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Application of the modified Q-slope classification system for sedimentary rock slope stability assessment in Iran

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ABSTRACT

The Q-slope system is an empirical method for discontinuous rock slope engineering classification and assessment. It has been introduced recently to provide an initial prediction of rock slope stability assessment by applying simple assumptions which tend to reflect different failure mechanisms. This study offers a correlation relationship between Q-slope and slope stability degree using case studies of sedimentary rock slopes from 10 regions of Iran. To this end, we have investigated 200 areas from these regions, gathered the necessary geotechnical data, have classified the slopes from a Q-slope perspective, and have estimated their stability relationships. Based on artificial intelligence techniques including k-nearest neighbours, support vector machine, Gaussian process, Decision tree, Random-forest, Multilayer perceptron, AdaBoost, Naive Bayes and Quadratic discriminant analysis, the relationships and classifications were implemented and revised in the Python high-level programming language. According to the results of the controlled learning models, the Q-slope equation for Iran has indicated that the stability-instability class distributions are limited to two linear states. These limits refer to the B-Line (lower limit) as $\beta = 11.9\log_{10}(Q_{number}) + 46.3$ and the U-Line (upper limit) as $\beta = 17.2\log_{10}(Q_{number}) + 54.1$. We present the modified Q-slope equation (β) to correct the primary relation for sedimentary rock slopes in Iran. To this end, the β-relation from Bar and Barton (2017) that is illustrated by Eq. (2) was modified and refined by the U-line and B-line relations as presented by Eqs. (3) and (4).

1. Introduction

Application of empirical methods such as rock engineering classification for the quantification of rock mass condition has a quite long history that dates back to Ritter's work in 1879. Terzaghi has presented the first quantitative classification with steel frame tunnels in host rock conditions and support system design (Terzaghi, 1946). Lauffer (1958) introduced a stand-up time classification by using Terzaghi's theory for unsupported tunnels/underground caverns. Cecil (1975) modified Terzaghi's approach and applied it to estimate rock mass properties. Deere et al. (1966 and 1970) presented the Rock Quality Designation (RQD) index for the assessment of the rock mass characteristics and discontinuity properties in rocks which were later modified (Deere and Deere, 1989). The Geomechanics classification or Rock Mass Rating (RMR), as well as the Q-system, can be stated as turning points in rock mass classification (Bieniawski, 1973; Barton et al., 1974; Tomás et al., 2012; Chen et al., 2017; Li et al., 2019; Kleinbrod et al., 2019) which led to describe the rock mass conditions in design applications. The latest version of RMR was introduced in 1989 (Bieniawski, 1989) and the Q-system has released its most recent improvement in 2014 (Barton and Grimstad, 2014). The geomechanical classification was mainly developed for underground spaces after making some modifications to be utilised for surface discontinuous rock structures (Zheng et al., 2016; Azarafza et al., 2017a) whereas the Q-system is not deemed appropriate for cut slope assessments. Marinos et al. (2005) have modified the Geological Strength Index (GSI) classification from 1997 to 2005. Hoek

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Table 1
The important relationships in estimating RQD.

No.	Relationship	Parameters	References
1	$RQD = 115 - 3.3J_v$	J_v: Sum of the number of joints per unit volume	Palmstrom (1996; 2010), Sivakugan et al. (2013)
2	$RQD = 110 - 2.5J_v$		Palmstrom (2005; 2010)
3	$RQD = 100\,(\lambda t + 1)\,e^{-0.1\lambda}$	t: Conventional threshold value (0.1 m); λ: discontinuity frequency	Hudson and Harrison (1997); Brady and Brown (2005); Zhang (2005)
4	$RQD = 110.4 - 3.68\lambda$	Modified Palmstrom relation for RQD > 50% and $6 < \lambda < 16$	Romana (1993); Hudson and Harrison (1997); Brady and Brown (2005)
5	$RQD = A^x B^y D_v$	A^x: Coefficient (105 to 120); B^y: Coefficient (2 to 12); D_v: Palmstrom's J_v	Goel and Singh (2011)
6	$RQD = 100\left(1 + \frac{0.1J_v}{1+\alpha+\beta}\right)\exp\left(-\frac{0.1J_v}{1+\alpha+\beta}\right)$	J_v: Palmstrom's J_v; α and β: Heterogeneity coefficient	Şen and Eissa (1991)

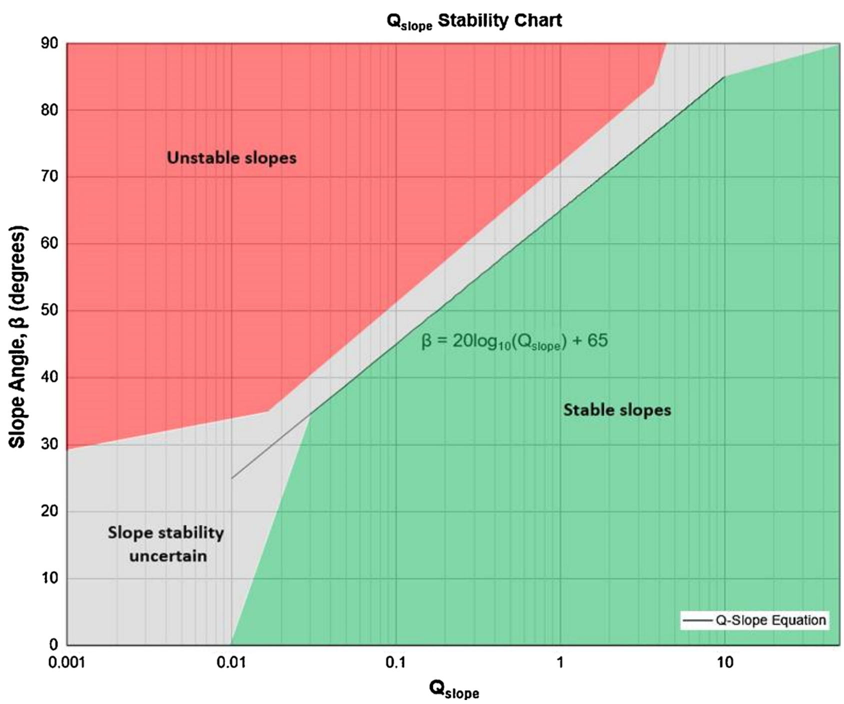

Fig. 1. The Q-slope chart (Bar and Barton, 2017).

et al. (2013) have presented its revised version in 2013 (Hoek and Bray, 2014; Somodi et al., 2018).

In general, the RMR and Q-system classifications have received attention and were commonly used as starting points in developing many other specialised classifications for several different rock engineering purposes such as Mining Rock Mass Rating (Laubscher, 1977), Rock Mass Strength (Stille et al., 1982), Modified Basic Rock Mass Rating (Kendorski et al., 1983), Simplified Rock Mass Rating (Brook and Dharmaratne, 1985), Slope Rock Mass Rating (Robertson, 1988), Modified-Mining Rock Mass Rating (Haines et al., 1991), Natural Slope Methodology (Shuk, 1994), Rock Condition Rating (Goel et al., 1995), Chinese Slope Mass Rating (Chen, 1995), Rock Mass Number (Goel et al., 1996), Modified-Rock Mass Rating (Unal, 1996), Q_{TBM} (Barton, 1999), Slope Mass Rating (Romana et al., 2003), Slope Stability Probability Classification (Hack et al., 2003), Continuous Slope Mass Rating (Tomás et al., 2007), Alternative Rock Mass Classification System (Pantelidis, 2010), Fuzzy Slope Mass Rating (Daftaribesheli et al., 2011), Graphical Slope Mass Rating (Tomás et al., 2012), Slope Stability Rating (Taheri, 2013), Global Slope Performance Index (Sullivan, 2013) and Q-slope (Bar and Barton, 2016, 2017). In the meantime, some categories were specially provided for mining work, rock slopes or mechanised tunnel borings where all classifications aimed to present a real-time decision based on engineering judgement in dealing with rock masses on site. Some researchers combined the empirical rock mass classifications with analytical, kinematic and numerical methods to provide coupled methods for evaluating design features (Stead and Wolter, 2015; Azarafza et al., 2017b, 2017c) which have led to suitable results in stability analysis and discontinuous rock mass condition assessment.

The impressive expansion of the RMR and Q classifications has led them to become an integral part of geological engineering investigations all over the world. Nevertheless, Barton and Bar (2015) have suggested an application of the Q-system for slopes, and have extended their application in 2017 (Bar and Barton, 2017, 2018). The main feature of the Q-slope system is based on the utilisation of an empirical method for the analysis of the stability of different slopes in different regions of the world. It includes New South Wales, Queensland and Western Australia, Laos, Papua New Guinea, Turkey, Dominican Republic, Panama, Serbia, Slovenia, and Spain with diverse geological groups. Unlike other systems, the Q-slope focuses on the stability analysis of discontinuous rock slopes to classify rock slopes in stable, unstable, and uncertain states by applying elementary assumptions. The authors have used the Q_{number} to determine slope reliability, which

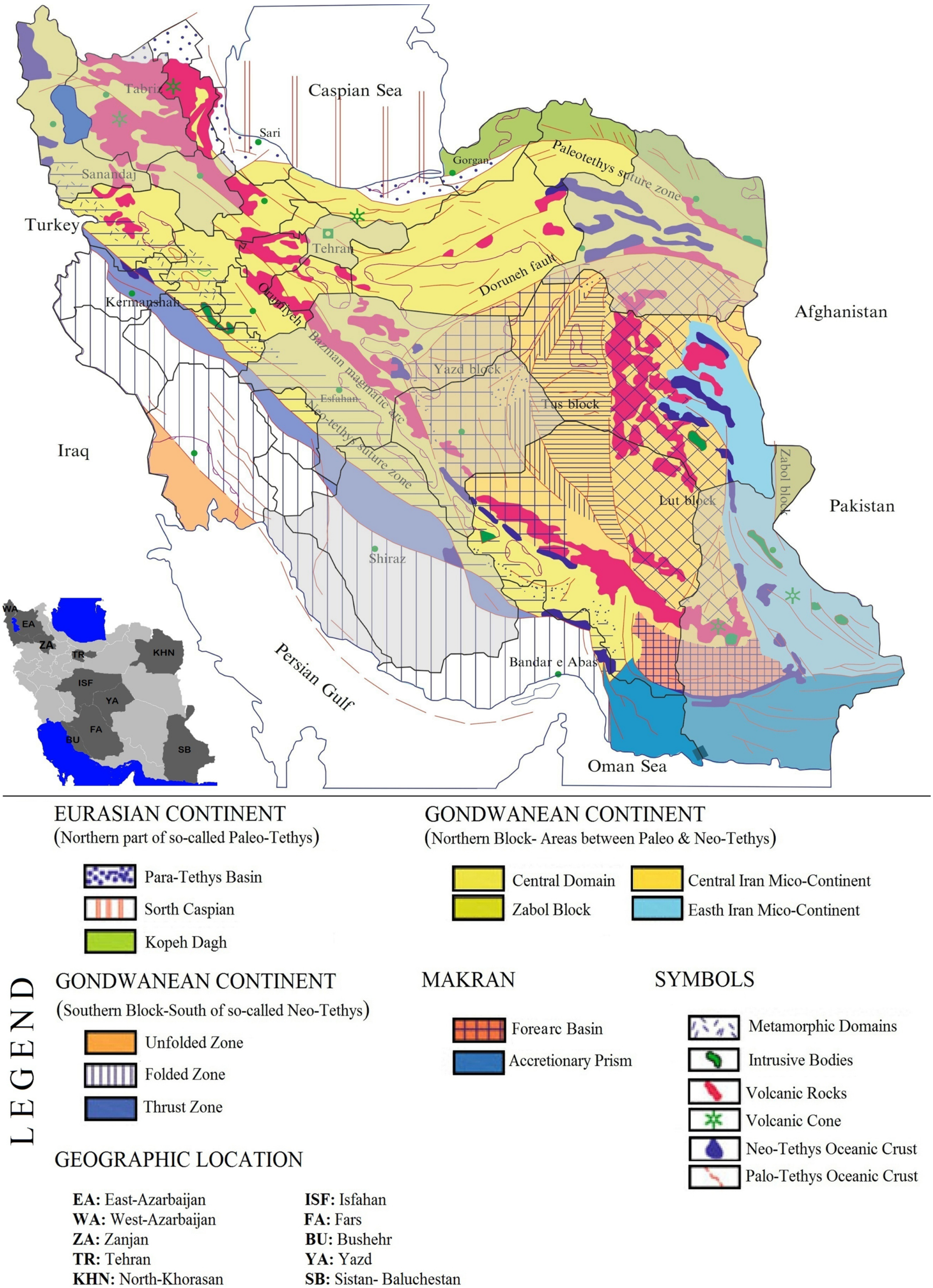

Fig. 2. The geographic location of the studied regions as plotted on the geo-lithological and tectostructural map (Adapted from Ghorbani, 2013).

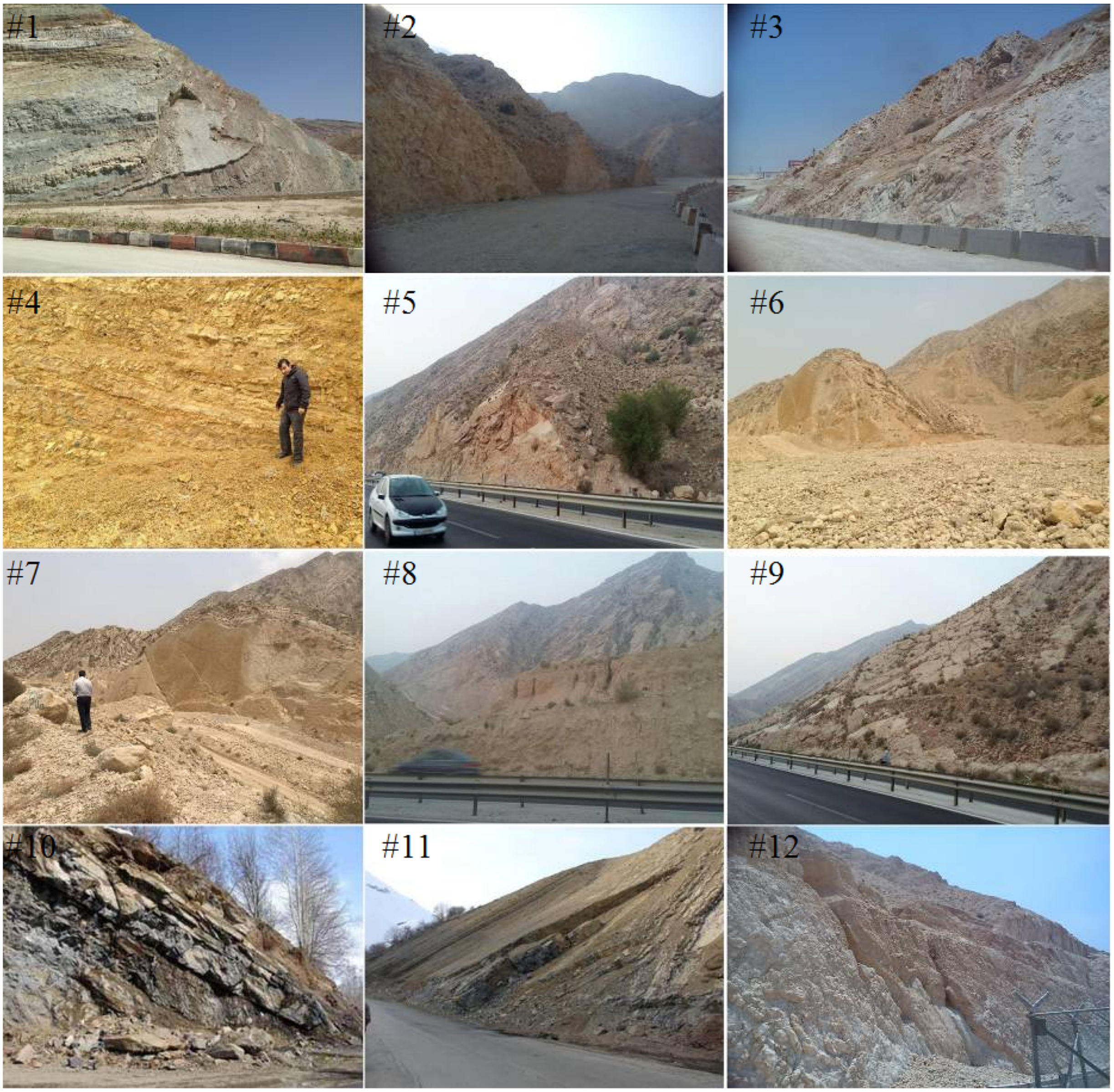

Fig. 3. An overview of several selected slopes (stable, unstable and uncertain) that represent a brief part of the field surveys (Note: Table 2 outlines the stability characteristics of each slope).

requires an assignment of the parametric values. The values contain block size (RQD/J_n), shear force element (J_r/J_a) and external loading/stress factor (J_{wice}/SRF_{slope}) as presented by Eqn. (1) (Bar and Barton, 2017). Azarafza et al. (2017d) and Jordá-Bordehore (2017) state that the Q_{number} can be determined by using engineering judgement, and slopes could be scored for each parameter.

$$Q_{number} = \frac{RQD}{J_n}\left(\frac{J_r}{J_a}\right)_0 \frac{J_{wice}}{SRF_{slope}} \quad (1)$$

where RQD is the rock quality designation, J_n is the discontinuity set number, J_r is the discontinuity roughness number, J_a is the discontinuity alteration number, J_{wice} is the environmental and geological condition number, and SRF_{slope} is the strength reduction factor. The SRF_{slope} factor is divided into three parts, namely, SRF_a: physical condition number, SRF_b: stress and strength number, and SRF_c: major discontinuity number.

2. The objective of the study

The territory of Iran has a complex tectonic, geologic and geomorphological setting (Aghanabati, 2006; Rahnamarad et al., 2008; Damani Gol et al., 2016). Geomorphologic and structural changes have led to the appearance of very different rocky outcrops. These features have led to slope instabilities in surface cuts related with construction projects, especially road/railway projects where the presence of these types of instabilities seemed more frequent than the other types of failures. In these cases, the application of the classical and conventional methods of stability determination may create a range of computational errors. Therefore, the use of any empirical classification requires adaptive implementation based on an inclusion of particular assumptions. So far in Iran, there is no widespread use of the Q-slope rating for sustainability analysis. The primary objective of this study is to provide improved stability relationships and the use of the Q-slope classification in Iran for the interconnected sedimentary rock slopes. In this regard, the

Table 2
The main parameters of the several selected slopes from Fig. 3.

#[†]	Location	Geology	Tectostructural related zone	Sedimentary units	Slope height (m)	Slope angle (°)	Q_{Number}	Stability zone[‡]	Stability chart	Failure mode
#1	Yazd	Darreh-Zanjir-Taft Formations	Central Iran	Marly limestone	55	73	0.93	Uncertain	Uncertain	Wedge
#2	Bushehr	Aghajari Formation	South-Zagros	Calcareous clayey marlstone	63	45	0.37	Stable	Stable	–
#3	Bushehr	Aghajari Formation	South-Zagros	Calcareous marl	64	39	0.71	Stable	Stable	–
#4	East-Azarbaijan	Baghmesh Formation	Azarbaijan	Marlstone	110	81	1.13	Unstable	Uncertain	Wedge
#5	Fars	Gachsaran Formations	East-Zagros	Calcareous clayey marlstone	100	66	0.56	Uncertain	Uncertain	Wedge
#6	Bushehr	Aghajari Formation	South-Zagros	Marly limestone	92	70	1.90	Stable	Stable	–
#7	Bushehr	Aghajari Formation	South-Zagros	Marly limestone	37	88	2.31	Uncertain	Unstable	Toppling
#8	Fars	Pabdeh-Gurpi Formations	East-Zagros	Clayey limestone	100	47	0.35	Uncertain	Stable	Wedge
#9	West-Azarbaijan	Mila Formation	Azarbaijan	Marly limestone	85	37	0.075	Stable	Stable	–
#10	East -Azarbaijan	Dalichai-Lar Formations	Azarbaijan	Limestone	17	85	2.40	Unstable	Unstable	Toppling
#11	Zanjan	Qom Formation	West-Alborz	Limestone	17	74	1.03	Uncertain	Uncertain	Planar
#12	Bushehr	Aghajari-Mishan Formation	South-Zagros	Clayey marlstone	47	63	0.47	Uncertain	Unstable	Wedge

[†] The symbol indicates the slope number in Fig. 3.
[‡] The stability zone represents the location of the slope in the modified chart in Fig. 11 by which the stability chart represents the location of the slope in the Bar and Barton (2017) chart.

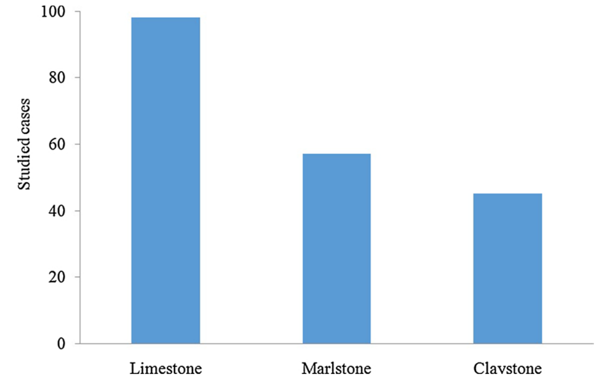

Fig. 4. Lithological description of the sedimentary rock masses in the studied slopes showing the three different rock types.

Table 3
Geomechanical survey points investigation data.

Parameters	Properties	Description
Slope geometry	Height	8-120 m
	Inclination	Suitable to unsuitable
	Topography	Mostly rough
Discontinuity network	Orientation	Suitable to unsuitable
	Spacing	Suitable to unsuitable
	Infilling	Mostly clay
	Roughness	Mostly smooth to moderate
	Continuity	High
Failure modes	Wedge	High frequency
	Planar	Moderate frequency
	Toppling	Low frequency
Stability	Stable	60%
	Unstable	40%

use of geo-engineering methods (i.e., support requirement relation or steepest slope angle (β) from Bar and Barton, 2017 (Eqn. (2)) is likely to be accompanied by errors. For this reason, this study offers corrected relationships of Q-slope for the mountainous slopes of Iran that consist of sedimentary units such as limestone, marl, and claystone.

$$\beta = 20\log_{10}(Q_{number}) + 65 \quad (2)$$

In this study, we have estimated the geometric and geomechanical properties of about 200 slopes in the field. The information collected included location, geology, tectonostructural related zones, sedimentary units, slope height (m), slope angle, discontinuity condition, failure mode and measurements and characterisation of rock mass discontinuities to determine the RQD of the rock masses. RQD is a measure of the quality of rock core taken from a borehole that signifies the degree of jointing or fracture in a rock mass measured in percentage (Deere and Deere, 1988). In the field studies, we were not able to perform core drilling to determine the RQD directly. For this purpose, we obtained the equivalent RQD and then the average RQD from six different methods which are mentioned in Hudson and Harrison (1997); Brady and Brown (2005); Zhang (2005); Hoek (2006); Palmstrom (2010); Goel and Singh (2011); Sivakugan et al. (2013) and Zhang (2016). For estimation of the RQD from the surface (i.e., from the rock mass outcrop in the absence of boring data), the typical empirical relationships shown in Table 1 that represent mean values were utilised. The mean RQD was estimated from the outcrop of each rock slope based on discontinuity orientation and density. The RQD was used for the computation of the Q-slope (Q_{number}) value by utilising Eqn. (1). In addition, the discontinuity and geometrical characteristics, including the dip, dip direction, spacing, roughness, seepage condition, etc. (Hudson and Harrison, 1997) and the discontinuity frequency (λ) and

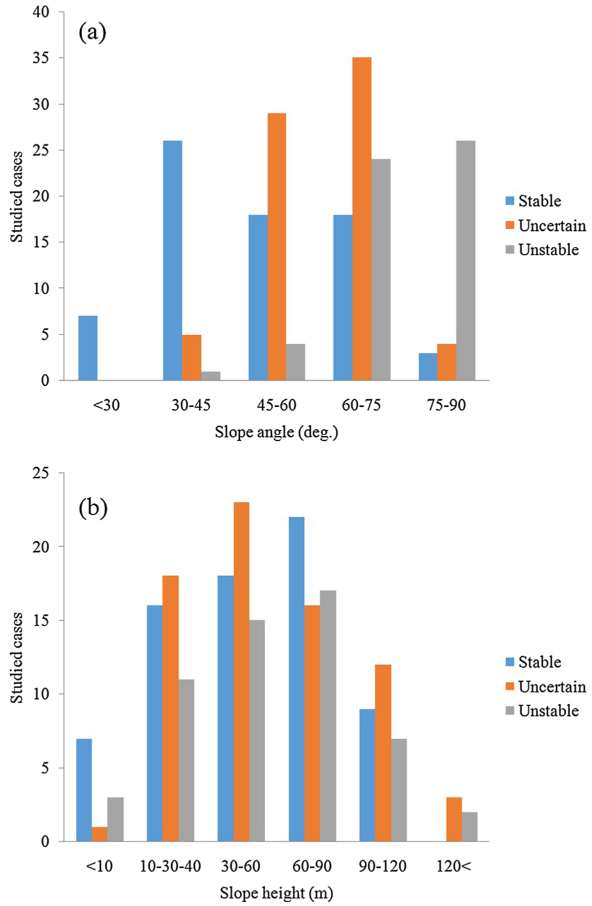

Fig. 5. The data-set from the studied areas for the Q-slope main parameters: (a) slope angle variation data-set, (b) slope height variation data-set.

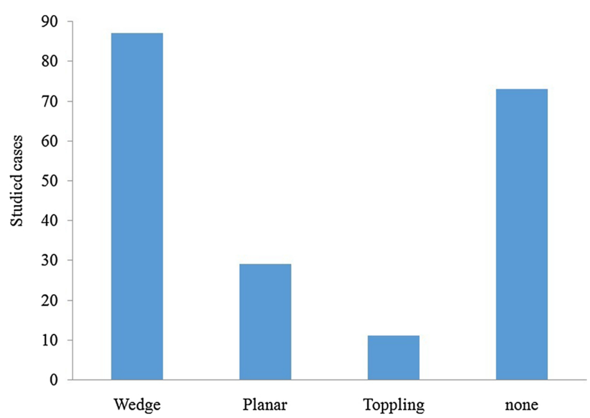

Fig. 6. The failure modes of the slopes.

the volumetric joint count (J_v) parameters (Palmstrom, 2005; Palmstrom and Broch, 2006) were determined. The measured parameters along with the determined RQDs were used in Eqn. (1) to estimate the Q_{number}. The Q_{number} was also determined by using the ratings listed in the tables provided by Bar and Barton (2017). Fig. 1 presents the Q-slope stability chart. By plotting the results of the studied slopes on the map, the slope instability was assessed and the sustainability data-set was created for the site. In this study, by using supervised learning models such as the k-nearest neighbours (k-NN), support vector machine (SVM), Gaussian process (GP), Decision tree (DT), Random-forest (RF), Multilayer perceptron (MLP), AdaBoost, Naive Bayes (NB), Quadratic discriminant analysis (QDA) (Russell and Norvig, 2009) and the data-set prepared for the sedimentary rock slopes in Iran, a modified support requirement relation was developed. The basic Eqn. (2) was used for the Q-slope separator line (Bar and Barton, 2017) and was modified for two limitations, which is represented by the modified separator lines for slope stability assessment.

3. Methodology of the study

In machine learning, supervised learning models are used for high-order regression analysis and for the classification of extensive information based on coupled learning, data mining and data analysis algorithms. The foundation of the controlled learning models/classifiers is data-clustering and data-classification. The model attempts to determine the best-fit in a quadric hypersurface with a more positive margin. We have used the application of the optimal line equation for the studied data by methods such as QP for pattern recognition of broad and distributed data which indicates the spatial distribution status of points related to different clusters and information gaps. In this regard, before linear/non-linear approximation clustering, data must be transferred to the high dimensional space by using the phi function. The machine can classify highly complex data. The utilisation of the proximity search algorithms to identify the best detachment for the data sets is efficiently helpful for pattern recognition and classifications.

In this study, we have used supervised learning models and have evaluated and categorised the 200 sedimentary rock slopes using field data. These models have been implemented in the Python programming language (Chollet, 2017; Raschka and Mirjalili, 2017). The utilised algorithms have been conducted in different concepts. They contain k-NN (k-NN is a type of lazy learning where objects are classified by plurality vote of their neighbours), SVM (SVM is a supervised learning model to analyse data by using the probabilistic binary linear/non-linear classifiers), GP (GP is a lazy learning based stochastic process where every finite collection of those random variables has a multivariate normal distribution), DT (decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences), RF (RF is a random decision forest that is an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees), AdaBoost (AdaBoost or Adaptive Boosting is a machine learning meta-algorithm in the sense that subsequent weak learners are tweaked in favour of those instances misclassified by several classifiers which is sensitive to noisy data and outliers), MLP (MLP or Multilayer perceptron is an algorithm for supervised learning of binary classifiers), NB (NB or naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features), QDA (QDA or quadratic classifier is used in machine learning and statistical classification to separate measurements of two or more classes of objects or events by a quadric surface) which have all been utilised for the classification and regression analysis of the Q-slope results for each slope. For this purpose, the Q-slope results were first plotted on the Bar and Barton (2017) chart followed by the identification of the existing variations that are related to ground data and re-categorisation by the learning algorithms. The mentioned parametric/non-parametric algorithms were used globally for the classification, regression and pattern recognition assessment, which were mainly considered to generate realistic relations in the modification of the Q-slope system. The aim of utilising several classifier algorithms was to achieve the best relationship with high accuracy and precision. To accomplish this task, initially, all of the studied slopes (200 cases) were considered, and the Q-slope parameters of each slope were determined. The results were applied to the mentioned artificial intelligence classifiers, and the best fits were evaluated for stable, unstable and uncertain status, which were grouped by the U-line and B-line relations. These relationships represent the modified limits for the Q-slope chart. In Fig. 1, it can be observed that the β-relation is presented for the district separation of

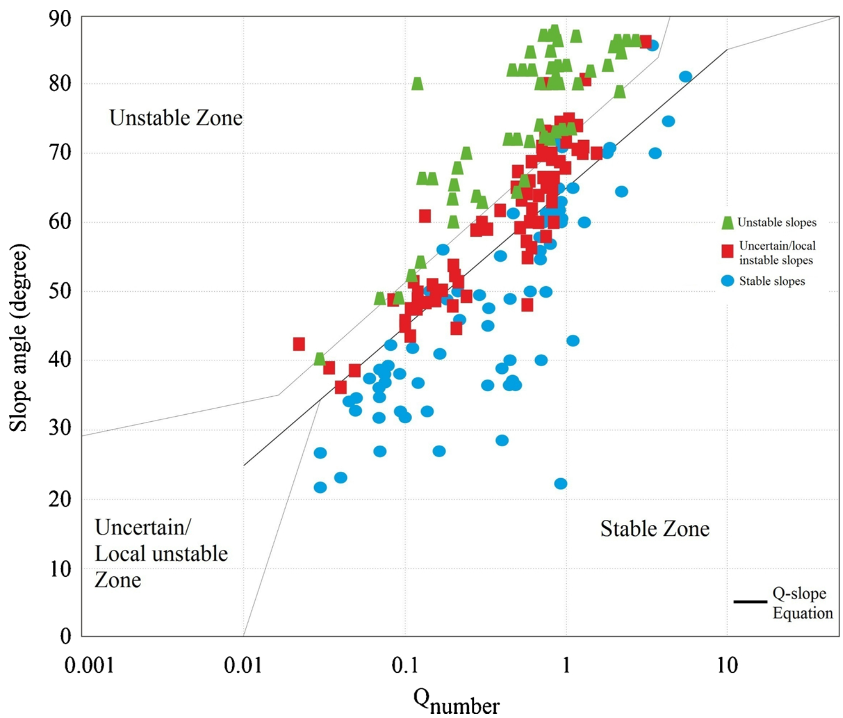

Fig. 7. The results of the stability of the studied slopes based on the Bar and Barton chart (Bar and Barton, 2017).

stable areas from uncertain areas. This study presented two limits referred to as the U-line and B-line which were used to separate the stable/uncertain/unstable zones. These limits were estimated with a 97% accuracy related with the k-NN methodology.

4. Investigation areas

Iran is considered as the largest Middle Eastern country with an extremely diverse climate, geology, tectonics, earthquake activity and paleogeology status (Aghanabati, 2006). The central plateau in the region covers an area of approximately 2,600,000 square kilometres, which includes Afghanistan and Pakistan. Of this area, about 1,648,195 square kilometres is related to Iran. In different geographic locations, various geological transformative processes can be observed which has created a wide variety of morphotectonic features, especially escarpments, landscapes and horst-grabens (Rahbar et al., 2017).

These activities have created various rock slopes of which two hundred of them from 10 different regions of Iran, namely East-Azarbaijan, West-Azarbaijan, Zanjan, Tehran, Isfahan, Fars, Bushehr, Yazd, North-Khorasan and Sistan- Baluchestan, respectively, have been evaluated by Q-slope which was initially developed by Bar and Barton (2016). Fig. 2 shows the approximate locations of the mentioned regions in Iran which are plotted on the geo-lithological and tectostructural map of the country (Adapted from Ghorbani, 2013). The ten regions and the studied slopes have been chosen to represent the main tectonic structures of the Iran platform such as Zagros, Alborz, Sanandaj-Sirjan, Central plate, Taftan and the Southeast Mountains of Iran. Fig. 3 shows views from some of the slopes which are used in this work for primary slope stability assessment by Q-slope. An example of a Q-slope based assessment process is presented in Fig. 3 and its characteristics are given by Table 2. The slopes present different discontinuity networks in rock masses, due to their tectonic background. They are mostly located in sedimentary rock masses (Fig. 4). Because calculations and investigations were carried out mainly in sedimentary rocks, most geotechnical failures occurred in such rocks. In the field survey processing stage, the Q-slope requirements were recorded for each slope and the Q_{number} was calculated based on the block size, shear force element and external loading/stress factors and the tables from Barton and Bar (2015). To this end, the main parameters such as J_n, J_r, J_a, J_{wice} were extracted for each slope and by application of the tables, the results presented by Figs. 4–6 were obtained.

5. Stability analysis by the Q-slope system

The geomechanical investigation data that covers 200 field records is presented in Table 3. The data-set presented in Fig. 5 has been obtained from the examined slopes for determining the main parameters of the Q-slope system. The kinematic analysis results and the expert system for the ruptured states of the examined slopes are shown in Fig. 6. The data related with the slopes were mainly recorded in the spring and summer (March-September) in 2018, and mostly on sunny days. Obtaining the data for the 200 cases required detailed field investigations. In addition, some previous ground data from several slopes have also been used to complete the comprehensive surveys. Hence, the effect of the seasonal changes and rainfall in the slopes were not studied. The Q-slope parameters were estimated based on the tables of Bar and Barton (2016, 2017) in the field from the studied cases.

Fig. 7 shows an evaluation of the results on the Bar and Barton (2017) stability chart. The relationship between support requirement relations required corrections. To find the best linear fit for determining the β-limit in Fig. 7, the data utilised was re-arranged by supervised learning models (Russell and Norvig, 2009). The upper and lower limits of the data were identified by the algorithms to determine the β-relation for the sedimentary rock slopes in Iran with high accuracy. The accuracy coefficient of each classifier is presented along with the results in Fig. 8 and Table 4. In Fig. 8, each algorithm is applied to the input data, which we have estimated from the ground survey, and control parameters, and the accuracy of the assessment was evaluated. In addition, in Fig. 9, the upper limit, U-Line, and the lower limit, B-Line, are provided for uncertainties, which can be reassessed for these support requirement relations for Iran. These fits, U-line and B-line, were calculated based on the results of the learning models that were prepared from the intelligence techniques and then estimated for each class. The information retrieval contexts and the results of the retrieved

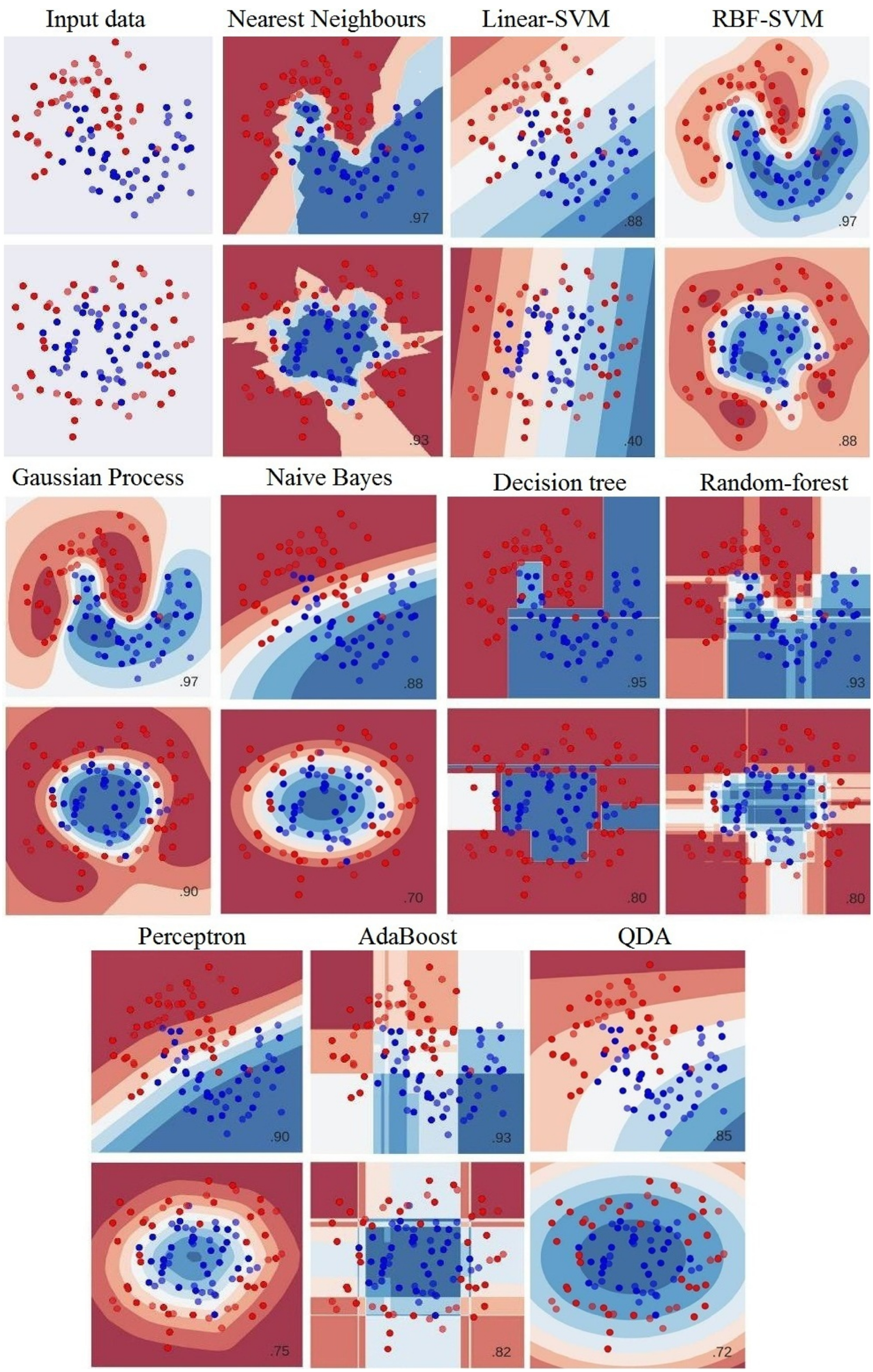

Fig. 8. The results of the artificial intelligence techniques implementation for Q_{number} distribution (k-NN, SVM, Gaussian process, Decision tree, Random-forest, Multilayer perceptron, AdaBoost, Naive Bayes, QDA).

Table 4
The controlled learning model results for the Q-slope system implementation.

Classifier	Parameter	Assessment score (%)				Accuracy
		Precision	Recall	f1-score	Support	
k-NN	Stable	0.80	0.71	0.75	17	0.97
	Unstable	0.50	0.62	0.55	13	
	Uncertain	0.67	0.60	0.63	10	
	Ave./Total	0.67	0.65	0.66	40	
SVM	Stable	1.00	1.00	1.00	10	0.88
	Unstable	0.79	0.69	0.73	16	
	Uncertain	0.69	0.79	0.73	14	
	Ave./Total	0.80	0.80	0.80	40	
Gaussian process	Stable	0.95	0.93	0.94	10	0.90
	Unstable	0.89	0.88	0.89	16	
	Uncertain	0.76	0.73	0.77	14	
	Ave./Total	0.90	0.87	0.90	40	
Decision tree	Stable	1.00	1.00	1.00	17	0.95
	Unstable	0.97	0.95	0.95	13	
	Uncertain	0.88	0.97	0.85	10	
	Ave./Total	0.95	0.80	0.95	40	
Random-forest	Stable	1.00	1.00	1.00	17	0.93
	Unstable	0.71	0.77	0.74	13	
	Uncertain	0.67	0.60	0.63	10	
	Ave./Total	0.82	0.79	0.82	40	
Multilayer perceptron	Stable	1.00	1.00	1.00	17	0.90
	Unstable	0.73	0.62	0.67	13	
	Uncertain	0.58	0.70	0.64	10	
	Ave./Total	0.81	0.80	0.80	40	
AdaBoost	Stable	1.00	1.00	1.00	17	0.93
	Unstable	0.90	0.69	0.78	13	
	Uncertain	0.69	0.90	0.78	10	
	Ave./Total	0.89	0.88	0.88	40	
Naive Bayes	Stable	1.00	1.00	1.00	17	0.88
	Unstable	0.77	0.77	0.77	13	
	Uncertain	0.70	0.70	0.70	10	
	Ave./Total	0.85	0.85	0.85	40	
QDA	Stable	1.00	1.00	1.00	17	0.85
	Unstable	0.79	0.85	0.81	13	
	Uncertain	0.78	0.70	0.74	10	
	Ave./Total	0.88	0.88	0.88	40	

documents are presented in Table 4. The confusion matrix that is related with the retrieved documents (i.e., precision, recall, f-measure or balanced f-score) and the accuracy of the implemented algorithms is presented in Fig. 10. In addition to these fits, the separation lines from the stable, unstable or uncertain areas in the modified Q-chart have been prepared for all of the 200 slope cases.

A plot of the slope coordinates on the Bar and Barton (2017) chart that is presented by Fig. 7 reveals that the stability results from the β relation does not cover the instability limits for the cases presented for Iran. This difference can be attributed to the geological, tectonic, climatic and morphological conditions of the Iran platform. As implemented by the controlled learning model in Fig. 8, the B-line and U-line can be described by using a regression analysis to indicate the modified limits for the instability factors in the Bar and Barton (2017) chart. These relations are considered as a β value to separate the stable, unstable and uncertain zones in the modified Q-slope chart. The results of the regression analysis are presented in Fig. 9, where the β-relation for the Iranian slopes is expressed as follows:

$$\text{B}-\text{ Line: } \beta = 11.9\log_{10}(Q_{number}) + 46.3 \quad (3)$$

$$\text{U}-\text{ Line: } \beta = 17.2\log_{10}(Q_{number}) + 54.1 \quad (4)$$

Fig. 9 presents the parametric distributions of the Q-slope system related data which is proposed to determine the upper and lower bounds/boundaries of the Q_{number} based stability assessment. Eqs. (3) and (4) have aided in setting the stability limits and to more accurately determine the status of the stability of the discontinuous sedimentary rock slopes based on simple assumptions. In other words, the U-line and B-line present the modified instability-stability limits for the Bar and Barton (2017) original chart (Fig. 1) for stable-unstable rock slopes based on the Q-system assumptions. After the implementation of the modified Q-slope chart and preparation of the modification limits (U-line and B-line) for accurate separation of the stability-unstability classes, the slopes have been plotted in the refined chart that is presented by Fig. 11. As seen in Fig. 11, several changes have been created in the slope stability identifications which are further presented by Fig. 12. According to Fig. 12, the modified Q-slope chart appears to be more conservative for the lower and upper limits (B-line/U-line). For example, in some circumstances, the estimated stability status of the slopes in the Q-slope chart are classified as 'Stable' whereas in the modified chart the slopes are classified as 'Uncertain' which implies that the lower limit (B-line) of the modified chart is conservative as compared to the original Q-slope chart. On the other hand, the U-line is known for the detachment of the uncertain and unstable zones which is used for classification of instable slopes and questionable circumstances (i.e., local failure of the slope may occur, but globally, the slope may be stable. Such situations are important under rainfall or earthquake conditions). Thus, a conservative approach leads to the labelling of these 'Uncertain' classes or sensitive slopes as 'Unstable' classes in the Q-slope chart that is modified in this study. The stability status in both classifications based on the B-line and U-line (a total of 3 discrepancies identified) represents more accuracy in lower-upper limits evaluation in regards to the instability analysis of the Iranian sedimentary rock slopes. The estimated accuracy for these limitations covers 97% accuracy according to the k-NN algorithm and 95% precision according to the DT algorithm.

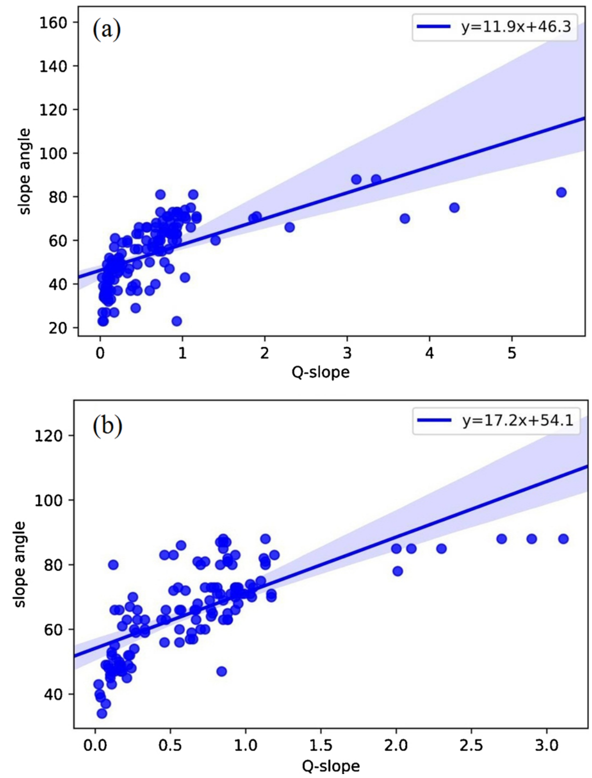

Fig. 9. The B-line/U-line estimation by using regression analysis: (a) B-line regression, (b) U-line regression.

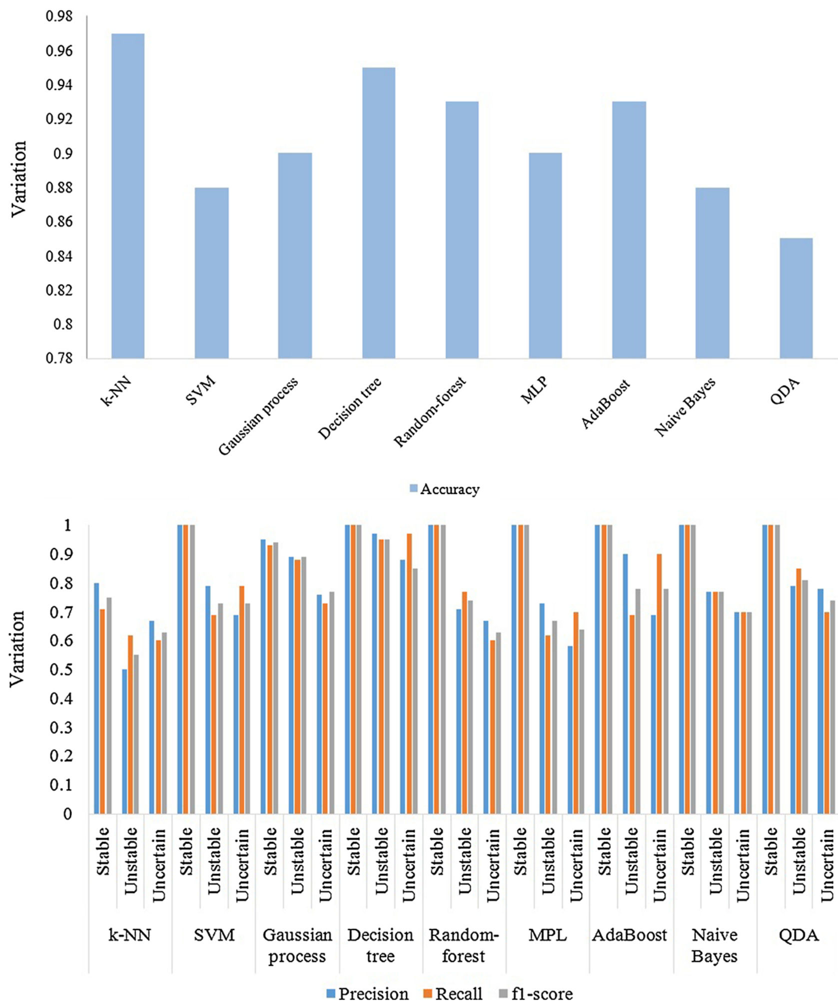

Fig. 10. The confusion matrix for the retrieved documents.

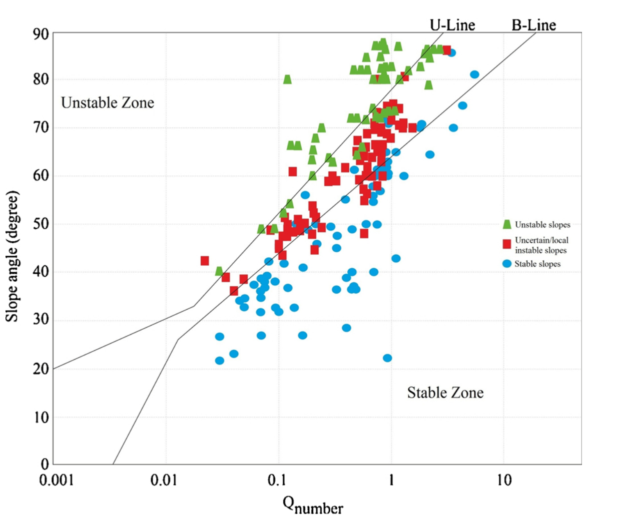

Fig. 11. The results of the classifier algorithms implementation for sedimentary rock slope stability correction in Iran.

6. Conclusions

Q-slope system is an empirical method for engineering classification and for the rapid assessment of the sustainability of discontinuous rock slopes based on engineering judgement that can be used as a preliminary assessment in the field investigation stage. The Q-slope method relies on engineering geological and field geological experience by using engineering judgment like other empirical methods to analyse the stability of mountainous slopes. Classical stability analyses are associated with uncertainties, and their outcomes may lead to non-engineering impacts on design and construction. In this study, the authors have implemented the Q-slope system to the sedimentary rock slopes of Iran to provide a correlation relationship for Q-slope and the stability degree of the slopes. For this purpose, 200 slopes from 10 regions of Iran that represent the tectonic structures of the Iran platform such as Zagros, Alborz, Sanandaj-Sirjan, Central plate, Taftan and the Southeast Mountains have been evaluated by the Q-slope method, and controlled learning models have been used for obtaining a correlation. According to the results of the controlled learning models, the relationship obtained for Iran has indicated that the instability class distribution is limited to two linear states which are referred to as the U-Line (upper limit) and the B-Line (lower limit). These relationships were inserted into the Q-slope primary relationship which led to obtaining a modified Q-slope relationship for Iran. The B-line presents the boundary of stability and uncertain area based on the Q_{number} and the U-line presents the critical state for rock slope stability where instability has occurred.

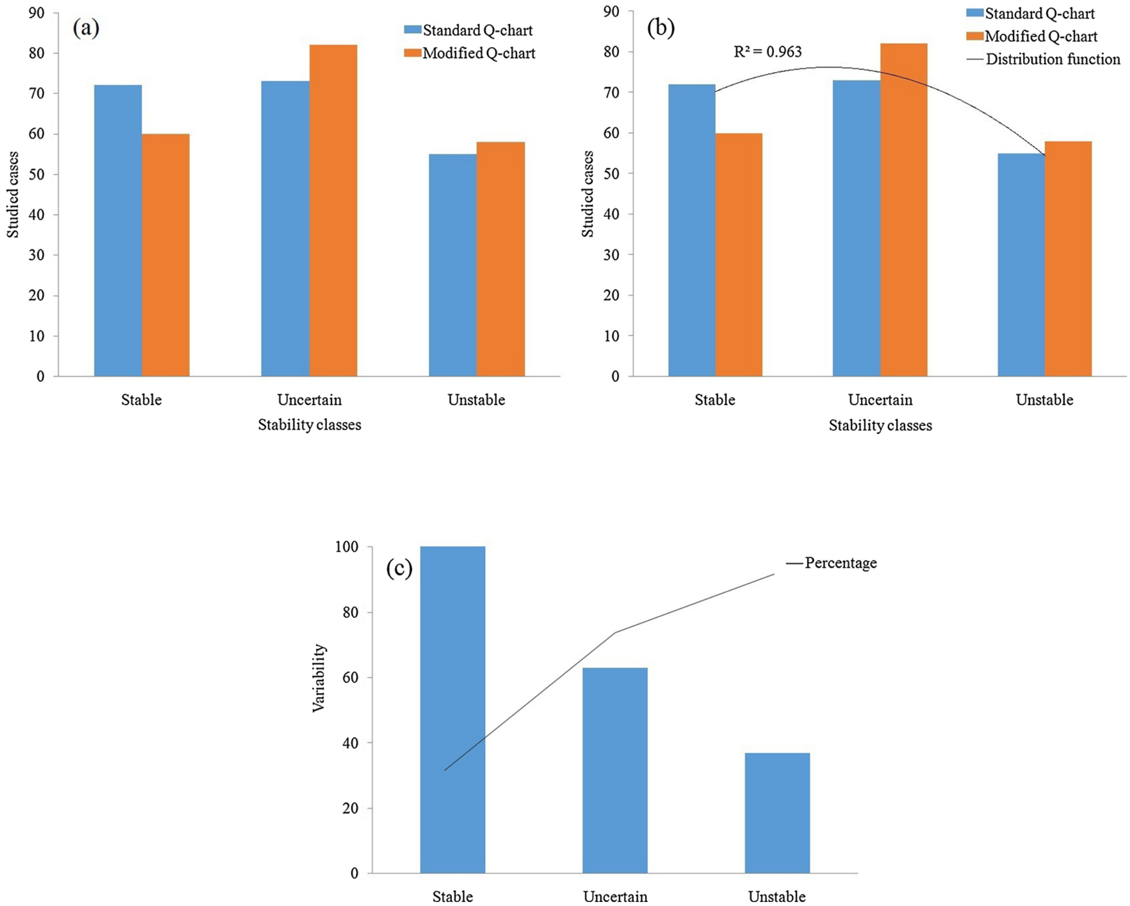

Fig. 12. The results of the variability analysis for the modified Q-chart: (a) standard and modified results discrepancy, (b) variation's distribution function, (c) accuracy percentage of variability evaluation (The term "standard" implies the Bar and Barton (2017) chart in Fig. 1).

Declaration of Competing Interest

There are no conflicts of interest.

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