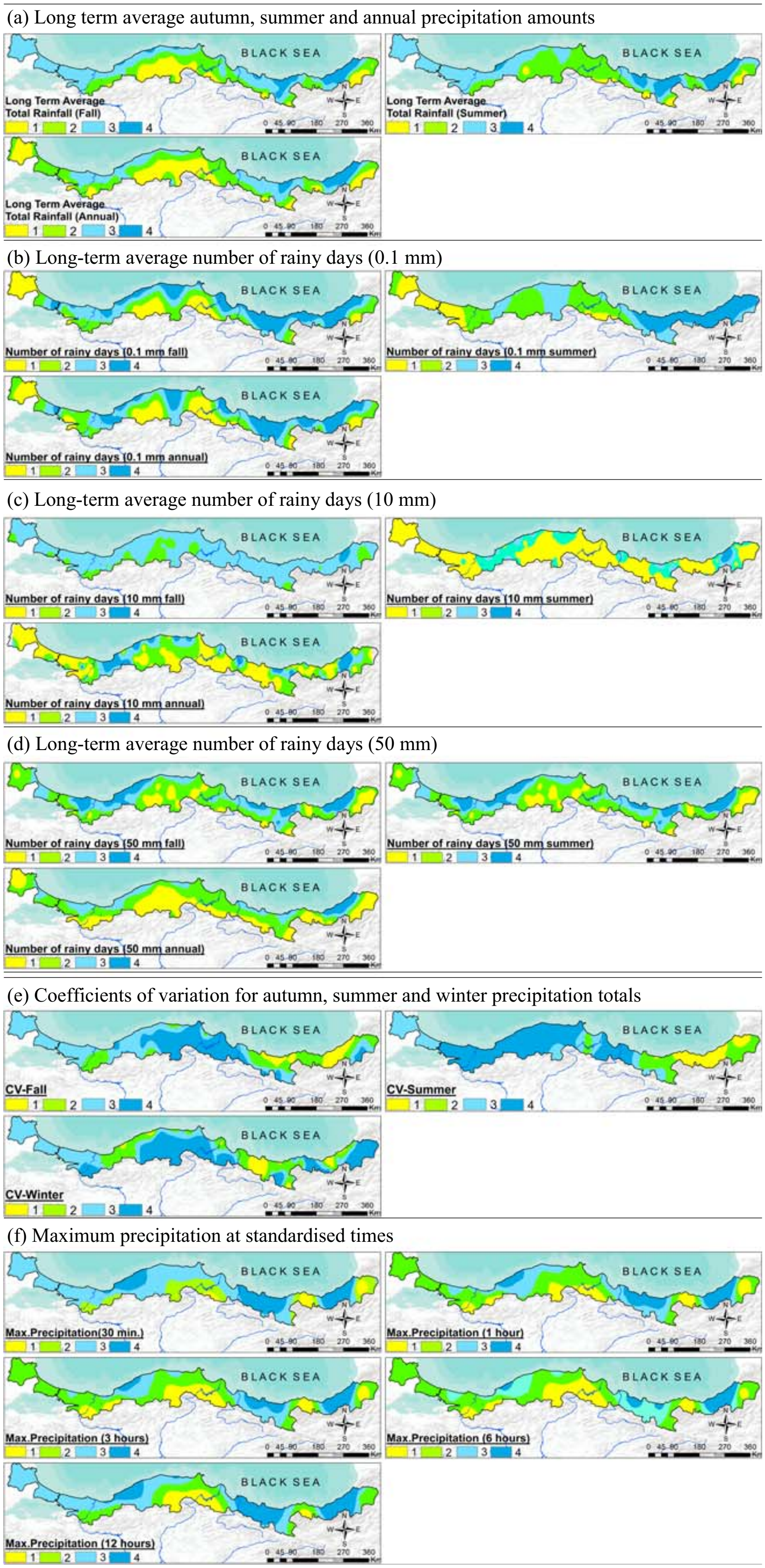

Fig. 3 Classified spatial distribution patterns of precipitation-related factors over the study region of the larger Black Sea Region of Turkey

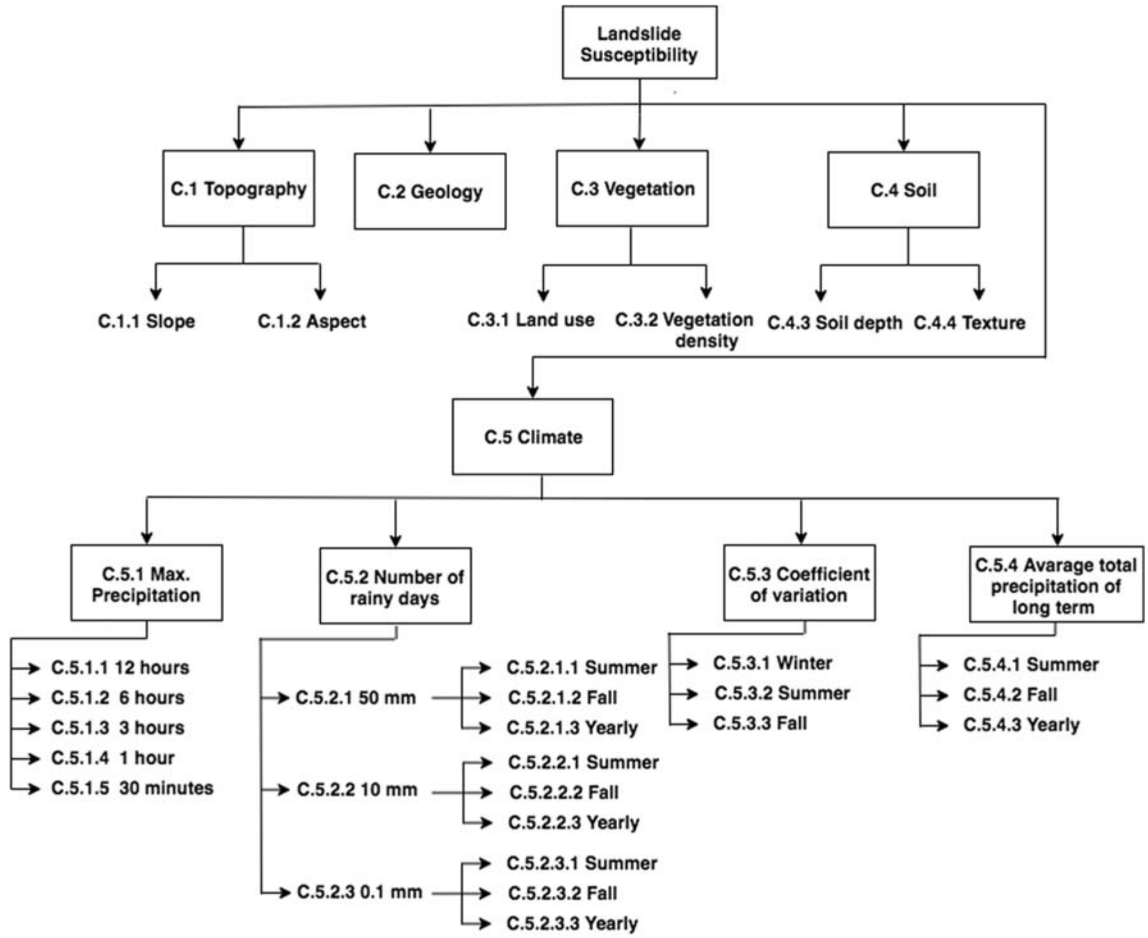

Fig. 4 The hierarchical model of landslide susceptibility

sub-region of Turkey where there is year round plentiful precipitation and low year to year variability. The patterns of autumn and winter precipitation totals are somewhat similar for the areas classified as having medium to high landslide vulnerability, which are mainly in the western, central Black Sea sub-regions and Thrace's Black Sea coast. When the classified distribution patterns for the maximum precipitation totals at various standard times were compared over the larger Black Sea Region of Turkey, there were two similar patterns. The first pattern was seen for the maximum precipitation totals at the standard times of 30 min and 12 h. Both of these maximum precipitation patterns are characteristic of the western and eastern Black Sea coastal belts which were classified in the medium and high level of landslide susceptibility classes. The other three maximum precipitation totals at the standard times of 1, 3 and 6 h are associated with smaller areas of medium to high vulnerability to landslide occurrence that are generally in the same areas. The main observed difference among these two precipitation patterns is that the latter group covers a larger area characterised by less (low to low-medium) vulnerability that is mainly located on Thrace's Black Sea coast and in the central Black Sea sub-region (Fig. 3).

Table 4 Main criteria comparison matrix used for landslide susceptibility assessment of the Black Sea Region of Turkey

	C.1	C.2	C.3	C.4	C.5
C.1	1	$\tilde{7}$	$\tilde{5}$	$\tilde{5}$	$\tilde{3}$
C.2	$\tilde{7}^{-1}$	1	$\tilde{5}^{-1}$	$\tilde{3}^{-1}$	$\tilde{7}^{-1}$
C.3	$\tilde{5}^{-1}$	$\tilde{5}$	1	$\tilde{3}$	$\tilde{3}^{-1}$
C.4	$\tilde{5}^{-1}$	$\tilde{3}$	$\tilde{3}^{-1}$	1	$\tilde{7}^{-1}$
C.5	$\tilde{3}^{-1}$	$\tilde{7}$	$\tilde{3}$	$\tilde{7}$	1

Table 5 Main criteria triangular fuzzy numbers comparison matrix used for landslide susceptibility assessment of the Black Sea Region of Turkey

	C.1	C.2	C.3	C.4	C.5
C.1	(1,1,1)	(6,7,8)	(4,5,6)	(4,5,6)	(2,3,4)
C.2	(1/8,1/7,1/6)	(1,1,1)	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1/8,1/7,1/6)
C.3	(1/6,1/5,1/4)	(4,5,6)	(1,1,1)	(2,3,4)	(1/4,1/3,1/2)
C.4	(1/6,1/5,1/4)	(2,3,4)	(1/4,1/3,1/2)	(1,1,1)	(1/8,1/7,1/6)
C.5	(1/4,1/3,1/2)	(6,7,8)	(2,3,4)	(6,7,8)	(1,1,1)

Table 6 Local and global weightings of main LSM criteria used for landslide susceptibility assessment of the Black Sea Region of Turkey

Landslide susceptibility criteria		Local Weights	Global Weights
C1	Topography	0.466	
C1.1	Slope	0.700	0.326
C1.2	Aspect	0.300	0.140
C2	Geology	0.036	0.036
C3	Vegetation	0.136	
C3.1	Land use	0.350	0.048
C3.2	Vegetation density	0.650	0.089
C4	Soil	0.067	
C4.1	Soil depth	0.600	0.040
C4.2	Texture	0.400	0.027
C5	Climate	0.294	
C5.1	Max. Precipitation	0.378	
C5.1.1	12 h	0.422	0.047
C5.1.2	6 h	0.215	0.024
C5.1.3	3 h	0.183	0.020
C5.1.4	1 h	0.111	0.012
C5.1.5	30 min	0.070	0.008
C5.2	Number of rainy days	0.149	
C5.2.1	50 mm	0.727	
C5.2.1.1	Summer	0.519	0.017
C5.2.1.2	Fall	0.308	0.010
C5.2.1.3	Yearly	0.173	0.006
C5.2.2	10 mm	0.190	
C5.2.2.1	Summer	0.637	0.005
C5.2.2.2	Fall	0.233	0.002
C5.2.2.3	Yearly	0.129	0.001
C5.2.3	01 mm	0.083	
C5.2.3.2	Summer	0.251	0.001
C5.2.3.3	Fall	0.169	0.001
C5.2.3.1	Yearly	0.580	0.002
C5.3	Coefficient of variation	0.131	
C5.3.1	Winter	0.512	0.020
C5.3.2	Summer	0.345	0.013
C5.3.3	Fall	0.143	0.006
C5.4	Mean annual precipitation of long term	0.341	
C5.4.1	Summer	0.629	0.063
C5.4.2	Fall	0.263	0.026
C5.4.3	Yearly	0.107	0.011

3.2 Production of a landslide susceptibility map with SMCA

Landslides are closely linked to geo-environmental conducive parameters that include geomorphology, geology and land cover type, and are frequently triggered by human interference, heavy rainfall and many other dynamic variables (Erginal et al. 2009; Türkeş 2013). In the present study, firstly the criteria to be used in landslide susceptibility analysis were determined through a comprehensive literature search. Subsequently, a hierarchical model consisting of 27 sub-criteria nested under 5 main criteria was developed. Then, pairwise comparison matrices were used to determine the weightings of the criteria. Nine pairwise comparison matrices were developed from the hierarchical structure displayed in Fig. 4. Separately, the double comparison matrix for the main criteria is provided in Table 4.

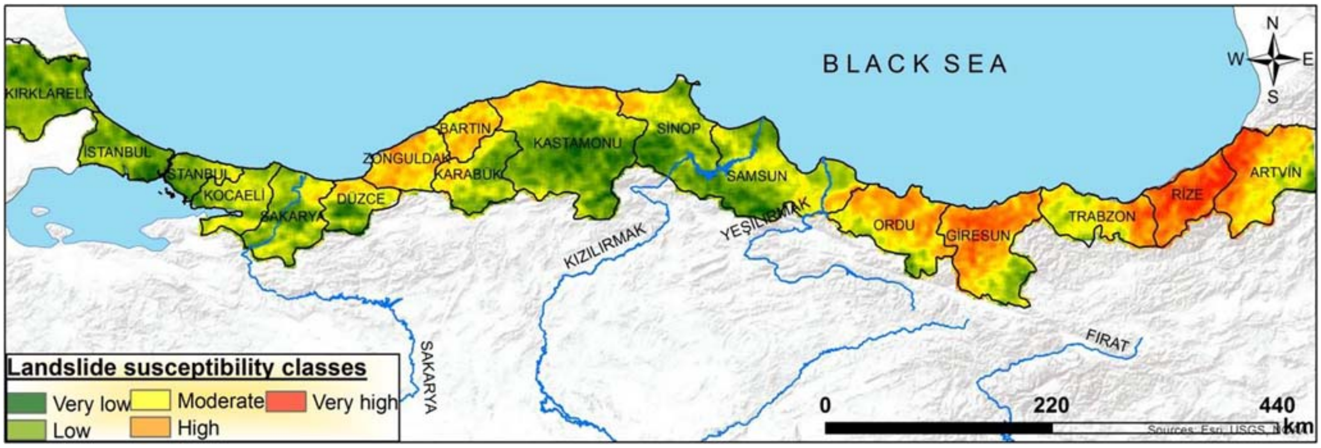

Fig. 5 Landslide susceptibility map of the Black Sea Region of Turkey

After the completion of the pairwise comparisons, the values were converted to triangular fuzzy numbers (Table 4). The matrix for the main criteria converted into triangular fuzzy numbers is presented in Table 5.

After the binary comparison matrix had been transformed into triangular fuzzy numbers, the $\widetilde{r}_i$ values were calculated by using Eq. (8) to calculate the fuzzy weightings of the criteria. Using $\widetilde{r}_1$ as an example:

$$\widetilde{r}_1 = (1 \times 6 \times 4 \times 4 \times 2)^{1/5}(1 \times 7 \times 5 \times 5 \times 3)^{1/5}$$
$$(1 \times 8 \times 6 \times 6 \times 4)^{1/5} = (2.862, 3.500, 4.095)$$

Similarly, the remaining $\widetilde{r}_i$ values were calculated, as follows:

$\widetilde{r}_2 = (0.231, 0.267, 0.322)$, $\widetilde{r}_3 = (0.803, 1.000, 1.246)$, $\widetilde{r}_4 = (0.401, 0.491, 0.608)$, $\widetilde{r}_5 = (1.783, 2.178, 2.639)$.

Then, the $\widetilde{w}_i$ values were estimated by using Eq. (12). Using $\widetilde{w}_1$ as an example:

$$\widetilde{w}_1 = (2.862, 3.500, 4.095) \otimes \Big(1/\big(4.095 + 0.322 + 1.246 + 0.608 + 2.639\big),$$
$$1/(3.500 + 0.267 + 1.000 + 0.491 + 2.178),\ 1/(2.862 + 0.231 + 0.803 + 0.401 + 1.783)\Big)$$
$$= (0.321, 0.471, 0.674)$$

Similarly, the remaining $\widetilde{w}_i$ values were calculated, as follows:

$$\widetilde{w}_2 = (0.026, 0.036, 0.053), \widetilde{w}_3 = (0.090, 0.134, 0.205), \widetilde{w}_4$$
$$= (0.045, 0.066, 0.100), \widetilde{w}_5 = (0.200, 0.293, 0.434).$$

The COA defuzzification method (Eq. 10) was then used to calculate the BNP weightings of the criteria. Thus, the local weightings of the criteria were derived. Using BNP_1 as an example:

$$BNP_1 = 0.321 + [(0.674–0.321) + (0.471–0.321)]/3 = 0.466$$

The sub-criteria, which are below a main criterion in a hierarchical structure, are the weights between themselves. The sum of the local weights of the sub-criteria under one main criterion should be 1. The weight obtained by multiplying each sub-criterion by the weight of the main criterion to which it is hierarchically bound is the global weight (the local and global weightings of all criteria are given in Table 6). The global weighting of C5.1.1 was calculated as an example, as follows:

$0.422 \times 0.378 \times 0.294 = 0.0469$

In this study, a landslide susceptibility map of the Black Sea Region of Turkey was produced by employing a geographical information system-based multi-criteria decision method. Susceptibility map of the landslide was analysed with spatial multi-criteria analysis and it was determined that the proportion of the study area rated as having very high susceptibility was 11.4%, high susceptibility was 21.5%, moderate susceptibility was 28.1%, low susceptibility was 26.4% and very low susceptibility was 12.7% (Fig. 5). From Fig. 5, it can be seen that low and very low landslide susceptibility classes mostly cover western provinces such as Kırklareli, İstanbul, Kocaeli and Sakarya, and central-southern provinces (Kastamonu, Sinop and Samsun). These classifications are attributable to low slope and low precipitation whereas especially Ordu, Giresun and Rize Provinces, and some parts of Artvin and Trabzon Provinces, were classified as the high and very high level in landslide susceptibility classes due to the combination of steep slope, high rainfall and lithological characteristics.

4 Conclusions

In the current study, an LSM model was created for the Black Sea Region of Turkey, which includes semi-humid and humid terrestrial ecosystems, by using the spatial multi-criteria analysis method which is based on fuzzy environment integrated with GIS techniques and the AHP approach. In this model, 9 environmental indicators that had been utilized in many models for landslide occurrence or referenced in the literature, and 27 sub-indicators, were used. This study particularly focused on detailed precipitation climatology and the methodology of the SMCA system in the development of its model because there are almost no precedents for the incorporation of temporal and spatial variation of precipitation types in landslide modelling. In addition, the AHP method is a decision-making approach that actively prioritizes qualitative and quantitative criteria by making pairwise comparisons. However, especially in pairwise comparisons where there is no certainty, the AHP method is inadequate in that it cannot effectively incorporate the decisions of the decision maker in the process. The reason for this is that decision-makers have difficulty in using crisp numbers, especially when comparing qualitative criteria. This problem can be managed by using fuzzy numbers. Therefore, in the current study, the FAHP approach was performed to detect criteria weightings.

Overall, the multifaceted approach adopted in this study to better understand landslide susceptibility in the Black Sea region of Turkey revealed that approximately 33% of the study area has high or very high susceptibility to landslide occurrence, whereas the low and very low susceptibility classes contain about 37% of the research area. Moreover, this study contributes an alternative perspective in the application of firstly fuzzy sets with AHP by taking into adopting the Buckley approach in LSM modelling.

Acknowledgements The authors thank Dr. Gregory T. Sullivan for helpful comments and editing the English in an earlier version of this manuscript.

References

Acar DKC, Tasoglu H, Kerem İ (2019) Comparison of GIS-based landslide susceptibility assessment of the Satuk village (Yenice, NW Turkey) by frequency ratio and multi-criteria decision methods. Environ Earth Sci 78:81–94

Atkinson PM, Massari R (2011) Autologistic modelling of susceptibility to landsliding in the central Apennines, Italy. Geomorphol 130:55–64

Ba Q, Chen Y, Deng S, Wu Q, Yang J, Zhang J (2017) An improved information value model based on gray clustering for landslide susceptibility mapping. ISPRS Int J Geo-Inf 6(18):1–20

Bathrellos GD, Skilodimou HD, Chousianitis K, Youssef AM, Pradhan B (2017) Suitability estimation for urban development using multi-hazard assessment map. Sci Total Environ 575:119–134

Bera A, Mukhopadhyay BP, Das D (2019) Landslide hazard zonation mapping using multcriteria analysis with the help of GIS techniques: a case study from eastern Himalayas, Namchi. South Sikkim Natural Hazards 96:935–959. https://doi.org/10.1007/s11069-019-03580-w

Buckley JJ (1985) Fuzzy hierarchical analysis. Fuzzy Sets Syst 17(3): 233–247

Chang DY (1996) Applications of the extent analysis method on fuzzy AHP. Eur J Oper Res 95(3):649–655

Chen J, Yang ST, Li HW, Zhang B, Lv JR (2013) Research on geographical environment unit division based on the method of natural breaks (Jenks). Int Arch Photogramm Remote Sens Spatial Inf Sci XL-4/W3:47–50, https://doi.org/10.5194/isprsarchives-XL-4-W3-47-2013

Cheng CH (1997) Evaluating naval tactical missile systems by fuzzy AHP based on the grade value of membership function. Eur J Oper Res 96(2):343–350

Dağdeviren M, Yavuz S, Kılınç N (2009) Weapon selection using the AHP and TOPSIS methods under fuzzy environment. Expert Syst Appl 36(4):8143–8151

Dai F, Lee C, Ngai YY (2002) Landslide risk assessment and management: an overview. Eng Geol 64:65–87

Dehnavi A, Aghdam IN, Pradhan B, Morshed Varzandeh MH (2015) A new hybrid model using step-wise weight assessment ratio analysis (SWARA) technique and adaptive neuro-fuzzy inference system (ANFIS) for regional landslide hazard assessment in Iran. Catena 135:122–148

Deng H (1999) Multicriteria analysis with fuzzy pairwise comparison. Int J Approx Reason 21(3):215–231

Durán O, Aguilo J (2008) Computer-aided machine-tool selection based on a fuzzy-AHP approach. Expert Syst Appl 34(3):1787–1794

Erginal AE, Öztürk B, Ekinci YL, Demirci A (2009) Investigation of the nature of slip surface using geochemical analyses and 2-D electrical resistivity tomography: a case study from Lapseki area, NW Turkey. Environ Geol 58:1167–1175

Ersoy H, Yalçınalp B, Arslan M, Babacan AE, Çetiner G (2016) Geological and geomechanical properties of the carbonate rocks at the eastern Black Sea region (NE Turkey). J Afr Earth Sci 123:223–233

Ertuğrul İ, Karakaşoğlu N (2008) Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. Int J Adv Manuf Technol 39(7–8):783–795

Ferentinou M, Chalkias C (2013) Mapping mass movement susceptibility across Greece with GIS, ANN and statistical methods, landslide science and practice. Springer, Berlin Heidelberg, pp 321–327

Feizizadeh B, Roodposhti MS, Jankowski P, Blaschke T (2014) A GIS-based extended fuzzy multi-criteria evaluation for landslide susceptibility mapping. Comput Geosci 73:208–221

Generali M, Pizziolo M (2013) The susceptibility map for landslides with shallow initiation in the Emilia Romagna region (Italy). Springer, Berlin, Heidelberg

Görür N (1988) Timing of opening of the Black Sea basin. Tectonophysics 147:247–262

Heo E, Kim J, Boo KJ (2010) Analysis of the assessment factors for renewable energy dissemination program evaluation using fuzzy AHP. Renew Sust Energ Rev 14(8):2214–2220

Hong HY, Ilia I, Tsangaratos P, Chen W, Xu C (2017) A hybrid fuzzy weight of evidence method in landslide susceptibility analysis on the Wuyuan area, China. Geomorphology 290:1–16

Huang CC, Chu PY, Chiang YH (2008) A fuzzy AHP application in government-sponsored R&D project selection. Omega 36(6): 1038–1052

Jaafari A, Najafi A, Pourghasemi HR, Rezaeian J, Sattarian A (2014) GIS-based frequency ratio and index of entropy models for landslide susceptibility assessment in the Caspian forest, northern Iran. Int J Environ Sci Technol 11(4):909–926

Jakhar SK, Barua MK (2014) An integrated model of supply chain performance evaluation and decisionmaking using structural equation modelling and fuzzy AHP. Prod Plan Control 25(11):938–957

Jenks GF (1967) The data model concept in statistical mapping. International yearbook of cartography 7:186–190

Laarhoven PJM, Pedrycz W (1983) A fuzzy extension of Saaty's priority theory. Fuzzy Sets Syst 11(3):229–241

Lahaoi H, Rhinane H, Hilali A, Lahssini S, Moukrim S (2017) Desertification assessment using MEDALUS model in watershed Oued El Maleh, Morocco. Geosciences 7:1–16

Mallick J, Sing RK, AlAwadh MA, Islam S, Khan RA, Qureshi MN (2018) GIS-based landslide susceptibility evaluation using fuzzy-AHP multi-criteria decision-making techniques in the Abha watershed, Saudi Arabia. Environ Earth Sci 77:276–301

Mandal B, Mandal S (2018) Analytical hierarchy process (AHP) based landslide susceptibility mapping of Lish River basin of eastern Darjeeling Himalaya, India. Adv Space Res 62:3114–3132

Margarint MC, Grozavu A, Patriche CV (2013) Assessing the spatial variability of coefficients of landslide predictors in different regions of Romania using logistic regression. Nat Hazards Earth Syst Sci 13:3339–3355

Meng QK, Miao F, Zhen J, Wang XY, Wang A, Peng Y, Fan Q (2016) GIS-based landslide susceptibility mapping with logistic regression, analytical hierarchy process, and combined fuzzy and support vector machine methods: a case study from Wolong Giant panda natural reserve. China Bull Eng Geol Environ 75(3):923–944

Mihálikova M, Özyazıcı MA, Dengiz O (2016) Mapping soil water retention on agricultural lands in central and eastern parts of the Black Sea region in Turkey. J Irrig Drain Eng 142(12):05016008–05016001

Mondal S, Maiti R (2013) Integrating the analytical hierarchy process (AHP) and the frequency ratio (FR) model in landslide susceptibility mapping of Shiv-khola watershed, Darjeeling Himalaya. Int J Disaster Risk Sci 4(4):200–212

Roodposhti MS, Rahimi S, Beglou MJ (2014) PROMETHEE II and fuzzy AHP: an enhanced GIS-based landslide susceptibility mapping. Nat Hazards 73(1):77–95

Shahabi H, Khezri S, Ahmad BB, Hashim M (2014) Landslide susceptibility mapping at central Zab basin, Iran: a comparison between analytical hierarchy process, frequency ratio and logistic regression models. Catena 115(4):55–70

Shahabi H, Hashim M, Ahmad BB (2015) Remote sensing and GIS-based landslide susceptibility mapping using frequency ratio, logistic regression, and fuzzy logic methods at the central Zab basin, Iran. Environ. Earth Sci 73:8647–8668

Sharam LP, Patel N, Debnath P, Ghose MK (2012) Assessing landslide vulnerability from soil characteristic-a GIS based analysis Arab J Geosci 5:789–796

Sharma LP, Patel N, Ghose MK, Debnath P (2015) Develop/ment and application of Shannon's entropy integrated information value model for landslide susceptibility assessment and zonation in SikkimHimalayas in India. Nat Hazards 75(2):1555–1576

Skilodimou HD, Bathrellos GD, Chousianitis KAM, Pradhan B (2019a) Multi-hazard assessment modeling via multi-criteria analysis and GIS: a case study. Environ Earth Sci 78:47

Skilodimou HD, Bathrellos GD, Chousianitis K, Youssef AM (2019b) Multi-hazard assessment modeling via multi-criteria analysis and GIS: a case study. Environ Earth Sci 78:47–68

Sosson M, Stephenson R, Sheremet Y, Rolland Y, Adamia S, Melkonian R, Kangarli T, Yegorova T, Avagyan A, Galoyan G, Danelian T, Hassig M, Meijers M, Mualler C, Sahakyan L, Sadradze N, Alania V, Onice Enukidz O, Mosar J (2016) The eastern Black Sea-Caucasus region during the cretaceous: new evidence to constrain its tectonic evolution. Compt Rendus Geosci 348:23–32

Sun CC (2010) A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods. Expert Syst Appl 37(12):7745–7754

Turan Demirağ İ, Dengiz O, Özkan B (2019) Spatial assessment and mapping of soil quality index for desertification in the semi-arid terrestrial ecosystem using MCDM in interval type-2 fuzzy environment. Comput Electron Agric 164. https://doi.org/10.1016/j.compag.2019.104933

Türkeş M (2010) Analysis of the UN convention to combat desertification with respect to the climate, climate change and drought, and applications in Turkey. In proceeding of symposium on combating desertification. Corum:601–616 (in Turkish)

Türkeş M (2013) Observed and projected climate change, drought and desertification in Turkey. Ankara Univ J Environ Sci 4:1–32

Türkeş M (2015) Biogeography: a paleogeography and ecology approach. Revised Second Edition, Kriter Publisher - Physical Geography Series No: 3

Türkeş M (2017) Drought vulnerability and risk analysis of Turkey with respect to climatic variability and socio-ecological indicators. Ege Coğrafya Dergisi 26(2):47–70

Tüysüz O, Yılmaz İÖ, Švabnicka I, Kirici S (2012) The Unaz formation: a key unit in the Western Black Sea Region, N Turkey. Turk J Earth Sci 21:1009–1028

Wang Y, Jung KA, Yeo GT, Chou CC (2014) Selecting a cruise port of call location using the fuzzy AHP method: a case study in East Asia. Tour Manag 42:262–270

Xu C (2015) Preparation of earthquake-triggered landslide inventory maps using remote sensing and GIS technologies: principles and case studies. Geosci Front 6:825–836

Xu C, Dai F, Xu X, Lee YH (2012) GIS-based support vector machine modeling of earthquake-triggered landslide susceptibility in the Jianjiang River watershed, China. Geomorphology 145:70–80

Wu Y, Li W, Wang Q, Liu Q, Yang D, Xing M, Pei Y, Yan S (2016) Landslide susceptibility assessment using frequency ratio, statistical index and certainty factor models for the Gangu County, China. Arab J Geosci 9:84. https://doi.org/10.1007/s12517-015-2112-0

Yan F, Zhang Q, Ye S, Ren B (2019) A novel hybrid approach for landslide susceptibility mapping integrating analytical hierarchy process and normalized frequency ratio methods with the cloud model. Geomorphology 327:170–187

Yan G, Liang S, Gui X, Xie Y, Zhao H (2018) Optimizing landslide susceptibility mapping in the Kongtong District, NW China: comparing the subdivision criteria of factors. Geocarto Int. https://doi.org/10.1080/10106049.2018.1499816

Yang JL, Chiu HN, Tzeng GH, Yeh RH (2008) Vendor selection by integrated fuzzy MCDM techniques with independent and interdependent relationships. Inf Sci 178(21):4166–4183

Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353

Zheng G, Zhu N, Tian Z, Chen Y, Sun B (2012) Application of a trapezoidal fuzzy AHP method for work safety evaluation and early warning rating of hot and humid environments. Saf Sci 50(2):228–239

Zhou SH, Chen GQ, Fang LG, Nie YW (2016) GIS-based integration of subjective and- objective weighting methods for regional landslides susceptibility mapping. Sustain For 8(4):334–349