An Application of Quantitative Geomorphometric Indicators in identifying '[Susceptible Zones by Using SVM Model (Case study: Khorramabad- Pol Zal Freeway)

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An Application of Quantitative Geomorphometric Indicators in identifying '[Susceptible Zones by Using SVM Model (Case study: Khorramabad- Pol Zal Freeway)

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Abstract

Geomorphomety is the quantitative measurement of landforms based on height changes influenced by distance function. Geomorphomety indices express the characteristics of the terrain quantitatively. The present study emphasizes the use of geo-morphometric parameters and SVM algorithm to identify areas prone to landslide in Khorramabad- Paul Zal freeway as one of the important roads in the country. Other indices include slope, aspect, lithology, fault condition, drainage and land use which are applied together with the geometric indices such as profile curvature, plan curvature and total curvature use, artificial intelligence approach and linear functions and polynomial SVM algorithm to identify areas prone to landslides. The results show using Geomorphometric indices play an important role in increasing accuracy of assessing and identifying areas with an increasing the risk of landslides and assessing the accuracy through using land survey data shows that polynomial functions are more accurate in identifying areas prone to landslides than SVM algorithm linear function.

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Introduction

Landslide has a negative effect on human life and economic activities all over the world (Pourghasemi et al., 2012, Nadim et al., 2006). According to 2012 World Disaster Report (2011-2002) landslide is among the world's seven natural disasters (IFRCRCS., 2012). Several methods have been proposed to evaluate the landslide susceptibility map that can be divided into two broad classification categories: qualitative (subjective) and quantitative (objective) (Fell et al., 2008). However, Landslides are usually complex systems and to predict the sensitivity of their occurrence there needs to be different geomorphologic, geologic, hydrological, land cover and other data on environmental factors (Ling Peng et al., 2014). There are no specific universal guidelines for the selection of the factors affecting global mapping of landslide susceptibility (Yalcin., 2008). Previous studies were usually willing to provide little information or a model with low quality performance (Guzzetti et al., 2006; Frattini et al., 2010)which were not satisfactory for final users and there were limitations associated with these studies) Chung and Fabbri., 2003). This is the necessity because of which methods with better criteria for identifying significant environmental factors leading to landslide in line with the environmental planning are needed. With regard to improved methods of data analysis and technical and artistic techniques such as of Artificial Neural Networks (Lee et al., 2004; Yesilnacar and Topal., 2005; Nefesliogluet al., 2008), fuzzy logic (Ercanoglu and Gokceoglu., 2004; Pradhan et al., 2009; Akgun et al., 2012), neural - fuzzy, (Oh and Pradhan, 2011; Bui et al., 2012) Decision tree (Saito et al., 2009; Wan., 2009; Nefeslioglu et al., 2010; Yeon et al., 2010) algorithm and support Mashyn¬Brdar Yao et al., 2008; Yilmaz., 2009; Marjanovi'c et al., 2011; Pradhan., 2013) The researchers were able to use these techniques for mapping the landslide. Yamani et al (2013) in a study in Darakeh basin, performed the landslide zoning using four functions of SVM algorithm. The results showed that through identifying areas prone to landslide, the external function of this algorithm best matches the reality. In another study, Chan Su and et al (2012) examined the ability of the SVM model in landslides caused by earthquakes using GIS software in China's Jianjiang Basin. The results suggest more appropriate radial function SVM algorithm in comparison to other functions, in predicting of landslides. A review of the literature in this area suggests few studies have been done on the involvement of the scope and impact geomorphometic indicators. Among such limited studies, one can mention the research Talebi and et al (2008) have done; He combined three longitudinal profiles (concave, flat and convex) and three types of plans (convergent, parallel and divergent) to provide the domain model for slope stability of the composition. In this model, the impact of the plans and profiles was investigated in unstable slopes and landslides. According to the results, it can be said that the slope of the convex and concave divergent and convergent are generally more stable than the steep, smooth slope, while the other two are located on the intermediate level. So far, there have been no comprehensive studies of landslide susceptibility assessment in the study area.

Furthermore, the limited information about the area, has not let us do a survey to assess the exact number of potential landslides. landslides occurred on Khorramabad - Pol Zal highway in south west of Iran (Figure 1) and near the historic landslide Simereh which is a serious threat to social and economic stability of the region; As a result of the construction of the main road which connects the central and western regions of Iran Khuzestan plain and the Persian Gulf, new trenches in susceptible geological formations, has increased the probability of potential landslides and slope instability, which has become a serious and inevitable problem (Yamani et al., 2014). That's why the prediction of landslides so as to prevent new landslide, new slips and also activation of older landslides, it is essential to reduce the risk of the zone. The purpose of this study is to evaluate SVM method to identify landslide prone zones with emphasis on the use of Geomorphometric parameters.

Extent of the study

The newly built Khorramabad - Paul Zal highway with a length of 104 km, connects the city of Khorramabad to Andimeshk. Beginning of the path has of latitude 33 26ó Northern and a longitude of 48 12 East is the direction of latitude 32 48 5 Northern and longitude 48 04 Eastern passes. This ranges from the northwest to the southeast of the Zagros Folded Belt clash and is part of the Himalayan Alps Upper Cretaceous platform that converges the Arabian and Eurasian there (Talbot & Alavi., 1996). The aforementioned path with an area of 480/968 KM²; is like a strip of variable width from 5 to 7 km that has been chosen based on the occurrence of landslides and their impact that can be dominant on the road slopes. The roads are often built in the mountains and at the confluence of the valleys,and they pass over embankments or bridges. The starting point of the

road is located in Zagros mountains folding along Zagros mountains which passes the approximate direction of North - South, at the height of 1200 meters, the middle points of the road, with a height of 2315 meters are located in the mountain and the road ends up at the height of 320 meters. According the relatively large difference in height, the area has several different climates. Therefore, based on Domarten four-staged climate classification there will be humid, sub-humid, Mediterranean and semi-arid (Yamani et al., 2014). The average annual rainfall is between 322-578 mm which varies from north to south. Geomorphological construction of the region can be divided into Northern and Southernareas by thrust fault Rit–Sultan. Differences in the extent and severity of folds and faults in tectonic result is of significant difference in both North and South Northern regions.

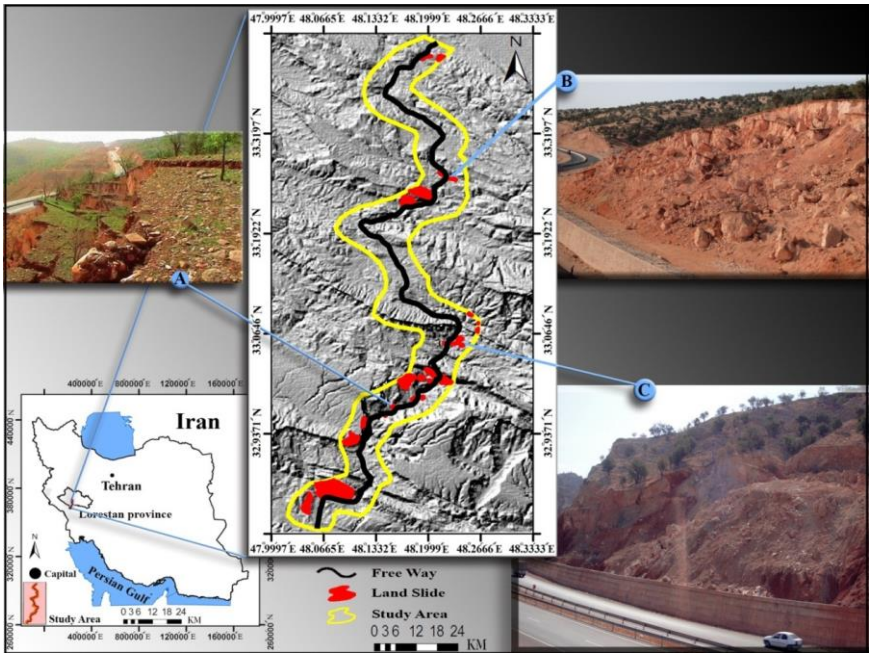


Fig. 1 Location map of the area in Lorestan province and dispersion of sliding

Data and Methods

In this research,three topographic maps of Khorramabad, Bydrubeh and Khalil Akbar with a scale of 1: 50,000 and two oil-company geological maps of Khorramabad and balarood with a scale of 1: 100,000 and 90 m SRTM DEM have formed the basic. Landsat TM images were used for the preparation of land use and IRS pictures (PAN) by the numbers (A48/66), (C47/66) Related to 2003 and 2005 to identify landslides before road construction. In addition, to complete landslide layer in inventory field work through using a GPS device height and the position of new landslides after construction operations on land, were registered on the ground matched with topographic maps and satellite images. Also geomorphometric indices were calculated by analyzing an equation in LANDSERF geomorphometric software and the output was found in raster format in ArcGIS environment.

SVM algorithm

SVM cognitive algorithms are used to evaluate and test a series of data (Yao et al., 2008). In recent years, the algorithm has grabbed much attention due to good performance in classifying and improved fault tolerance. SVM is actually a technique based on random sampling that can reduce cognitive complexity problem by maintaining the original information. Support vector machine (SVM) Algorithm was presented by Vapnik in 1995, based on statistical learning theory and dimensional theory and includes a training phase bound with the input and output goals. According to the statistical learning theory, Machine learning error rate for unclassified data can be considered as the extended error rate. These bounds are functions of the overall cognitive error rate and show the extent of complexity of the classifiers (Yamani et al., 2013). In order to minimize extended error rates training error rate and classifier's complexity, should be reduced. This can be done with maximizing separation margin.

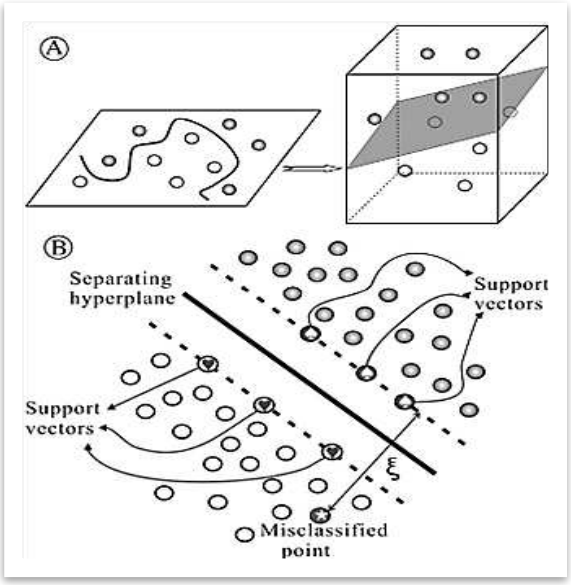


Fig. 2 Image of the principles of SVM(A) n-dimensional Page differences between the two classes with a maximum distance(B) The inseparable and imprecise variables

Details of the two-class SVM modeling is summarized as follows (Yao et al., 2008):

Given a set of distinct cell line

$$fX_i(i = 1, 2, \dots, n)$$

Cells which include two classes as $y_i = \pm 1$ Marked. The purpose of SVM model is to Find a distinction between two classes -N size, which is determined by the maximum gap. Mathematically, this concept can be taken with these words:

$$\frac{1}{2} \|W\|^2$$

Which is subject to the following restrictions:

$$Y_i \left((W.X_i)) + b \right) \geq 1$$

$\|W\|$ is the rule of a normal a numeric base and (.)Specifies the number of production operation. Using coefficient of Lagranzhyan the value of performance can be defined as follows:

$$\mathrm{L} = \frac{1}{2} \|\mathrm{W}\|^2 - \sum_{i-1}^{n} \lambda i \left(y_{i\,((}\, wx_{i\,)+}\, \mathrm{b}\,\right) - 1)$$

λi is a Lagranzhyan coefficient. This solution can be calculated through minimization of binary equation 3. Variation of variables bles B & W took place in standard valuation methods:

$$\lambda i \left(y_{i\,((}\, wx_{i\,)+}\, \mathrm{b}\,\right) \geq 1 - \xi_i.$$

$$\mathrm{L} = \frac{1}{2} \|\mathrm{W}\|^2 - \frac{1}{vn} \sum_{i=1}^{n} \xi_i$$

Geomorphometric indicators of the range

Geomorphometric characteristics express the shape of ranges which are prone to slip quantitatively. Using values obtained from the DEM products such as slope, profile curvature, plan curvature, width curvature, and the general curvature of range morphometric characteristics of landforms (landslide) (Fisher et al., 2004; Pike., 2000; Wood1996). Convexity and concavity and second derivatives with respect to the levels that are generally known under the name of curvature and curvature can be used to measure the roughness of the surface. The amount of curvature in different types in the raster digital elevation model is calculated pixel by pixel and for each cell of a fourth degree polynomial equation is used (Relationship between 1, 2 and 3). In a window with dimensions of 3 x 3 is calculated (Figure 3). Since the curvature has been calculated using a moving window of eight neighboring cells it is possible to identify cells and concave and convex surfaces there.

Equation 1: general of curvature

$$Z = Ax^2y^2 + Bx^2y + Cxy^2 + Dx^2 + Ey^2 + Fxy + Gx + Hy + I$$

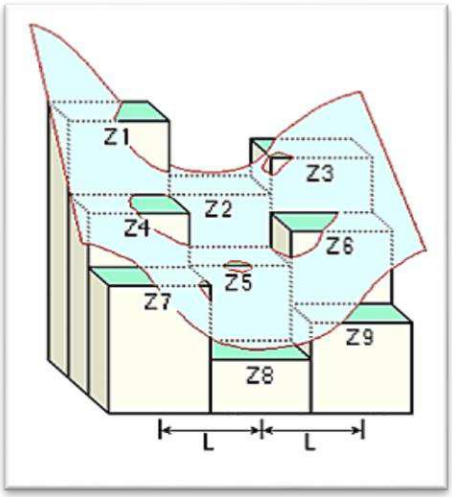


Fig. 3 Schematic representation of the parameters used in calculating the overall of curvature

Among a wide variety of curvatures, profile and plan of curvature can be noted as two geomorphometric index. The curvatures of the profile represent the degree of change in profile curvature along the way and therefore represent the intensity of water flow and sedimentation processes. So that the negative level of this curvature shows convex surfaces and the positive level shows concave surfaces (Pike., 2000).

Equation 2-2: the curvature profile.

$$n * g*(a*d^2+b *e^2+ c * d*e)/(d^2+ e^2)(1+(d^2+ e^2)^{1..5}$$

On the other hand the curvature of the plan represents a shift in direction through a curve, and therefore represents a topographical divergence and convergence. Negative values of the curvature of the plan indicates the current divergence, which includes the ridges and peaks and positive values (valleys) show (Goudie., 1990)current convergence. It is noteworthy that flat surfaces have a curvature of zero. The curvature is measured in radians or in meter (up to 100 m).

Equation 3: the curvature Plans

$$n * g * (b * d^2+ a * e^2-c * d * e)/(d^2+ e^2)^{1..5}$$

In all these relationships g: resolution of digital elevation model, n: the dimensions of the moving window.

Discussion and Results

Map of the existing landslides and the training samples

In this study, to determine landslide susceptibility, features of 39 landslides which had occurred in the study area were taken using satellite images (PAN) IRS and geographic information systems (GIS) were analyzed. Samples which were randomly collected from the landslide area were divided into two groups: first those are used for model production training and the examples which were used in model validating tests(Marjanovi'c et al., 2011). The main purpose of separating training and testing of samples was building a model and modeling test obtained by independent test samples. When the randomly collected samples for simultaneous training and testing are used with random samples based on the pixel slip spots, the model performance can be artificially increased (Taner San., 2014).

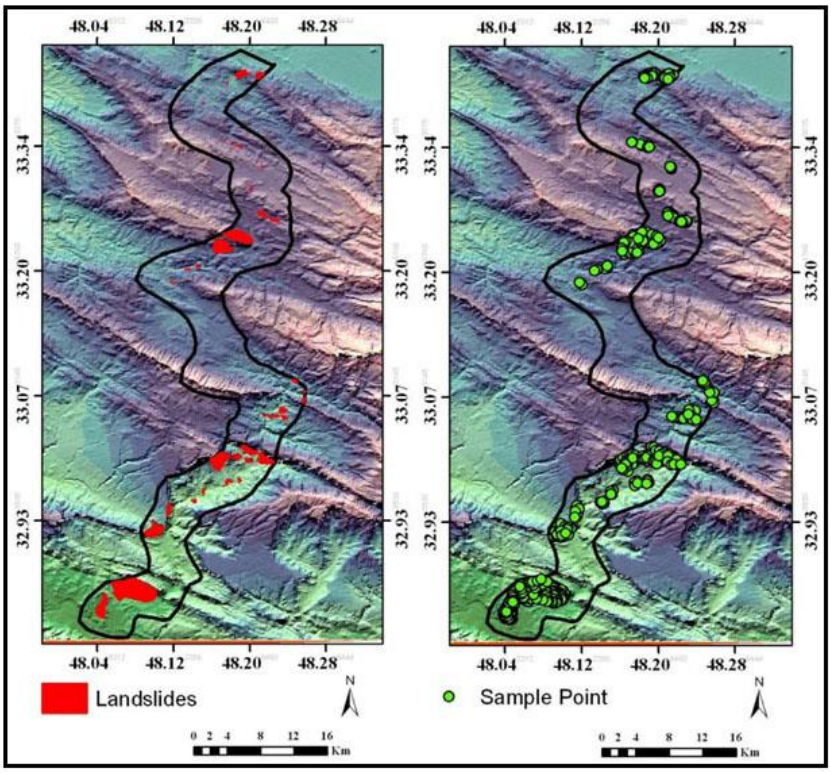


Fig. 4 Distribution of landslides and training samples in the study area

zoning the landslide using the controller parameters

All effective and landslide controller variables which are used as input in SVM model are shown as a map (Figure 5) and a table (1):

Direction range

Direction of range is taken from of the DEM layer and is defined as the frequency of slopedirections of surface complications aspects. Accordingly, ranges are classified in 9 levels as completely smooth, North, North East, East, South East, South, South-West, West and North West sorted (Figure 5).

slope degree

Slopes degree and its convexity, concavity and its being direct has a large impact on landslide occurance. Because of the slope geometry, a convex topographic surface is less steep (Lulseged et al,2004). Steep slope increases the shear stress caused by gravity and disrupts the range further (Dai et al., 2001). As one of the most important factors in instability, slope, was extracted from hypsometric layer (Figure 5).

land use

Freeway construction and excavation and embankment operations together with the destruction of oak forests and meadows, without any attention to principles of sustainability are among the most important factors which stimulate the dominant ranges over roads. In order to provide an efficient map using Landsat TM images were used and the general area was divided into four in which the categories of agricultural lands and gardens, meadows, forests and rocky surfaces.

Distance from drainage

Landslides on the sidelines of most of the waterways in the area, especially around the main river beds of Zal and Chameshk lead to instability of dominant ranges. For this purpose, six floors from long distances to those close to the waterways and rivers in Figure 5 are provided to determine the impact of these variables in case a landslide occurs (Figure 5)

Distance from the fault

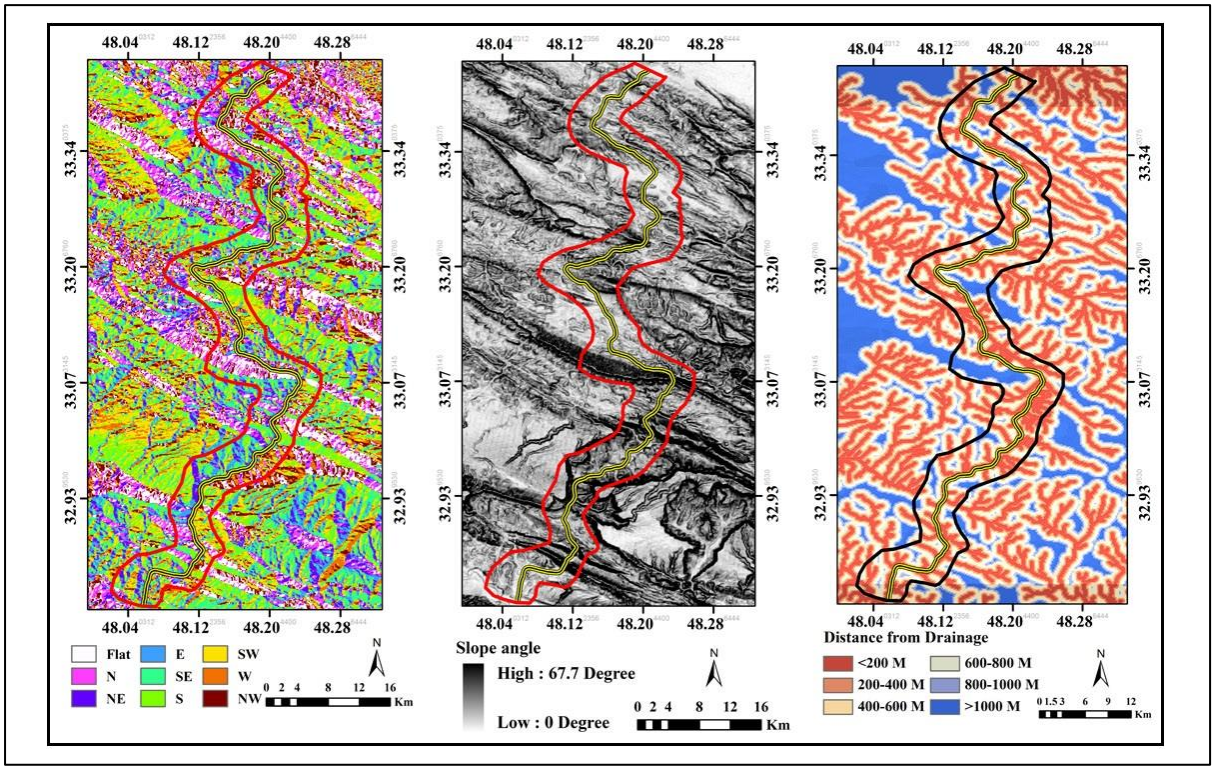
In the region, either directly (the energy of the fault) and indirectly (the effect of lithology and slope) landslides are caused by faults. To understand the impact of this parameter buffers were made from a distance of 5 Kilometers to the active fault line, in the form of five stories as <5, 5-10, 10-15, 15-20,> 20 km (Figure 5).

Lithology

Lithology is known as a key factor in creating landslide in the form of erosion and weathering (Anbalagan, 1992 Dai et al., 2001). Distribution of rocks in Fig. 4 and the descriptions of each of them is given in Table 1.

Table1 Geological units and their descriptions in the study area

Describing lithology	Geological units	The row number
Calcareous sandstone and silty marl with streaks column	MuPlaj	1
The cement conglomerate with limestone and marl	Plbk	2
Semi-hard conglomerate recent	Qc2	3
Dolomitic limestone, marl and clay with layers	EMass-Sb	4
Siltstone, sandstone, limestone marl	KPeam	5
Conglomerate sandstone and siltstone with interlayers	Ekn	6
Gypsum and clay marl with anhydrite	Mlgs	7
Marl and shale clay with traces of lime	Kgu	8
Shale and marl with limestone clay	Pb	9
Songs full of fossils	Tz – E - zang	10
Marl clay limestone with shale layers	Kbgp	11
Alluvium and debris recent	Qt2	12



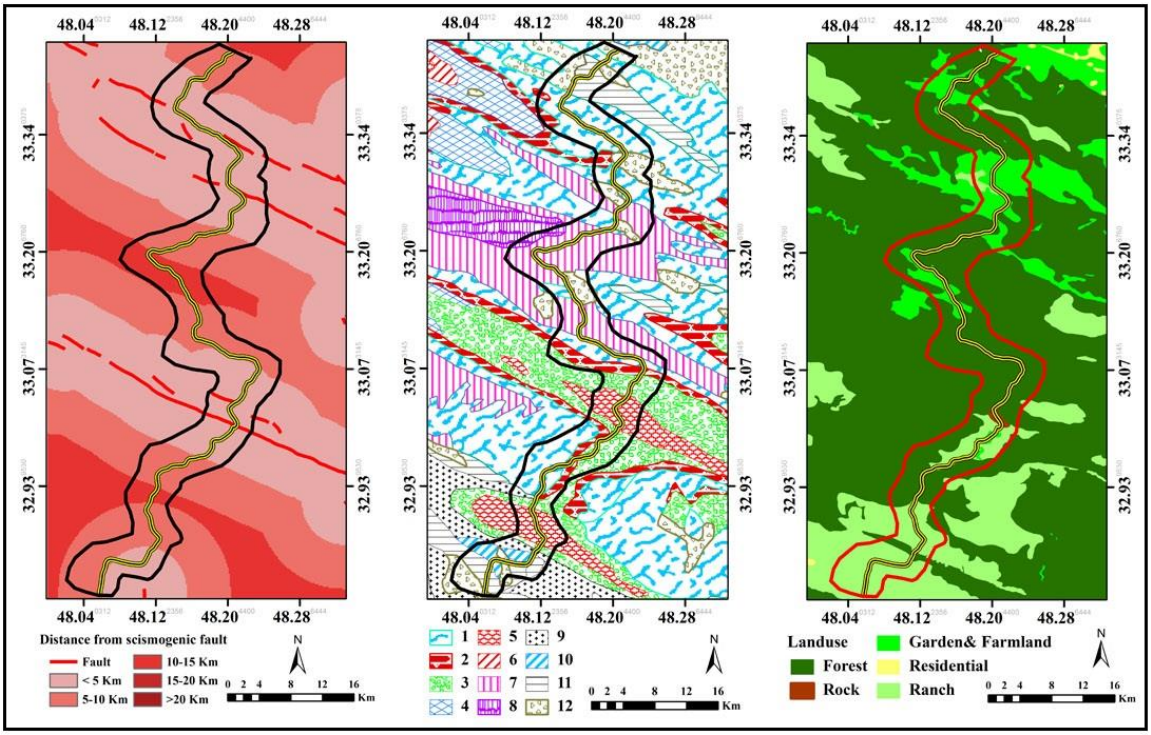
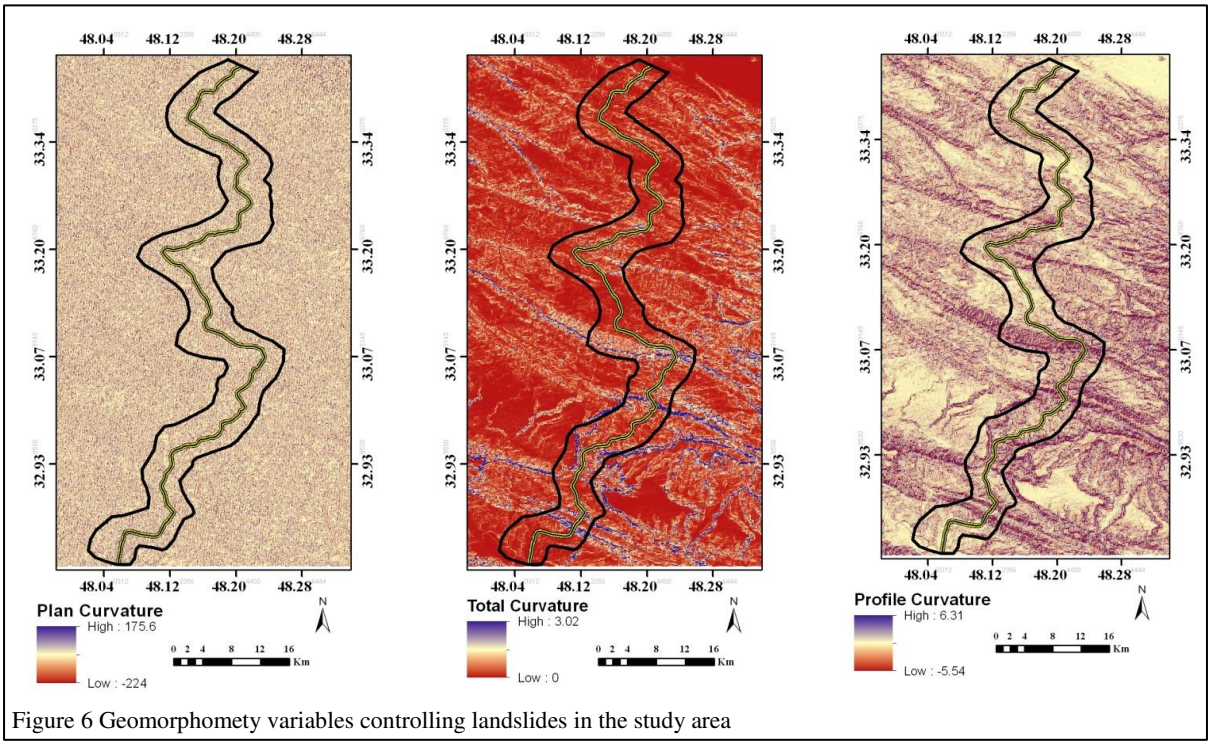


Fig 5 Landslide control variables in the study area

Geomorphometic variables

Rippling type of domains has a significant effect on the occurrence of landslides. In most studies to express rippling effect on the domain movement, slope factor cannot show all the features of uneven surface by itself. Therefore, in this study the Geomorphometic variables of profile curvature, and plan and the overall curvature which are derivatives of second grade were used for expressing roughness of the domain surface and their effect on landslides and an attempt has been made to use them for identifying areas prone to landslides and thus model them more accurately (Figure 6). The curve of the profile represents the amount of change in profile curvature along the way and therefore represents the intensity of water flow and sedimentation and transportation processes. Thus the amounts of negative curvature show convex surfaces and concave surfaces are shown by a positive amount. On the other hand, the curvature of the plan represents a shift in direction of the curve, and therefore represents a topographical divergence and convergence. Negative values of the curvature of the plan show the current divergence, which includes the ridges and peaks and positive values show flow convergence (valleys). The overall curvature specifies the overall shifts in the surface.



404 Figure 6 Geomorphomety variables controlling landslides in the study area

405 Using effective metrics on slip and
406 Geomorphometric indicators and using polynomial
407 and linear functions in SVM model, landslide prone
408 zones modeling was obtained in the study area,
409 which is done with regard to local modeling in the
410 ENVI software and model outputs are specified in
411 the form of a map (Figure 7). Maps of polynomial
412 and linear functions show zones which are sensitive
413 to landslide in Khorramabad - Paul zal highway.
414 Sensitivity values were between 0 and 1, and as we
415 got closer to 1 (Light Color on the map) aptness
416 and sensitivity for landslides in the study area
417 increases. The results show that more than 30
418 percent of the area under study, is located in areas
419 with more than 0.8 which indicates that the high
420 sensitivity of the study area of the slip. One reason
421 to the high sensitivity of the area is the passage of
422 the highway and cutting off the range and finally a
423 loss of balance in the region.
424

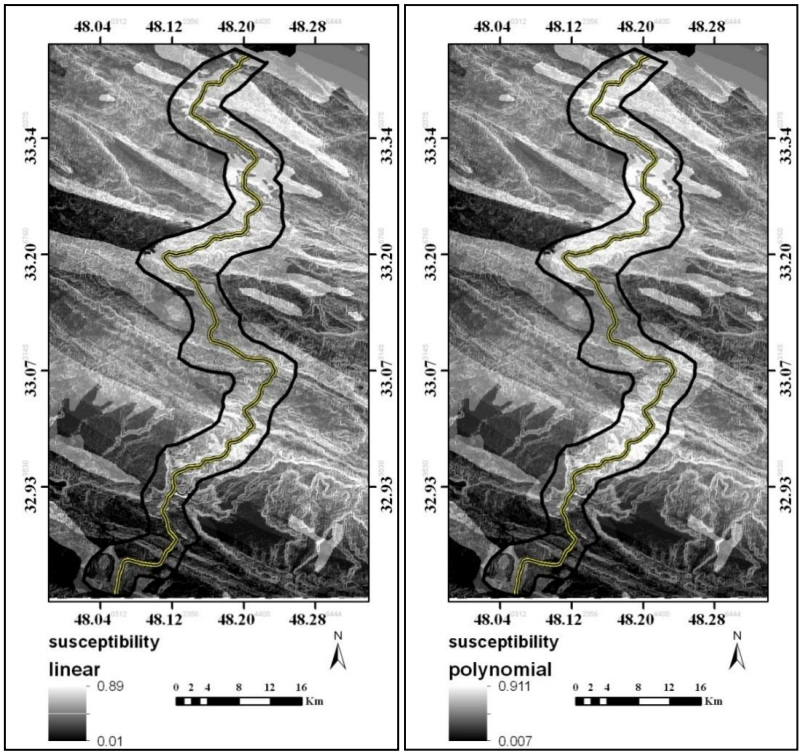


Figure 7 landslide susceptibility based on linear and polynomial function and SVM model in the study area

assessment of accuracy of slip zoning modeling

After application of each model, it is necessary to evaluate the accuracy to take action regarding the applicability and reality of results. In this study, twenty percent of the samples were used to assess accuracy carefully. First, an error matrix was formed and then using the overall accuracy, accuracy of the model was determined. The results show modeling through by polynomial function (polynomial) with an overall accuracy of 89% was more accurate and had a better performance and is more consistent with ground realities in comparison to the linear method with an overall accuracy of 84%. Given that the behavior of the slip control variables in the study area has not been linear and has a non-linear complex behavior, Polynomial method has had a better modeling capability and mapping results are more compatible with the ground reality.

Conclusion

Geomorphomety is the quantitative analysis of the shapes on the surface of the Earth and land surface conditions which carries out the quantitative analysis of uneven surfaces. In this study, the aforementioned indicators along with other variables have been used, in order to identify more precisely uneven surfaces and their effects on the slip and eventually increase the accuracy of modeling. The results showed that the use of polynomial functions and linear SVM model in zoning the the area under study with the involvement of Geomorphometric factors of the domains has well identified the points with high landslide potential. Also evaluating the accuracy of the modeling showed that polynomial functions with the overall accuracy of 89% have shown the areas prone to landslide better than that the linear function which seems to be due to the complex and nonlinear behavior of the variables which are involved in landslide occurrences.

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Figures

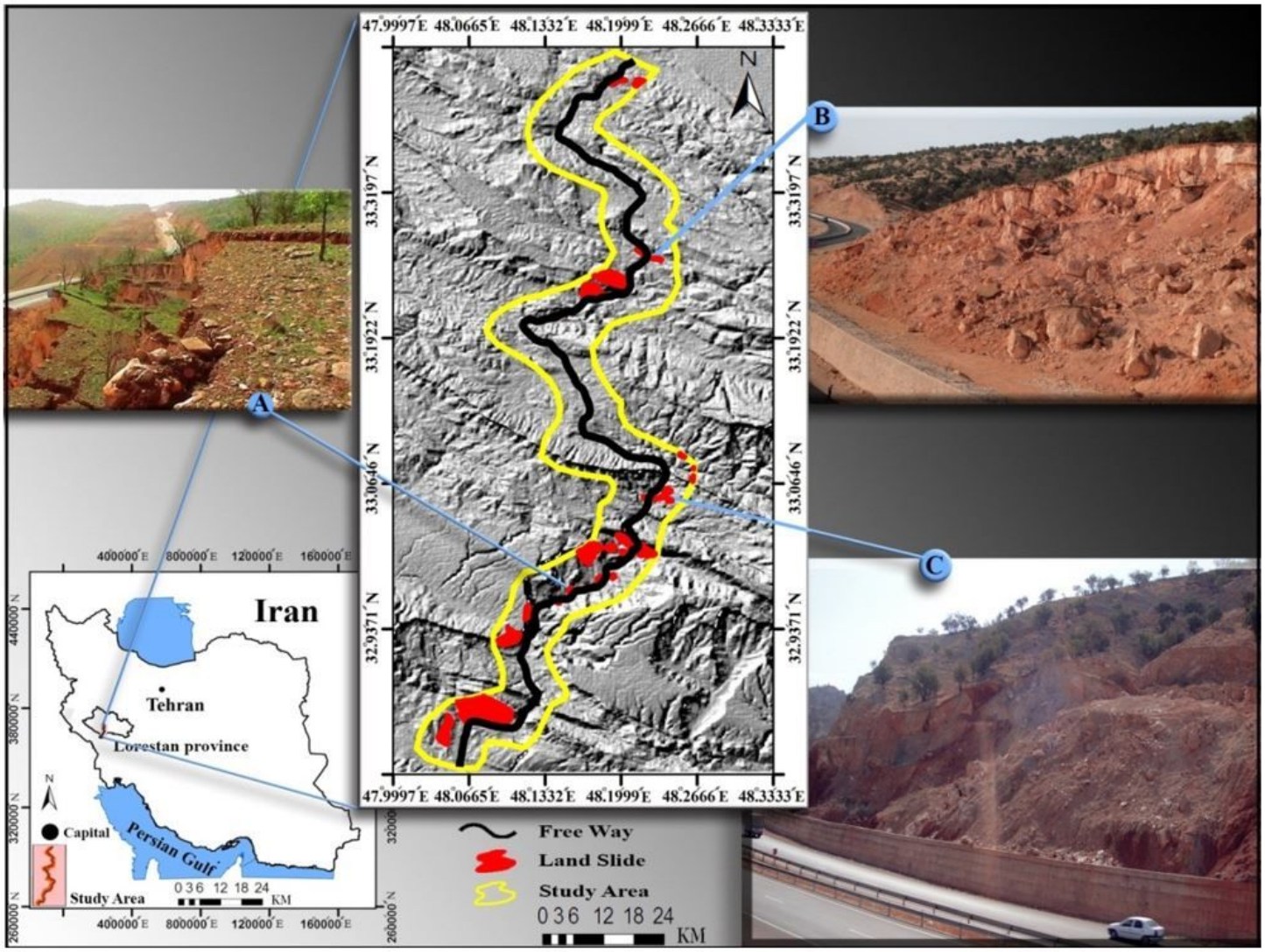

Figure 1

Location map of the area in Lorestan province and dispersion of sliding.

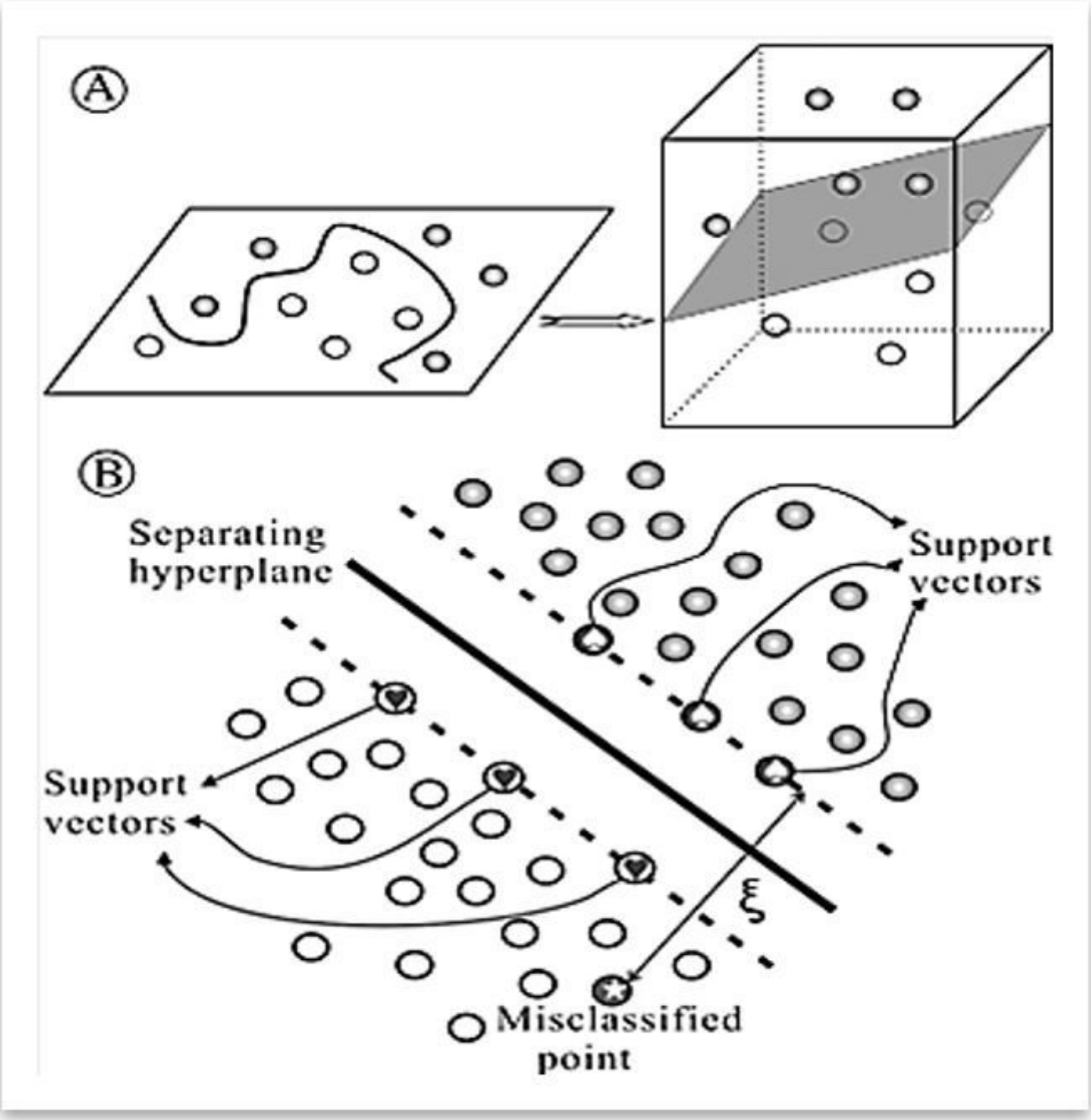

Figure 2

Image of the principles of SVM(A) n-dimensional Page differences between the two classes with a maximum distance(B) The inseparable and imprecise variables.

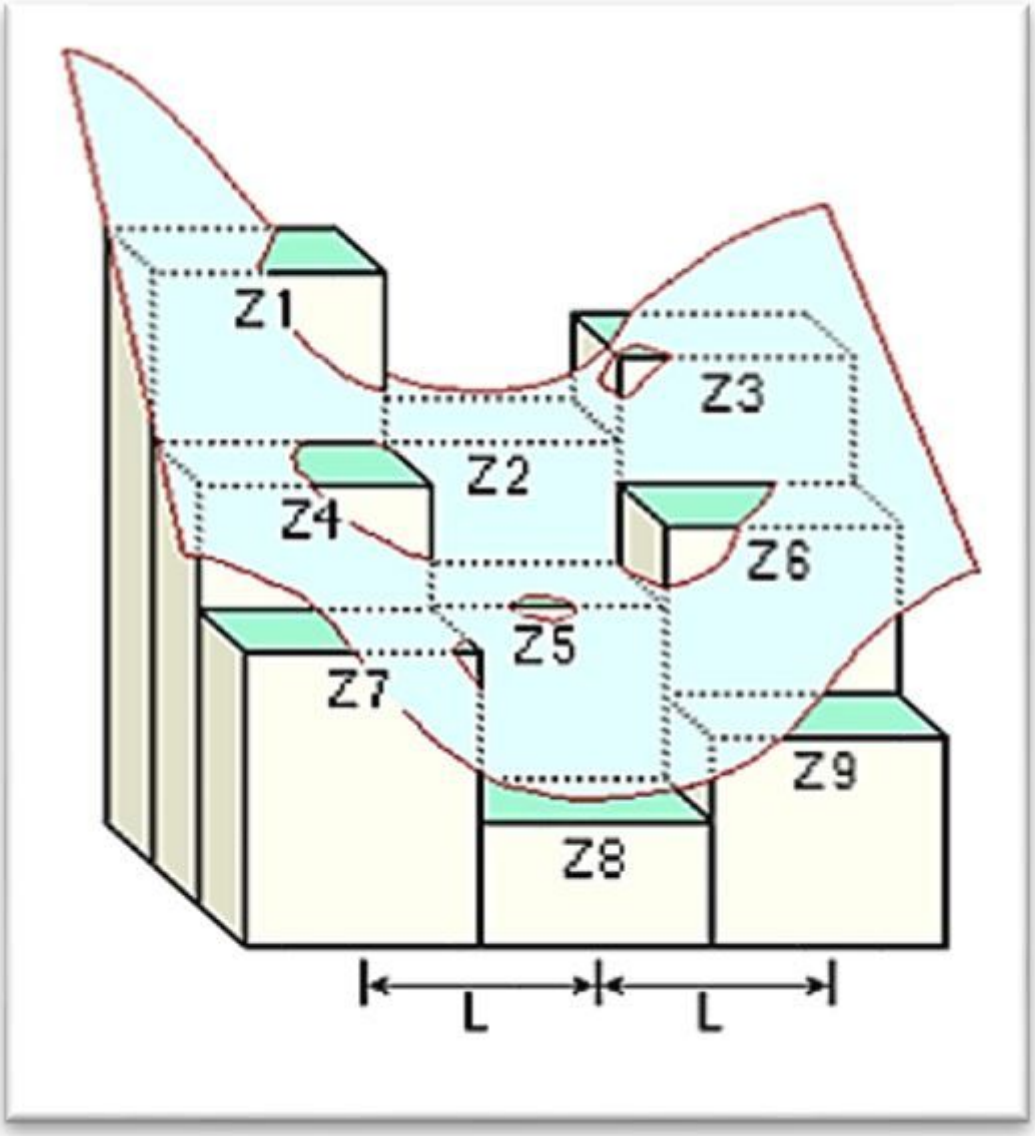

Figure 3

Schematic representation of the parameters used in calculating the overall of curvature.

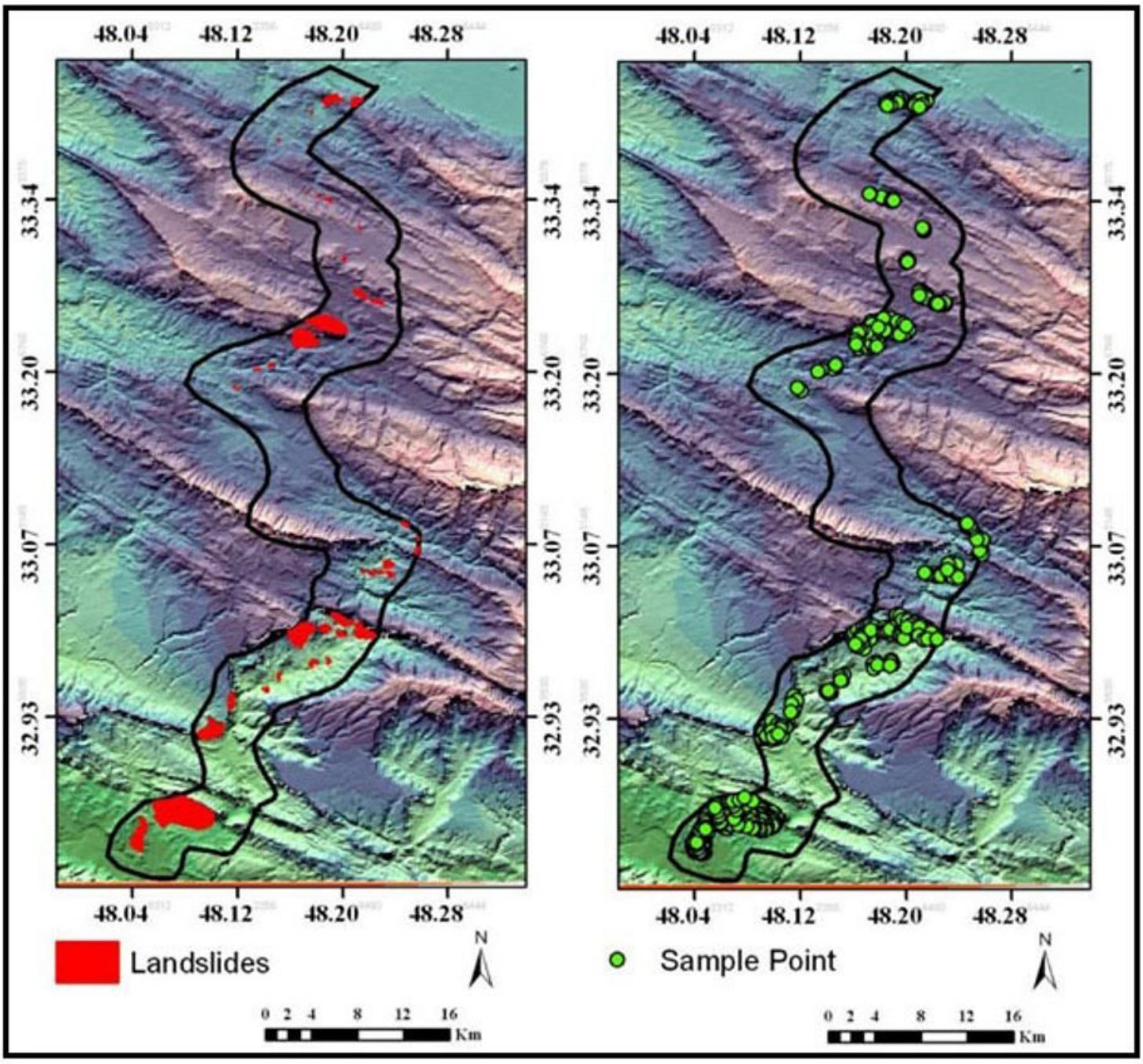

Figure 4

Distribution of landslides and training samples in the study area.

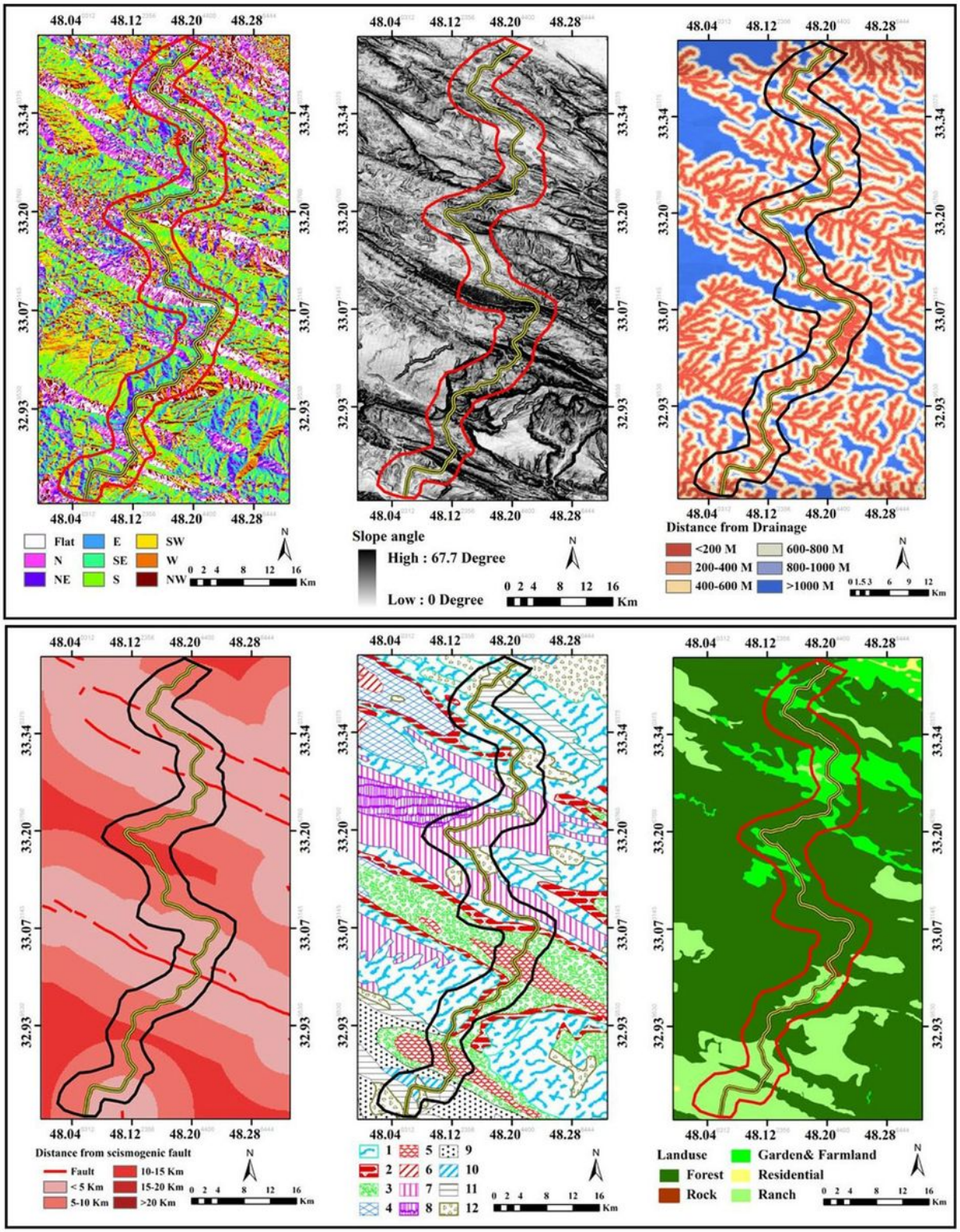

Figure 5

Landslide control variables in the study area.

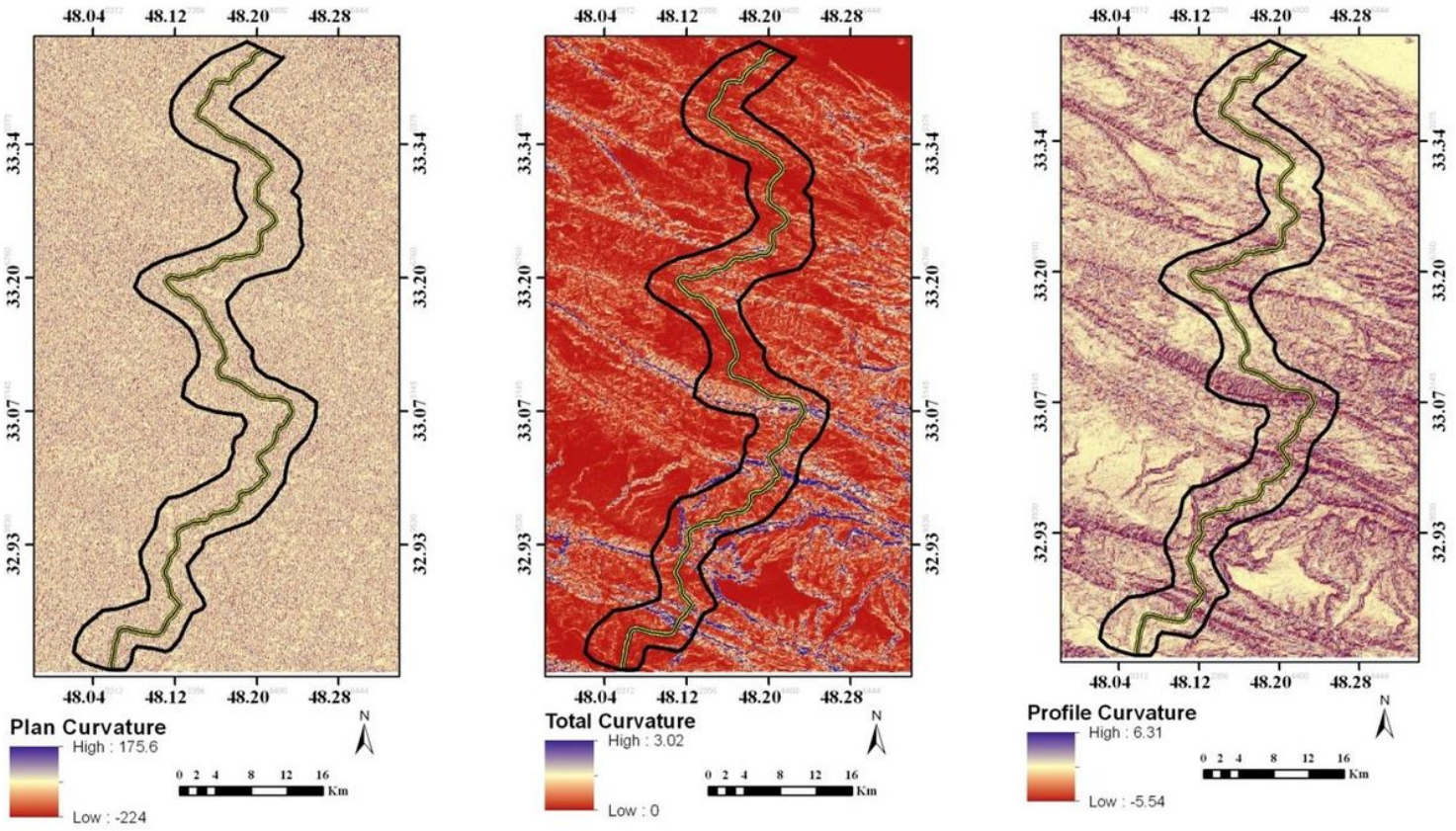

Figure 6

Geomorphomety variables controlling landslides in the study area.

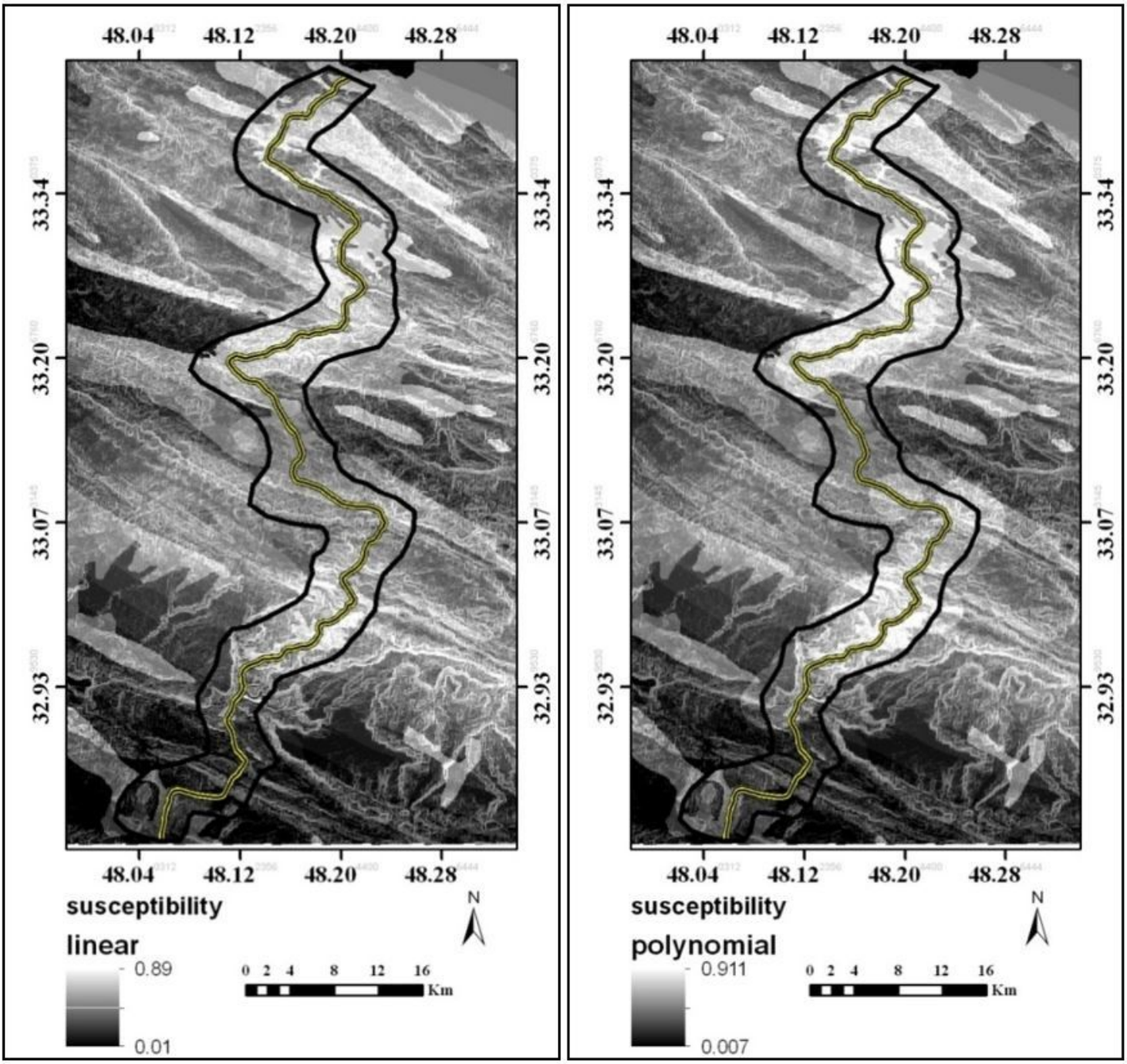

Figure 7

landslide susceptibility based on linear and polynomial function and SVM model in the study area.