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Morphological parameters causing landslides: A case study of elevation

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ABSTRACT

The history of landslide susceptibility maps goes back about 50 years. Hazard and risk maps later followed these maps. Inventory maps provide the source of all these. There are different parameters selected specially for each field in the literature as well as parameters selected because they are easy to produce and obtain data. This study tried to research the effect of elevation on landslides by reviewing the literature in detail. The used class ranges and elevation values were reviewed and applied to map sections selected from Turkey. By analyzing the results, the goal was to determine at which elevation ranges landslides occurred. The study tried to investigate the effect of the parameter of elevation using data from the literature. It works to compare the elevation values for map sections selected to compare with the literature. The study comprises two stages. The first step tried to acquire statistical data by researching the data from the literature. The data were investigated in the second stage. For this purpose, close to 1.500 studies prepared between 1967 and 2019 were reviewed. According to the literature, the parameter of was used in analyses because it is easy to produce and is morphologically effective.

1. Introduction

“Elevation is one of the most essential key factors that determine the stress distribution of slopes” (Althuwaynee et al., 2016; Hong et al., 2017*a, b;* Chen et al., 2018, 2019). There is strong evidence that elevation is an indicator for susceptibility to landslides. Elevation is also one of the simplest features of slopes (Kornejady et al., 2017*a, b*). For this reason, it is frequently preferred as a parameter in the preparation of landslides susceptibility maps. It is also a parameter chosen for danger maps. Many researchers around the world accept the importance of elevation in the formation of landslides (Juang et al., 1992; Pachauri and Pant 1992; Dai and Lee, 2001, 2003; Ercanoğlu and Gökceoğlu, 2002, 2004; Lee et al., 2002; Çevik and Topal, 2003; Gomez and Kavzoğlu, 2005; Gökçeoğlu et al., 2005; Mazman, 2005; Creighton, 2006; Duman et al., 2006; Lee and Pradhan, 2007; Chen and Wang, 2007; Dağ, 2007; Caniani et al., 2008; Ercanoğlu et al., 2008; Kamp et al., 2008; Yao et al., 2008; Özdemir, 2009; Akıncı et al., 2010; Balteanu et al., 2010; Bai et al., 2010; Park et al., 2010; Yılmaz, 2010; Oh and Pradhan, 2011; Rozos et al., 2011; Sezer et al., 2011; Yalçın et al., 2011; Dağ and Bulut, 2012; Kavzoğlu et al., 2012; 2014, Mashari et al., 2012; Pourghasemi et al., 2012*a, b, c, d, e*; Schicker and Moon, 2012; Xu and Xu XW, 2012; Yılmaz et al., 2012; Sabatakakis et al., 2013; Chen et al., 2013, 2015, 2016*a,b,* 2017, 2018, 2019; Devkota et al., 2013; Liu et al., 2013; Özdemir and Altural, 2013; Özşahin and Kaymaz, 2013; Akıncı et al., 2014; Avcı and Günek, 2014; Chalkias et al., 2014; Conforti et al., 2014; Jaafari et al., 2014; Jebur et al., 2015; Moradi and Rezaei, 2014; Nourani et al., 2014; Sujatha et al., 2014; Tazik et al.,

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2014; Umar et al., 2014; Youssef et al., 2014*a, b, c*; Zhu et al., 2014; Akıncı and Kılıçoğlu, 2015; Dehnavi et al., 2015; Dragicevi et al., 2015; Goetz et al., 2015; Özşahin, 2015; Pradhan and Kim, 2015; Youssef, 2015; Youssef et al., 2015; Aghdam et al., 2016; Avcı, 2016*a, b, c*; Balamurugan et al., 2016; Demir, 2016; Liu and Wu, 2016; Myronidis et al., 2016; Wang et al., 2016, 2017; Wu and Ke, 2016; Wu et al., 2016; Zhang et al., 2016*a, b*; Dou et al., 2017; Kornejady et al., 2017*a, b;* Pawluszek and Borkowski, 2017; Raja et al., 2017). Zhang et al. (2017), connected the use of elevation in the preparation of generally landslide-susceptible maps to different elevations being correlated to different environmental factors. Some researchers found that landslide activity in a certain basin materialized at certain elevations (Dai et al., 2001; Çevik and Topal, 2003; Yılmaz et al., 2012). The effects of different elevations on landslide susceptibility is different (Çellek, 2013). Jimenez-Peralvarez et al. (2009) in their study reported that elevation wasn't the most commonly used determinant parameter according to the literature (Fernandez et al., 2008) and that the effect of the parameter was determinant for mountainous areas with different elevation values like their own working areas. Elevation affecting landslide susceptibility at different ranges obfuscates the relationship between landslide activity and elevation (Dai and Lee, 2002; Kavzoğlu and Çölkesen, 2010; Kavzoğlu et al., 2012; Tazik et al., 2014). Because determining the elevations of the landslides that have occured in any region can only be considered as preliminary data (Özşahin, 2015).

2. Elevation (Relative Elevation-Topographic Elevation)

The maximum and minimum elevations in the working area are determined with this parameter (Ramesh and Anbazhagan, 2015). Elevation can be defined as the height of a point from sea level or from a local reference point. Elevation in susceptibility maps is considered as either "topographic elevation" based on altitude values from sea level or as "relative elevation" based on elevation differences of topographic elements in the study area. Relative elevation is commonly used and is considered by some researchers (Ercanoğlu, 2003; Görüm, 2006). The general tendency among researchers is to use topographic elevation (Dağ, 2007; Dağ and Bulut 2012; Kavzoğlu et al., 2012; Çellek, 2013; Akıncı and Kılıçoğlu, 2015). The parameter was used as topographic elevation in 51 studies reviewed by Hasekioğulları (2011) and as relative elevation in seven studies. Süzen and Kaya (2011) stated that elevation was used as an input parameter in 34.27% of researchers in the studies they reviewed. Relative and topographical elevation being used together leads to repetition and causes the consideration of the same parameter twice. Only one of the topographic and relative elevation parameters is therefore used, or the analysis results are compared, used separately in the evaluation of landslide susceptibility (Ercanoğlu, 2003; Ayalew and Yamagishi 2005; Görüm, 2006; Yüksel, 2007).

Relative Elevation: It is the elevation based on the height differences of the topographical elements in the study area or it defines the height difference between a point and another point taken as a reference (Carrara et al., 1991; Anbalagan, 1992; Pachauri and Pant, 1992; Anbalagan and Singh, 1996; Nagarajan et al., 2000; Ercanoğlu, 2003, Görüm, 2006; Yüksel, 2007; Nefeslioğlu et al., 2008; Chauhan et al., 2010; Çellek, 2013; Raja et al., 2017). In other words, relative elevation describes the range of elevations between the lowest and highest points in a region. Generally, there are three ways to define the difference in relative elevation. The differences lie in the definition of base elevation. In the first, the smallest absolute elevation of the entire field is used as the base elevation; in the second, elevation is applied as the smallest elevation in each negative sub basin; and the third is based on a convolution process (Zhang et al., 2012).

Topographical Elevation: Topographical elevation is defined as the elevation from sea level or a local reference point (Moore et al., 1991; Ercanoğlu, 2003; Tangestani, 2003; Ercanoğlu and Gökçeoğlu, 2004; Lan et al., 2004; Süzen and Doyuran, 2004*a, b*; Ayalew and Yamagishi, 2005; Gomez and Kavzoğlu, 2005; Görüm, 2006; Dağ, 2007; Yüksel, 2007; Caniani et al., 2008; Gattinoni, 2009; Hasekioğulları, 2011; Dağ and Bulut, 2012; Kavzoğlu et al., 2012; Çellek, 2013; Nourani et al., 2014; Akıncı and Kılıçoğlu, 2015).

3. The Effect of Elevation on Other Parameters and Landslides

If we are to assess previously conducted research, the parameter of elevation is a widely used parameter in the preparation of susceptibility maps, and the relationship between the formation of landslides (toppling, rock falls, rock slides, etc.) and the parameter is complex due to its effect over many parameters that cause the occurrence of landslides (morphology, soil type, tectonics, soil thickness, erosion-weathering, land cover, precipitation, etc.). As a result, elevation is evaluated as a parameter that has an indirect effect together with the variances of the other parameter and affects the entire system (Zolotraev, 1976; Dai and Lee 2002, 2003; Yüksel, 2007; Rozos et al., 2008; Park, 2010; Yılmaz, 2010; Hasekioğulları, 2011; Yalçın et al., 2011; Çellek, 2013; Pourghasemi, et al., 2013*a, b*; Moradi and Rezaei, 2014; Nourani et al., 2014; Kouli, et al., 2014; Umar et al., 2014; Youssef et al., 2015; Pradhan and Kim, 2017). Gritzner et al. (2001) emphasized that elevation could be considered as a guide for other variables that are directly related to elevation. Jimenez-Peralvarez et al., (2009) stated that elevation has a range that is wide enough to cause significant changes in climatic conditions, like precipitation and temperature also represents variable vegetation units. Aniya (1985), however, stated that different elevations being exposed to different climate and weather conditions would lead to the formation of different types of plants and soil (Pourghasemi et al., 2014). Dai and Lee (2001) reported that the rocks at much higher elevations disintegrated with the freezing-thawing effect, while rocks at much lower elevations were inclined to accumulate thick alluvion (Pourghasemi et al., 2014).

Gravity: Relative elevation demonstrates the potential gravitational energy for each unit (Zhang et al., 2012). The elevation difference is a measure of the potential energy of landslides. Generally, an increasing difference in elevation corresponds to the possibility of an increasing failure tied to an increase in sliding force (Fernandez et al., 2003).

Biological Elements: According to the literature biological elements, biophysical parameters, and natural-artificial factors have an effect on landslides triggered by elevation. Landslides (Dai and Lee, 2002; Kavzoğlu et al., 2012; Akıncı and Kılıçoğlu, 2015). It is therefore stated that the factor of elevation has effects that can lead to slope stability and slope breakup (Vivas, 1992; Dai and Lee, 2002; Ayelew et al., 2005; Hasekioğulları, 2011; Kavzoğlu et al., 2012, 2014; Akıncı et al., 2015).

Anthropogenic Activity: It is known that elevation affects anthropogenic activity and anthropogenic activity triggers landslides. Many high-altitude areas in their study area are desolate (devoid of human activity), the ground is covered in glaciers and snow and, thus, is rarely affected by human activities. There are fewer landslides and low susceptibility for this reason. Exactly the opposite, settlements, transportation, and consequently human activity is greater at altitudes (Vivas, 1992; Dai and Lee, 2002; Ayalew et al., 2005; Hasekioğulları, 2011; Kavzoğlu et al, 2014; Kouli et al., 2014; Yang et al., 2015; Aghdam et al., 2016; Meng et al., 2016; Wang et al., 2017).

Erosion - Disintegration - Degradation - Soil: Elevation can be evaluated as a parameter that controls the processes of erosion-disintegration-degradation and the type and degree of erosion in the formation of landslides (Zolotraev, 1976; Pachauri and Pant, 1992; Vivas, 1992; Dai and Lee, 2002; Lan et al., 2004; Ayelew et al., 2005; Yüksel, 2007; Rozos et al., 2008; 2010; 2011; Hasekioğulları, 2011; Jaafari et al., 2015*a, b*; Youssef et al., 2015; Aghdam et al., 2016; Ilia and Tsangaratos, 2016; Pham et al., 2016; Pham et al., 2017). He et al., (2011) and Erener and Lacasse (2007) connected the occurrence of landslides at low elevations in their study areas to erosion and flowing water corrosion. Hasekioğulları (2011) reported in a study that low topographical elevations in areas with landslides are composed of soil materials that are the mostly the products of degradation. The slopes steepening with erosion leads to increased elevation above the threshold value that is then followed by landslides (Raja et al., 2017). Typically, higher mountain elevations receive greater rainfall than areas at lower elevations (Coe et al., 2004*a, b*). This increases soil moisture in higher mountain elevations and can lead to the decrease of soil strength and the increase of stress in the soil matrix (Ray and Jacobs, 2007). Furthermore, slopes are inclined toward landslides due to a fine colluvium cover because erosion generally is seen in connection with accumulation in these regions. However, the frequency of landslides is low in low elevations because the terrain itself is soft and covered in thick colluvium and/or residual soil, and a higher settled water table will be necessary to instigate a landslide (Dai and Lee, 2002; Opiso et al., 2016). Elevation is a parameter that regulates soil depth and development along with physical erosion and chemical disintegration (Opiso et al., 2016).

Ochoa (1978) stated that elevation was related to the effect over the properties of the physical-chemical soil at Cordillera de Me'rida (Opiso, et al., 2016). Aniya, (1985) reported that weather and climate conditions vary greatly at different elevations and that this reflects on soil differences (Dou et al., 2017).

Precipitation: Elevation is used as a factor for frequent climatization for landslide susceptibility analyses (Wu et al., 2016). If we are to speak generally, they affect elevation, precipitation/snow (Koukis and Ziourkas, 1991; Nagarajan, 2000; Gökçeoğlu and Ercanoğlu, 2001; Görcelioğlu, 2003; Tangestani, 2004; Görüm, 2006; Rozos et al., 2008;2011; Yüksel, 2007; Hasekioğulları, 2011; Tazik et al., 2014; Yang et al., 2015; Dölek and Avcı, 2016*a, b, c*; Balamurugan et al., 2016; Chen et al., 2017). Climate conditions, however, do have potential influence over slope stability (Kavzoğlu et al., 2014; Meng et al., 2015; Wang et al., 2016). Yang et al. (2015) reported that numerous high-altitude regions are covered in glaciers and snow in their study area, that these areas are scant affected by earthquakes and human activities and therefore encounter fewer landslides and have low susceptibility. Elevation is greatly important in terms of affecting accumulated amounts of precipitation (Görcelioğlu, 2003; Yüksel, 2007; Avcı and Günek, 2014). Indeed, Yılmaz and Keskin (2009) reported that precipitation accumulated at the bottom of the slope due to the incline along with the decrease in elevation and, consequently, created a higher vacuum pressure and could lead to a greater risk of landslide at low elevations (on valley floors). Clerici et al. (2006) connected the observation of the loss of slope in their study area at different elevations between 401-600 m and 801-1000 m to the snow precipitation and the freeze-thaw cycle. Koukis and Ziourkas (1991) observed in their study landslides in areas with elevation values of at most 600-1000 m. Researchers have correlated this situation with the high sections in mountainous regions receiving greater precipitation. The literature features researchers who state that in their study areas heavy rainfall falls mostly on low elevations in causes an inverse relationship between landslides and elevation in this (Carrara, 1983; Gallart and Clotet, 1988; Baeza and Corominas, 2001; Wang and Li, 2017; Chen et al, 2017). "Gruber and Haeberli, (2007) noted that the hard precipitation rate increased with the decrease in elevation and that temperature dropped and contributed to the cooling of the slopes" (Chen et al., 2017). The relationship of these with landslides should be revealed with precipitation analyses to define relative elevation in detail. Landslide distribution based on morphology can be shown by not evaluating the factor of precipitation in situations where there are not enough precipitation stations in the study area, and the graphic of the density of landslides can be drawn based on the class of elevation. Elevation information isn't used most of the time in superficial flow conjectures in classic hydrological methods because the procurement of elevation data is an inconvenient process (Dölek and Avcı, 2016).

Temperature: Generally speaking, the increase of elevation affects all systems (Rozos et al., 2008; Rozos, et. al., 2010). Namely, elevation affects temperature (Tazik et al., 2014; Meng et al., 2016). Atmospheric heat decreases 0.5 C° every 100 m (Sancar, 2000; Yılmaz, 2009*a, b*; Kavzoğlu et al., 2012; Avcı and Günek, 2014; Avcı, 2016*a, b, c*). The rate of hard precipitation increases at increasing elevations and temperature drops. This leads to the cooling of rocks, the growth of different species of flora, and landslides (Zolotarev, 1976; Vivas, 1992; Nagarajan et al., 2000; Gruber and Haeberli, 2007; Kavzoğlu et al., 2014; Tazik et al., 2014; Meng et al., 2015; Balamurugan et al., 2016; Wang et al., 2016; Chen et al., 2017; Wang and Li, 2017; Dou et al., 2017).

Land Cover: Elevation has a significant effect over the topographic properties that explain the spatial variability of different landscaping processes like the distribution of flora. Thus, it creates an indirect effect in the ocurrence of landslides (Aniya, 1985; Moore et al, 1991; Vivas, 1992; Dai and Lee 2003; Tangestani, 2003; Ercanoğlu and Gökçeoğlu, 2004; Lan et al., 2004; Süzen and Doyuran, 2004*a, b*; Ayalew and Yamagishi, 2005; Goméz and Kavzoğlu, 2005; Gruber and Haeberli, 2007; Yüksel, 2007; Kamp et al., 2008; Park, 2010; Yılmaz, 2010; Oh and Pradhan, 2011; Yalçın, et al., 2011; Mohammady et al., 2012; Pourghasemi et al., 2012*a, b, c*; Kavzoğlu et. al., 2012; Kavzoğlu et al., 2014; Jaafari et al., 2015*a, b*; Meng et al., 2015, 2016; Wang et al., 2016; Chen et al., 2017; Ding et al., 2017; Dou et al., 2017). Decreases are seen in temperature and precipitation as elevation increases, and different vegetation zones form at the changing stages of elevation. Thus, variable elevation conditions in topography are influential over biological and natural elements (Vivas, 1992; Kavzoğlu et al., 2012). Researchers think that, although there is no clear relationship between landslides and elevation, there is an effect related to forest density. Elevation has significant influence over the surface of the Earth and topographical properties. These properties demonstrate the spatial variability of different landscaping processes like flora distribution generally affected by topographical influences (Saadatkhah et al., 2014; Ding et al., 2017).

Lineament: Elevation does not directly contribute to the formation of a landslide but can cause landslides with other parameters like tectonic, and this affects the entire system (Zolotarev, 1976; Koukis and Ziourkas, 1991; Nagarajan et al., 2000; Görüm, 2006; Rozos et al., 2008; 2010; 2011; Yang et al., 2015; Dölek and Avcı, 2016*a, b, c*; Ilia and Tsangaratos, 2016). Researchers have reported that a relationship of relative elevation with landslides must emerge by considering its detailed study and definition and the seismic effects of these (Vivas, 1992; Nagarajan, 2000; Gökçeoğlu and Ercanoğlu, 2001; Görüm, 2006; Özdemir, 2009; Jaafari et al., 2015*a, b*; Avcı, 2016*a, b, c*; Dölek and Avcı, 2016). "Elevations in their working area extended along the Yinxiu - Beichuan Lineament line and, when the direction of incline is guided parallel to the Lineament, has an increasing susceptibility to landslides" (Zhang et al., 2012). Because the horizontal components of seismic acceleration in vertical sections for high segments in seismically active mountainous regions have a greater impact, these segments are more sensitive to landslides. The correlation of seismic analysis with landslides should be conducted in these areas. There was a requirement for this for seismographic stations (Gökçeoğlu and Ercanoğlu, 2001). It was reported that because the horizontal component of seismic acceleration in the vertical segments of mountainous areas have an effect that is 1.2 to 1.5 times greater than that of valleys, these areas were more susceptible to landslides (Zolotarev, 1976; Nagarajan et al., 2000; Görüm, 2006; Gökçeoğlu and Ercanoğlu, 2001; Avcı, 2016*a, b, c*). Bai et al. (2013) stated that most landslides in their study area (more than 84%) were triggered by earthquakes at elevations below 2100 m. Bai et al. (2014) reported in their study that most of all landslides triggered with earthquakes (more than 84.09%) took place at altitudes below 1900 m. Tanoli et al. (2017) reported that 86% of landslides occurred at elevations of 1000 to 3000 m before earthquakes in their study area and that 90% of earthquakes occurred at elevations of 1500 to 3500 m after earthquakes. They reported in this that there was proof that coseismic landslides occurred at higher altitudes compared with landslides before earthquakes.

Geology: Elevation is accepted as one of the significant parameters in the formation of landslides because it is controlled by various geological processes (Dai and Lee, 2001, 2002; Ayalew and Yamagishi 2005; Gorsevski et al., 2012; Pradhan and Kim, 2014; Jaafari et al., 2014). Landslide susceptibility increases as elevation increases but is different in increases at different geological levels (Dai and Lee, 2001; Zhu et al., 2014; Raja et al., 2017). Some researchers reported that the units at much higher elevations comprised rock-type materials and were less susceptible to landslides because they have greater durability compared with the materials at lower elevations (Caniani et al., 2008; Avcı, 2016). Ercanoğlu (2005) said that durable rocks belonging to the Ulus Formation have at high elevations an incline greater than 45 degrees and at low elevations a mild slope (0-20°). Liu et al. (2013) reported that landslides occurred in their study area in the middle section of hilly and mountainous areas and that few landslides occurred in peaks or the peaks of mountains because most rocks on peaks were worn and hard. Pachauri and Pant (1992) stated that their study area comprised resistant lithological units (Limestone) at high elevations, despite having reported that high areas were more sensitive to landslides. Kouli et al. (2014) reported that elevation indirectly caused landslides in their study area, that landslides that occurred at high elevations were composed of adhesive units, and that the unit was affected by poor climate conditions such as precipitation. They gave the highest score in their study area to vertical morphological areas that occurred from flysch and phyllite-quartzites between 700 and 1000 m. Çevik and Topal (2003) reported that landslides between 10-150 m in their study area occurred mostly (63.1%) due to the lithological character and structural control of the units. Rozos et al. (2010) reported that the density of landslides in their working area was not directly correlated to elevation but that Plio-Pleistosen sediments were influential in landslides that occurred between 250 and 500 m.

Geomorphology: Tangestani (2003) showed the elevation between geomorphic or terrain-based risk factors that increase susceptibility to landslides.

Drainage: The change in elevation for each region is one of the influential factors in the ocurrence of mass movement. This factor controls the direction of flow and the rate of drainage intensity (Abedini et al., 2017). Erener and Lacasse (2007) reported that landslides in the working area demonstrating high correlation at low elevations from 0 to 15 m originates from inclination into rivers and from erosion. On the contrary, He et al. (2011) reported that landslides that occurred at low elevations in their study area occurred because they were defenseless against corrosion and erosion by flowing water.

4. Elevation Classes

The literature contains research suggesting that landslides increase with the increase in elevation. In other words, it is shown that landslides tend to appear more in places of high altitude (Koukis and Ziourkas, 1991; Pachauri and Pant, 1992; Pachauri et al., 1998; Gökçeoğlu and Ercanoğlu, 2001; Gritzner et al., 2001; Ercanoğlu et al., 2004; Gökçeoğlu et al., 2005; Görüm, 2006; Lee and Pradhan, 2007; Caniani et al., 2008; Akıncı et al., 2010; 2011; Özdemir, 2009; Özşahin and Kaymaz, 2013; Pradhan and Kim, 2014, 2015; Özşahin, 2015; Avcı, 2016 *b*; Dölek and Avcı, 2016; Wu and Ke, 2016). On the contrary, there are studies in which landslide intensity decreases as elevation increases and in which landslides occur at low and medium elevations (Yüksel, 2007).

High Elevations: The literature contains research that asserts that landslides aren’t frequently encountered at high elevations. Researchers connect this to units at very high elevations forming from rock-type materials and having high cutting resistance compared with disintegrated rocks at lower elevations (Dai and Lee, 2001; Ercanoğlu, 2003; Görüm, 2006; Dağ, 2007; Yüksel, 2007; Caniani et al., 2008; Dragicevic et al., 2015; Avcı, 2016*a, b, c*; Abedini et al., 2017; Pradhan and Kim, 2017). To the contrary, the literature contains views that assert that high elevations cause landslides together with other parameters. This view has two fundamental causes. The first is that high segments get much more precipitation (Nagarajan, 2000; Görüm, 2006). Typically, higher mountain elevations receive greater rainfall than areas at lower elevations (Coe et al., 2004*a, b*). This increases soil moisture in higher mountain elevations and can lead to the decrease of soil strength and the increase of stress in the soil matrix (Ray and Jacobs, 2007; Opiso et al., 2016). The second is that these have a 1.2 to 1.5 times greater impact for vertical components of seismic acceleration in the segments that are relatively more horizontal than valleys (Nagarajan, 2000; Görüm, 2006). Pradhan and Kim (2017) reported that the possibility of landslide formation is greater for high-altitude areas because of the existence of remaining soil cover on rocks. Kavzoğlu et al. (2012) in their study connected the landslides that occurred in the 600-1000 m field to these segments receiving greater precipitation compared to the literature review they conducted while some studies correlated the landslides to densely forested areas as the reason for the for their occurrence at >600 m. Clerici et al. (2006) connected the observation of the landslides in the study area in areas with much higher elevations to there being greater rain and snow precipitation in this area and the freezing-thawing cycle. Bai et al. (2013) reported in their study area that only 7.06% of all landslides occur at elevations greater than 2400 m. Bai et al. (2014) reported in their study that only 3.04% of all landslides triggered by earthquakes occurred at elevations above 2500 m. On the other hand, Bai et al. (2013) reported in their working area that most landslides (more than 84%) occurred at elevations below 2100 m, while Bai et al. (2014) reported in their study that most of all landslides (more than 84.09%) occurred at elevations below 1900 m. Tanoli et al. (2017) reported that 90% of coseismic landslides occurred at elevations of 1500 to 3500 m.

Medium Elevations: Fields at medium elevations are assessed as more susceptible to landslides because of the ground cover that forms due to accumulating of materials, weathering, and erosion coming from higher fields (Dai and Lee, 2001; 2002; Ercanoğlu, 2003; Lan et al., 2004; Ayalew and Yamagishi, 2005; Görüm, 2006; Dağ, 2007; Yüksel, 2007; Gorsevski and Jankowski, 2008; Hasekioğulları, 2011; Kavzoğlu et al., 2012; Çellek, 2013; Elkadiri et al., 2014; Wang et al., 2015; Dragicevic et al., 2015; Avcı, 2016*a, b, c*; Opiso et al., 2016; Abedini et al., 2017; Pradhan and Kim, 2017). Yüksel (2007) determined in a study that medium-elevation areas are more susceptible to landslides compared with lower or higher sections. On the contrary, Liu et al. (2013) reported in their study that landslides occurred in the middle section of hilly and mountainous areas and that few landslides occurred in the upper elevations of peaks or mountains because most rocks on peaks were worn and hard.

Low Elevations: Low elevations generally are considered as less susceptible to landslides because slope incline includes less and thicker cover material. Because the terrain itself is soft, low elevations have low inclines. It is thus covered with thick alluvion or residual soil, and the possibility of landslide is lower as long as the water table doesn't rise up to instigate a landslide (Dai and Lee, 2001; 2002; Ercanoğlu and Gökçeoğlu, 2002; Çevik and Topal, 2003; Ercanoğlu, 2003; Ayalew and Yamagishi, 2005; Chau and Chan, 2005; Görüm, 2006; Dağ, 2007; Caniani et al., 2008; Kavzoğlu et al., 2012; Çellek, 2013; Dragicevic et al., 2015; Avcı, 2016*a, b, c*; Opiso et al., 2016; Abedini et al., 2017). Ercanoğlu and Gökçeoğlu (2002) explained the occurrence of landslides in lower topographic elevations in their study area with the high regions in the working area being composed of stable units and these regions being covered by dense vegetation, Çevik and Topal (2003) connected this situation to the lithologic character and structural control of the units that constitute the study area. Chau and Chan (2005) and Ayalew and Yamagishi (2005), however, connected it to there being large sections of road cuts in these regions because the population is greater at these elevations (Hasekioğulları, 2011). Erener and Lacasse (2007) reported that landslides in the study area demonstrated high correlation at low elevations from 0 to 15 m because of proximity to rivers and erosion. Zhuang et al. (2015) separated their study area into three regions. They reported that a vast majority of landslides occurred on Qin Mountain at 50-90m (45.18%), on Li Mountain at 10-70m (87.30%), and in Loess Tableland at 10-30m (44.90%). They also revealed that landslide frequencies increased proportionally to the difference of elevation in the Qin and Li Mountains but that the frequency started to fall in the altittude otherwise that defeat 60 m. They showed that the reason for this is that terrain with elevation differences that exceed this value is generally used for terrace harvesting.

5. Class Interval Ranges

The class ranges selected in the study areas vary. Most studies used literature-based classification, and it was reported that very few studies selected unique class ranges. Özşahin (2015) prepared the elevation values that affect landslide susceptibility in the study area by considering the class ranges made in the literature. Myronidis et al. (2016) adapted class ranges in their study based on Chen and Wang (2007) and Sabatakakis et al. (2013). Pourghasemi and Kerle (2016) utilized the literature in their study (Lee and Pradhan, 2007; Pourtaghi et al., 2014) and used equal class ranges. Pourghasemi and Rossi (2017) selected equal class ranges in their study, using the literature (Pourtaghi et al., 2014; Pourghasemi and Beheshtirad 2015). The class range numbers selected for the evaluation were determined by reviewing 90 selected studies (Figure 1).

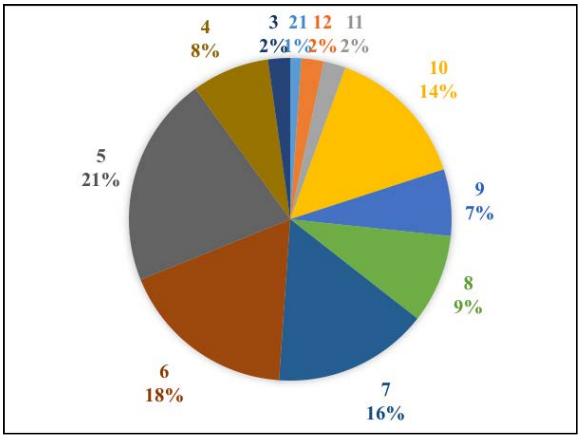


Figure 1- Class range numbers % distribution for 90 studies.

The number of class ranges selected in the studies was at most 21 and at least 3. Five class ranges in 19 studies, six class ranges in 16 studies, seven class ranges in 14 studies, and 10 class ranges in 13 studies were selected. Although not being selected as much as the others, the class ranges of 8, 4, and 9, respectively, were selected as well. The class ranges selected the least were 12, 11, and 3. While 21 class ranges were selected in only one publication, 13 class ranges weren't selected by any researcher.

Based on this, there was variance in the classifications selected in the studies. Table 1 provides the class ranges in 58 evaluated studies. The variable class ranges are notable when reviewing the table. While most researchers chose equal class ranges (Balamurugan et al., 2016; Chen et al., 2016*a, b*; 2017; Demir, 2016; Leonardi et al., 2016; Peng et al., 2014; Pradhan and Kim 2017; Pradhan et al., 2014; Rozos et al., 2010; Shrestha et al., 2017; Umar et al., 2014; Wang et al., 2015; Wu and Ke, 2016; Zhang et al., 2016*a, b*). While most researchers chose equal class ranges (Aghdam et al., 2016; Acharya and Pathak, 2017; Akıncı and Kılıçoğlu, 2015; Amirahmadi et al., 2017; Ataol and Yeşilyurt, 2014; Avcı, 2016*a, b, c*; Chen et al., 2016; 2017; Çellek et al., 2015; Dağ and Bulut, 2012; Dou et al., 2017; Eker et al., 2012; Fenghuan et al., 2010; Hasekioğulları, 2011; Ilia and Tsangaratos, 2016; Kornejady et al., 2014; Lee and Pradhan 2007; Liu and Wu, 2016; Moradi and Rezaei, 2014; Pourtaghi et al., 2015; Raja et al., 2017; Sadr et al., 2014; Tazik et al., 2014; Tsangaratos and Ilia, 2016; Wang et al., 2016; 2017; Wu et al., 2016; Xu et al., 2013; 2016*a, b*; Zare et al., 2014; Zhao et al., 2014).

The class range selection distribution was determined when 42 publications that used equal class range were examined (Figure 2). The most preferred interval values based on this are 200 m (29%) and 500 m (24%). The least preferred were 100 m (12%), 150 m, 250 m (7%), 50 m, 300 m, and 400 m (5%). The

Table 1- Class intervals (meters) used by some researchers in the literature.

Researcher (s) /Year	Sınıf (metre)	Gaps
Aghdam et al., 2016	<200, 200–400, 400–600, 600–800, 800–1000, 1000–1200, 1200–1400, 1400–1600, 1600–1800, 1800-2000, 2000–2200, 2200–2400, 2400–2600, 2600–2800, 2800–3000, 3000–3200, 3200–3400, 3400–3600, 3600–3800, 3800–4000, >4000	200
Acharya and Pathak, 2017	<800, 800-1200, 1200-1600, 1600-2000, 2000-2400, 2400-2800, >2800	200
Akıncı et al., 2014	180-250, 250-500, 500-750, 750-1000, 1000-1278	250
Akıncı and Kılıçoğlu, 2015	0-100, 100-200, 200-300, 300-400, 400-500, 500-600, 600-700, 700-800, 800-900, 900-1300	100
Amirahmadi et al., 2017	0-559,7, 559,7-1000, 1000-1500, 1500-2000, 2000-2500, 2500-3000, 3000-3500, 3500-4000, 4000-4500, 4500-5597	500
Ataol and Yeşilyurt, 2014	<800, 800-1000, 1000-1200, 1200-1400, >1400	200
Avcı, 2016*a*	1140-1300, 1300-1500, 1500-1700, 1700-1900, 1900-2100, 2100-2300, >2300	200
Avcı, 2016*b*	1150-1200, 1200-1400, 1400-1600, 1600-1800, 1800-2000, 2000-2200, 2200-2400, 2400-2600, >2600	200
Balamurugan et al., 2016	819-1086, 1086-1340, 1340-1630, 1630-1953, 1953-2452	yok
Chen et al., 2016*a*	80–330, 330–620, 620–1000, 1000-2000	yok
Chen et al., 2017	561–800, 800–1050, 1050–1300, 1300–1550, 1550–1800, 1800–2074	250
Chen et al., 2018	632-1284, 1284-1773, 1773-2206, 2206-2680, 2680-3940	yok
Chen et al., 2016*b*	720–850, 850–1000, 1000–1150, 1150–1300, 1300–1560	150
Çellek et al., 2015	0-100, 100-200, 200-300, 300-400, 400-500, 500-600, 600-700, 700-800, 800-900, 900-1000, 1000-1100	100
Dağ and Bulut, 2012	0-100, 100-200, 200-300, 300-400, >400	100
Demir, 2016	500-750, 750-950, 950-1200, 1200-1450, 1450-1700	yok
Duo et al., 2017	<1000, 1000-1500, 1500-2000, 2000-2500, 2500-3000, > 3000m	500
Eker et al., 2012	<300, 300-600, 600-900, 900-1200, >1200	300
Fenghuan et al., 2010	500- 1000, 1000-1500, 1500-2000, 2000-2500, 2500-3000, 3000-3500, 3500-4000, >4000	500
Hasekioğulları, 2011	0-250, 250-500, 500-750, 750- 1000, 1000-1250, 1250-1500, 1500-1750	250
Ilia and Tsangaratos, 2016	<220, 221-440, 441-660, 661–880, 881–1100,> 1101	220
Kornejady et al., 2014	<1000, 1000-1200, 1200-1400, 1400-1614	200
Lee and Pradhan, 2015	<100, 100–500, 500-1000, 1000–1500, 1500–2000, 2000–2500, 2500–3000, >3000	500
Leonardi et al., 2016	0-150, 151-300, 301-600, >601	yok
Liu and Wu, 2016	> 2400, 2200-2400, 2000-2200, 1800-2000, 1600-1800, 1400-1600, <1400	200
Moradi and Rezaei, 2014	<1400, 1400-1600, 1600-1800, 1800-2000, 2000-2500, 2500-3000, >3000	200
Nourani et al., 2014	<1,300, 1,300–1,700, 1,700–2,100, 2,100, 2,500, 2,500–2,900	400
Padrones et al., 2017	0-176, 176-352, 352-528, 528-704, 704-880, 880-1056, 1056-1232, 1232-1408, 1408-1584, 1584-1760	176
Peng et al., 2014	80-330, 330-620, 620-1000, 1000-2000	yok
Pham et al., 2015	0 - 600, 600 - 750, 750 - 900, 900 - 1050, 1050 - 1200, 1200 - 1350, 1350 - 1500, 1500 - 1650, 1650 – 1800, > 1800	150
Pham et al., 2016	<600, 600–750, 750–900, 900–1050, 1050– 1200, 1200–1350, 1350–1500, 1500–1650, 1650–1800, >1800	150

Table 1- continue.

Pham et al., 2017	0-700, 700–900, 900–1100, 1100–1300, 1300–1500, 1500–1700, 1700–1900, > 1900 m	200
Pourghasemi and Kerle, 2016	<100, 100–500, 500-1000, 1000–1500, 1500–2000, 2000–2500, 2500–3000, >3000	500
Pourghasemi and Rossi, 2017	<500, 500–1000, 1000–1500, 1500–2000, >2000	500
Pourghasemi et al., 2014	<1,500, 1,500–2,000, 2,000–2,500, 2,500–3,000, 3,000–3,500, >3,500	500
Pourtaghi et al., 2014	<100, 100–500, 500-1000, 1000–1500, 1500–2000, 2000–2500, 2500–3000, 3000 m	500
Pradhan and Kim, 2017	<75, 75–100, 100-150, 150–200, 200-250, >250	yok
Pradhan et al., 2014	0–20, 20–25, 25–35, 35–65, 65–115, 115–252, 252–465, 465–705, 705–950, 950–2,000	yok
Raja et al., 2017	<50, 50–100, 100-150, 150–200, >200	50
Rozos et al., 2010	<250, 250–500, 501–800, 801–1200, >1200	yok
Saadatkhah et al., 2014	0-50, 50–100, 100–200, 200–300, >300	yok
Sadr et al., 2014	0-100, 100-200, 200-300, 300-425	100
Shrestha et al., 2017	<1281, 1281–1755, 1755-2254, 2254–3302, 3302–3850, 3850–4424, 4424– 4973, 4973-5621, 5621-6968> 6968	yok
Simon et al., 2017	<30, 30-60, 60-90, >90	30
Tazik et al., 2014	500-1000, 1000-1500, 1500-2000, >2000	500
Tsangaratos and Ilia, 2016	<400, 401–600, 601–800, >801	200
Umar et al., 2014	0-9.01, 9.01-18.02, 18.02-45.07, 45.07-90.14, 90.14-135,21, 135.21-198.31, 198.31-297.45, 297.46-458.73, 468.73-748.18, 748.18-2298.62	yok
Wang et al., 2015	20–850, 850–1000, 1000–1150, 1150–1300, 1300–1560	yok
Wang and Li, 2017.	<900, 900–1300, 1300–1700, 1700–2100, 2100–2500 ve> 2500	400
Wang et al., 2016	<150, 150–200, 200–250, 250–300, 300–350, 350–400, 400–450, 450–500, 500–550, >550	50
Wu et al., 2016	<1400, 1400–1600, 1600–1800, 1800-2000, 2000-2200, 2200–2400, > 2400	200
Wu and Ke, 2016	720-850, 851-1000, 1001–1150, 1151–1300 and 1301-1560	yok
Xu et al., 2013	<1000, 1000–1500, 1500–2000, 2000–2500, 2500–3000, 3000–3500, 3500–4000, 4000–4500, 4500–5000, 5000–5500, >5500	500
Xu et al., 2016*a*	2207-2300, 2300-2400, 2400-2500, 2500-2600, 2600-2700, 2700-2800, 2800-2900, 2900-3000, 3000-3100, 3100-3200, 3200-3340	100
Zare et al., 2014	<300, 300-600, 600-900, 900-1200, 1200-1500, 1500-1800, 2100-2400, 2400-2700, 3000- 3300, >3300	300
Zhang et al., 2016*a*	0-50, 50–200, 200–350, 350–500, >500 m	yok
Zhang et al., 2016*b*	<1000, 1000–1600, 1600-2200, 2200-2880 and >2800	yok
Zhao et al., 2014	60–80, 800–1000, 1000–1200, 1200– 1400, 1400–1600 m, 1600–1800, 1800– 2060	200

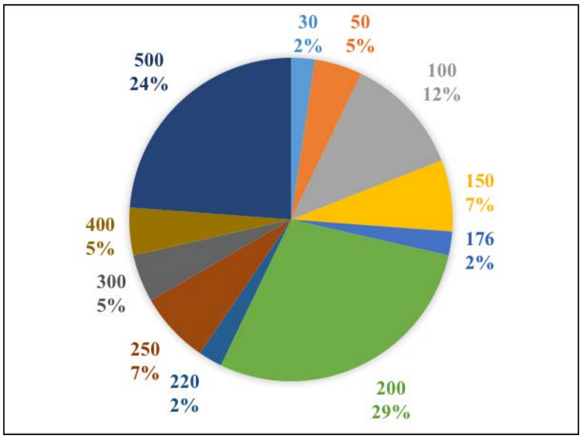


Figure 2- The preferred class range distributions in the literature.

least preferred interval values were 30 m, 176 m, and 220 m (2%). Intermediate values such as 350 m and 450 m weren't chosen.

6. Materials and Methods

It is accepted that elevation has influence over the formation of landslides, despite researchers not fully reaching a consensus. This study tried to research the influence of the parameter over landslides. For this purpose, close to 1500 studies prepared between 1967 and 2017 were reviewed. According to the literature, the parameter of elevation was used in analyses because of its effect on the formation of landslides, because it's easy to produce, and because it is morphologically effective. A review of previous studies determines that landslides are encountered at various elevations. It was determined that any elevation triggers landslides, remaining under the influence of a different parameter.

For the purpose of comparison with the data in the literature, 64 out of 2945 landslide map sections at a scale of 1/25.000 prepared by Mineral Research and Exploration (MRE) were selected and were digitized by adjusting the cell size to 28 pixels. For elevation maps to be created, digitized topographic maps at a scale of 1/25.000 in which the contours belonging to the selected landslide regions pass once every 10 m were procured from the General Command of Cartography. Using the ArcGIS 10.4 software, the attributions of the numerical contours and TIN (Triangulated Irregular Network) model and numerical elevation models were acquired in the form of triangular networks. The numerical elevation model (NEM) was obtained with the prolongation from the acquired TIN models (TIN to Raster). This model is incredibly important in terms of constituting a base for the other data used as topographical data in the studies. Thus, procuring the elevation parameter from other secondary topographical data was more easily provided and was converted into a raster data format. Elevation classes were made considering the conditions of the terrain. These range distances can be increased and decreased based on the conditions of the terrain. Using the literature, the class ranges of 50 and 100 m were selected for elevation. By digitalizing inventory maps for 50 selected map sections, they were superposed with elevation maps. The result maps were produced with "reclassify" and "raster to polygon" by selecting the class ranges. At which elevation values landslides occurred was determined by analyzing the prepared maps, and they were compared with their corresponding values in the literature.

7. Findings

The selected map sections were classified with 100 m ranges, and a total of 32 ranges were procured. Figure 3 provides the results in percentage distributions.

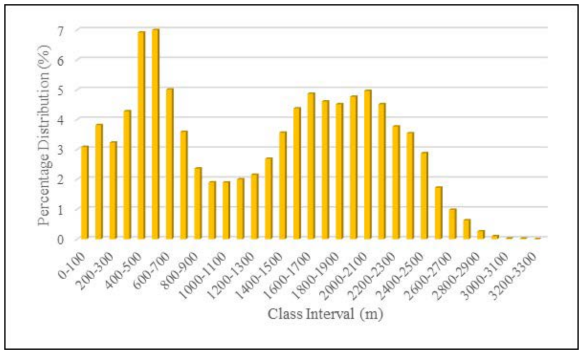


Figure 3- Distributions of the analyzed map sections in % based on 100 m class ranges.

As a result of the analysis of approximately 50 map sections, the range values were evaluated between 0 and 3300 because the areas had different elevation values. There are no significant differences between class ranges, and it was reported that about 20% of landslides occurred between 500-700 m. The lowest values were found in areas above 2600 m.

It was seen that range values increased in providing a stable value because class ranges are unique to each area. The 10 map sections selected have values that can be classified with 50 m ranges. The analysis values are seen in figure 4.

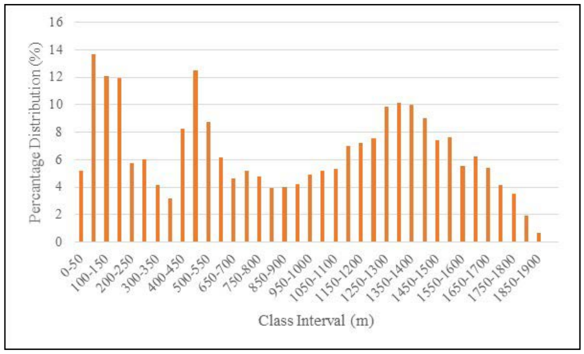


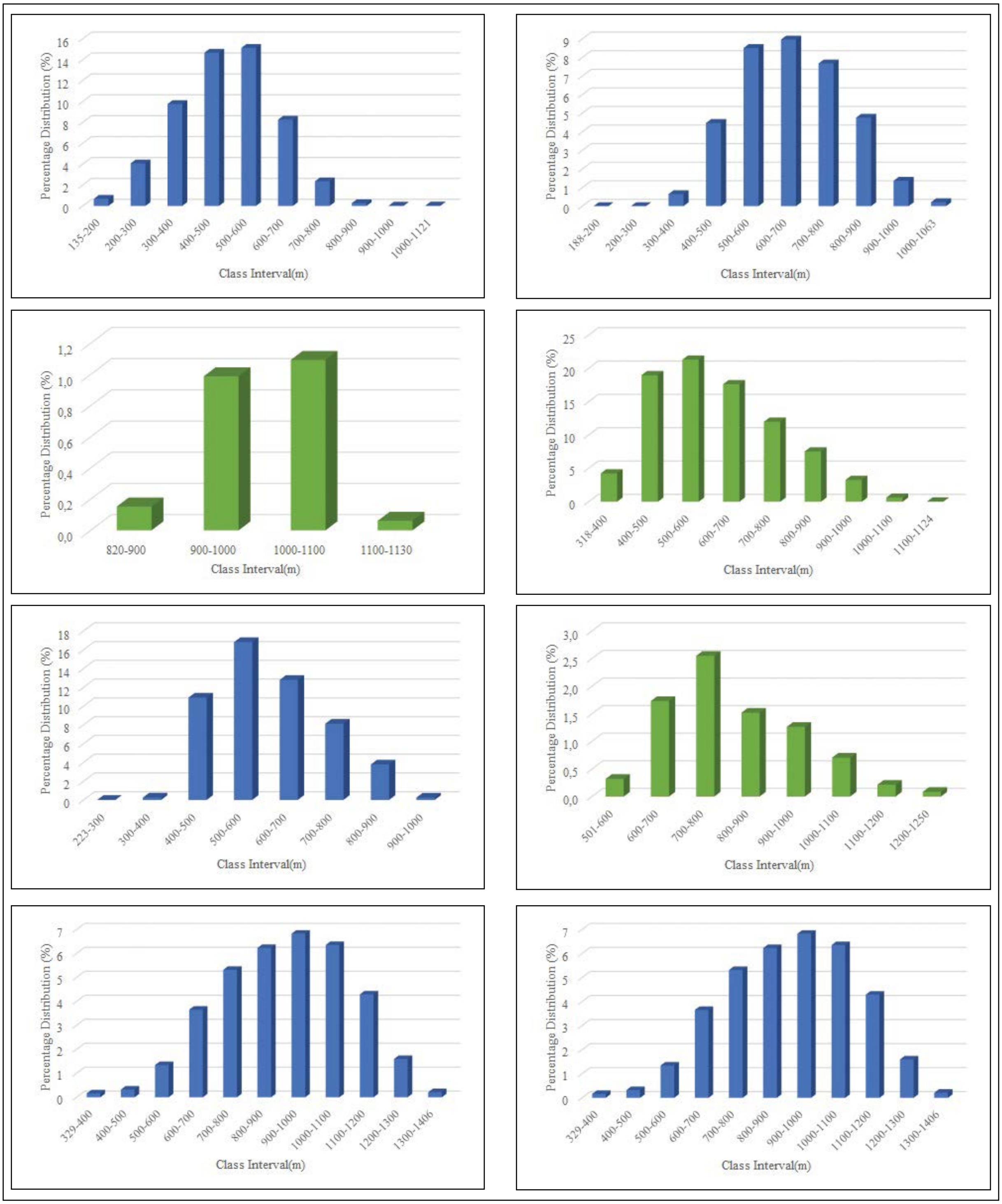
Figure 4- Distributions of the analyzed map sections in % based on 50 m class ranges.

The 50-100-meter range with 14% is the area at which the most landslides are seen. The 100-150 m range and the 450-500 m class range follow that with 12%. The lowest values are encountered after 1900 m. The reason for this is that elevations that allow for short ranges have comparatively low elevation values.

Finally, elevation distribution graphics were created for each area. The reason for this is that each field will be unable to resort to generalization from there being unique elevation values but that how distribution changes based on the terrain is examined (Figure 5).

The graphics show that gradually increasing values decreases again gradually after reaching a peak point. A drop occurred after a regular increase in all areas. If we are to generalize, landslides occurred at the average elevation values for the study area.

Figure 5- Elevation class range-landslide field distribution for the map sections used in the study (km^2).



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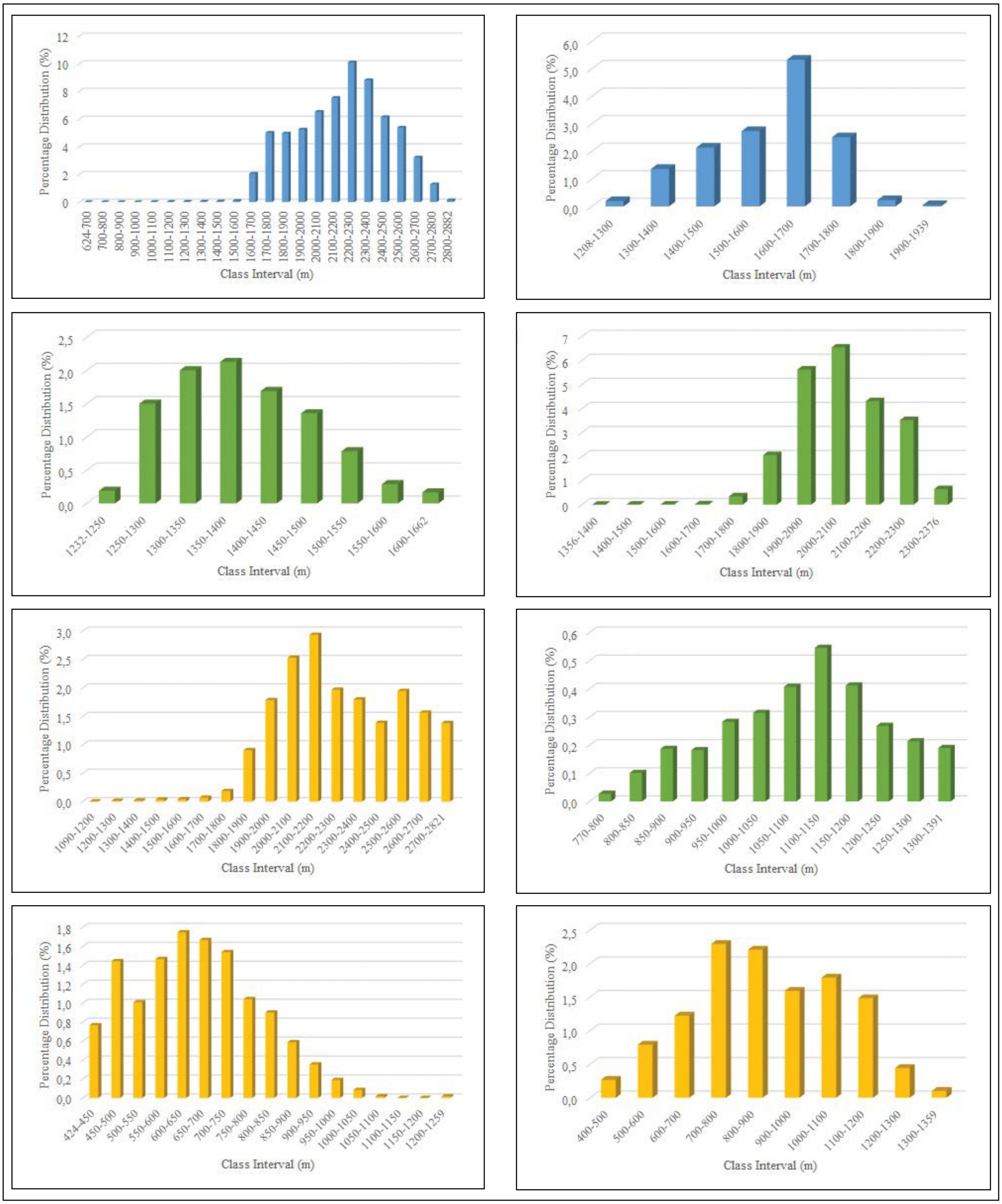

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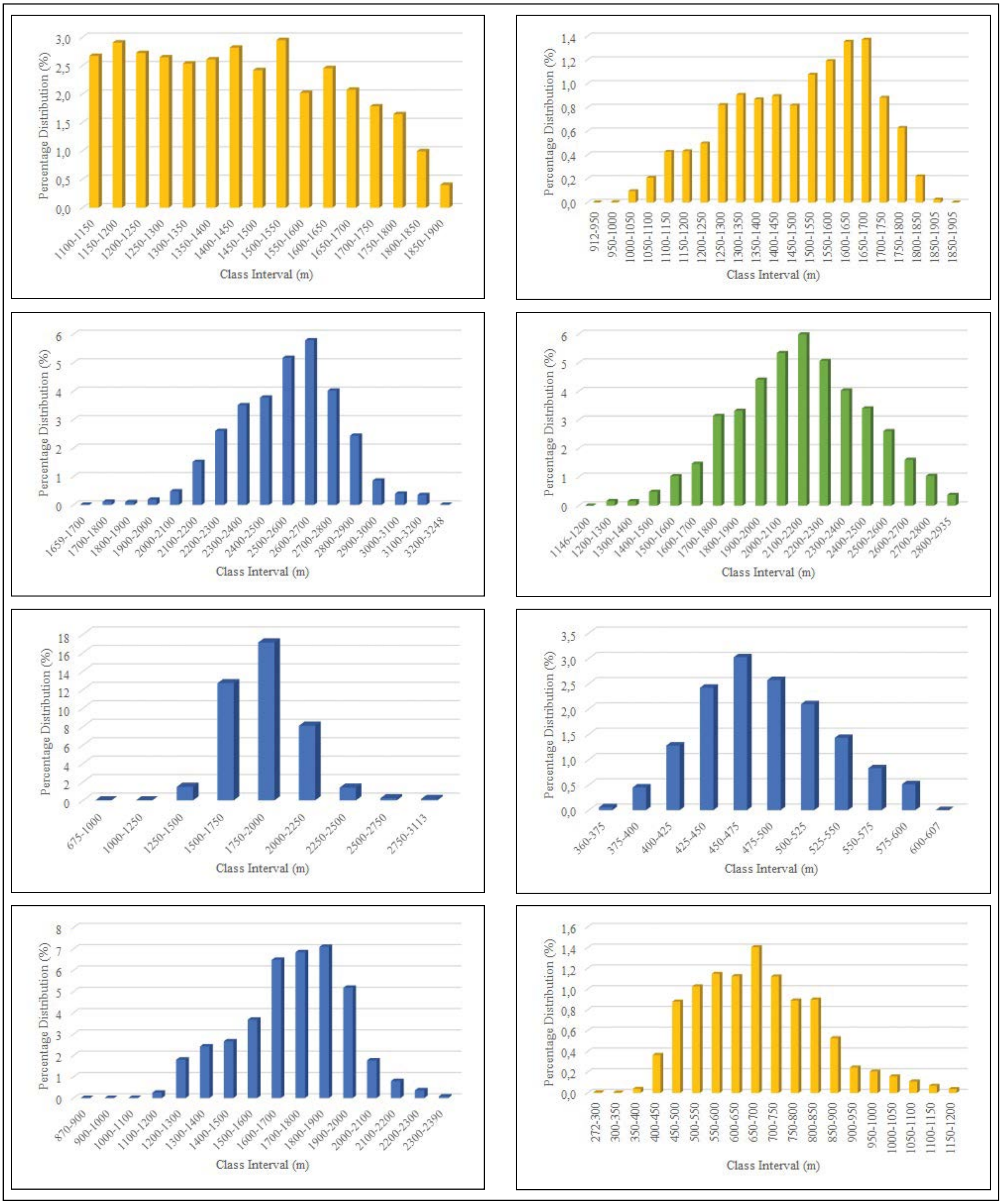

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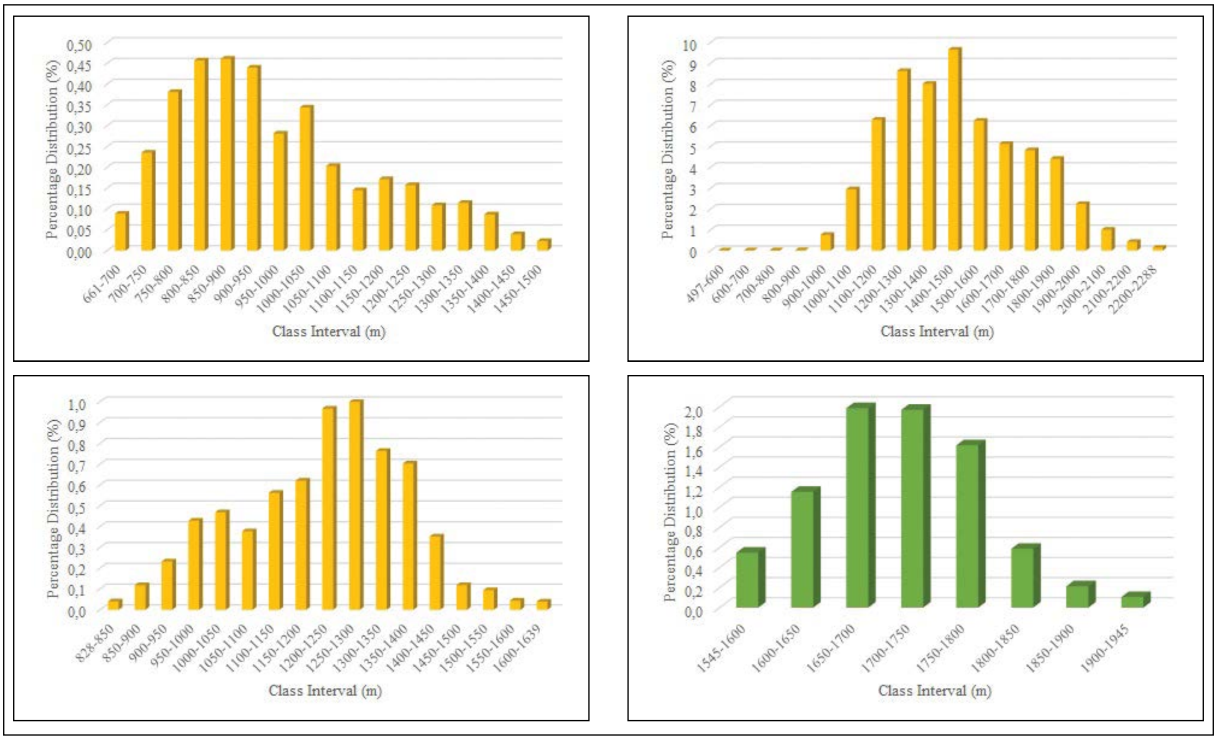

Figure 5- Continued.

8. Results and Discussion

The literature uses elevation values in two forms: relative and topographical. But topographical elevation is more commonly chosen. The most important reason that it is used as a parameter in susceptibility maps is that it is easy to access and produce.

When the parameter is evaluated by itself, an indirect effect from the influence of the other parameters becomes relevant, even if it is not influential. The effect of the parameter affects the entire system. The most affected parameter was the effect of precipitation, seismicity, temperature, flora and humans.

There is no clear elevation range at which landslides occur. Each area has unique properties. The increase of elevation in an area with seismicity also increases the severity of the formation of landslides. The change of climate conditions and flora with elevation concludes the same results. While terrain sometimes forms from lower elevations, it sometimes has higher elevations.

There are landslides that form in many different classes in the literature. Each area has its own unique elevation values. Therefore, elevation classes must reflect the character of the selected area. If this subject is to be assistance from the literature, determining the class range for the same areas is providing ideas about the effects of different areas but similar parameters (such as climate, terrain, anthropological effect, and temperature) as well as how they would be assessed.

Most studies in the literature assert that the intensity of landslides increases with the increase of elevation. Contrary to this, there are studies that assert that landslides cannot be seen at certain elevations. In addition to this, there are studies that assert that it is more susceptible to landslides at low and medium elevations. Some studies according to the literature say that landslides intensify at certain elevations while there are studies that assert that the effects of different elevations on susceptibility to landslides are also different.

It was seen in the selected map section analyses that each area has its own characteristics elevation values. Landslides varies based on the elevation values for their own study areas. Just as landslides can occur at very high elevations in other areas compared to one area, landslides can occur at low elevations. The results of the analysis showed that landslide intensities increase gradually in any study area and reach a peak value at a certain point of elevation. If we are to generalize, while it cannot be envisaged that landslides will occur at a certain elevation value, landslides peak at average values at their own elevation values for the area for each area. This peak point, compared to other variables, is observed two or three more times in some areas.

Although it is not a determinant parameter for each area, the effect of elevation consequently is determinant if the study area comprises mountainous areas with different elevation values. The effect value also changes based on the parameter variables found for the same system. Landslides should be expected at the average elevation values of an area. It was reported that landslides occurred at certain elevation values for the study area (medium elevations for the field), although not at a certain elevation value.

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