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STABILITY CONDITIONS EVALUATION OF SLOPE BY MULTIVARIATE ANALYSIS

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ABSTRACT
Technological advances have contributed to applications of nonparametric methodologies. The objective of this paper was to determine a discriminant function capable of predicting the stability condition of the slopes of the database under study. It is important to note that the methodology does not replace the stability analysis, but it can work very well for a preliminary analysis by selecting the slopes that must be intervened. The database used is composed by 59 slopes. A combination of multivariate statistical techniques, specifically principal component analysis and discriminant analysis, was used to determine the slope stability condition. The cross validation presented a global probability of success of 89.83%, the errors obtained in the cross validation were in favor of safety, with 5 stable slopes classified as unstable and only 1 unstable slope classified as stable. In the external validation were used 12 new slopes, which 8 slopes were correctly classified correctly.

KEYWORDS: Stability condition prediction, Multivariate analysis, Principal component analysis, Discriminant analysis, Non-parametric techniques.

AVALIAÇÃO DAS CONDIÇÕES DE ESTABILIDADES DE TALUDES POR MEIO DE ANÁLISES MULTIVARIADAS

RESUMO
Os avanços tecnológicos têm contribuído para aplicações de metodologias não paramétricas. Este trabalho teve como objetivo determinar uma função discriminante capaz de prever a condição de estabilidade dos taludes do banco de dados em estudo. Importante observar que a metodologia não substitui a análise de estabilidade, mas pode funcionar muito bem para uma análise preliminar selecionando os taludes que devem ser intervindos. O banco de dados utilizado é composto por 59 taludes. Para determinação da condição de estabilidade dos taludes foi utilizada uma combinação de técnicas da estatística multivariada, especificamente a análise de componentes principais e a análise discriminante. A validação cruzada apresentou probabilidade global de acerto de 89,83%, os erros obtidos na validação cruzada foram a favor da segurança, sendo 5 taludes estáveis classificados como instáveis e apenas 1 talude instável classificado como estável. Já na validação externa foram utilizados 12 novos taludes, dos quais 8 taludes foram classificados corretamente.

PALAVRAS-CHAVE: Condição de Estabilidade, Análise Multivariada, Análise de Componentes Principais, Análise Discriminante, Técnicas não Paramétricas.

1 INTRODUCTION

Slope failures are complex natural phenomena that constitute a serious natural hazard in many countries (Wang et al., 2005). They are responsible for hundreds of millions of dollars of damage to public and private property every year (Wang et al., 2005). Figure 1 shows an example of a 165 m high mine slope failure. Currently, new methodologies to approach the problem are frequently proposed in the literature, such as Wang et al. (2005), Zare Naghadehi et al. (2013), Santos et al. (2018), Feng et al. (2018).

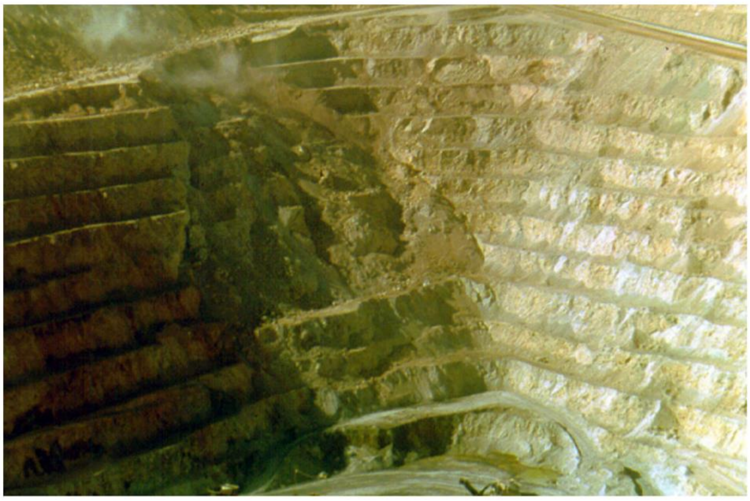

Figure 1: Mine slope failure (Hoek et al., 2000).

Studies related to slope failures are traditionally carried out by stability analyzes such as Ordinary (Fellenius, 1936), Janbu (1954), simplified Bishop (1955), Morgenstren and Price (1965) and Spencer (1967). The technological advances in data acquisition and processing prioritize the application of probabilistic approaches in detriment to deterministic ones, in addition to presenting more precise results. In the same line of research, technological advances contribute to the applications of non-parametric methodologies for predicting slope stability conditions, which differs from the determination of safety factors.

Several studies in the literature have presented solid methodologies for predicting slope stability conditions. Santos et al. (2018) proposed a methodology for predicting mine slope stability conditions using a multiclass boosting algorithm via discriminant function, in this case for three types of stability conditions. Zare Naghadehi et al. (2013) proposed the MSII a mine slope stability index obtained through artificial neural networks with Rock Engineering Systems (RES) parameters proposed by Hudson (1992). Ferentinou and Fakir (2018) used artificial neural networks to select parameters and later predict slope stability conditions. Silva et al. (2018) used a set of multivariate analysis techniques for slope sectorization.

According to Feng et al. (2018) recently, soft computing methods, such as Artificial Neural Networks (ANNs) and Support Vector Machine (SVM), have been increasingly applied to predict slope stability such as works of Wang et al. (2005), Gordan et al. (2016), Li and Kong (2014), Rukhaiyar et al. (2017), Xue (2017). Thus, this paper presents the application of a methodology, based on multivariate statistical techniques, to determine a discriminant function capable of predicting slope classification, according to stability condition. The methodology applied resembles that proposed by Santos et al. (2018).

The database used in this research for created of model was compiled and organized by Feng et al. (2018), from 59 slopes subject to circular failure, resulting from the compilation of databases of Feng (2000), Sah et al. (1994), Wang et al. (2005), Xu et al. (1999), Zhou and Chen (2009). Another database (new database) also compiled by Feng et al. (2018) was used to validate the model. This new database used for external validation was obtained from 12 case of literature that were not included in the training data set, and resulting from the compilation of databases of Hoek and Bray (1981), Lin et al. (1988), Madzic (1988), Yan and Li (2011).

The database of Feng et al. (2018) is result of compilation published articles and books, which encompass many worldwide, slope stability case histories, for example natural slope and open pit mine. Information from the database used in this study is wide and it was representative of many different situations all over the world. The different types of slopes that make up the database in studies reinforce the premise of generalizing the proposed model.

2 MATERIALS AND METHODS

The database used in this research is composed of 59 slopes with variables relevant parameters in slope stability analysis with circular failure. The database parameters are geometry of the slope slope height H (m) and slope angle α; shear strength of the geomaterial: cohesion (kPa) and friction angle ϕ; gravity: unit weight γ (kN/m³) and water condition: pore pressure ratio ru, which is defined as the ratio of the pore pressure to the overburden pressure. In addition to these variables, there is information about the stability condition of the slopes and the current safety factor, which allowed the evaluation of the results obtained.

To determine the slope stability condition, a combination of multivariate statistical techniques with specific objectives was used. The first technique used was the principal components analysis (PCA) and then the discriminant analysis in the scores of PCA. Figure 2 shows the flowchart of the applied methodology. The script developed for statistical techniques was implemented using R Development Core Team (2006) developed by Foundation for Statistical Computing, located in Vienna, Austria.

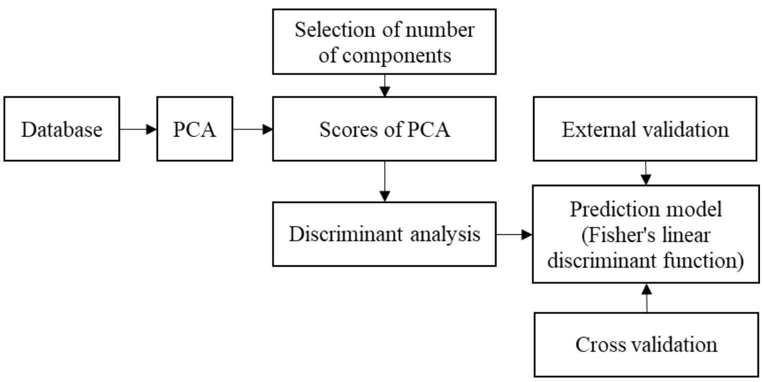

Figure 2: The flowchart of the applied methodology.

The PCA was used with the purpose of reducing the size of the database allowing the visualization of a model with two dimensions. The selection of the number of components for

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retention was performed based on the variance explained by each component, in addition to using the methods of Kaiser (1958) and Catell (1966).

Fisher linear discriminant analysis was applied to scores resulting from principal component analysis. From the discriminant analysis an equation was generated that limited the two slope populations, stable and unstable. In order to evaluate the quality of the generated discriminant function, two types of validation were applied: cross validation and external validation.

The cross validation consisted of the application of the discriminant function obtained in the slopes of the database, comparing the results and associated errors. The external validation consisted of the application of the discriminant function in new slopes, validation database, proposed by Feng et al. (2018). The main difference between the two types of validation is that cross-validation is influenced by the construction of the model, which is not verified by external validation, since new slopes are used.

The methodology used to determine the quality of the discriminant function is in agreement with Santos et al. (2018). The overall probability success (OPS) is determined based on the total number of correctly classified slopes. The errors from the discriminant function were of three distinct natures, being the apparent error rate (AER), the error rate at which an unstable slope is classified as stable (Error1), and the error rate at which a stable slope is classified as unstable (Error2). From the errors it is possible to evaluate the discriminant function. Table 1 and Equations (1) to (4) present a general analysis of the methodology of evaluation of the discriminant function.

Table 1: General analysis of the methodology of evaluation of the discriminant function.

Conditions	Stable (predicted condition)	Unstable (predicted condition)
Stable (real condition)	n_{11}	n_{12}
Unstable (real condition)	n_{21}	n_{22}

$$OPS = \frac{n_{11} + n_{22}}{n_{11} + n_{12} + n_{21} + n_{22}} \tag{1}$$

$$AER = \frac{n_{12} + n_{21}}{n_{11} + n_{12} + n_{21} + n_{22}} \tag{2}$$

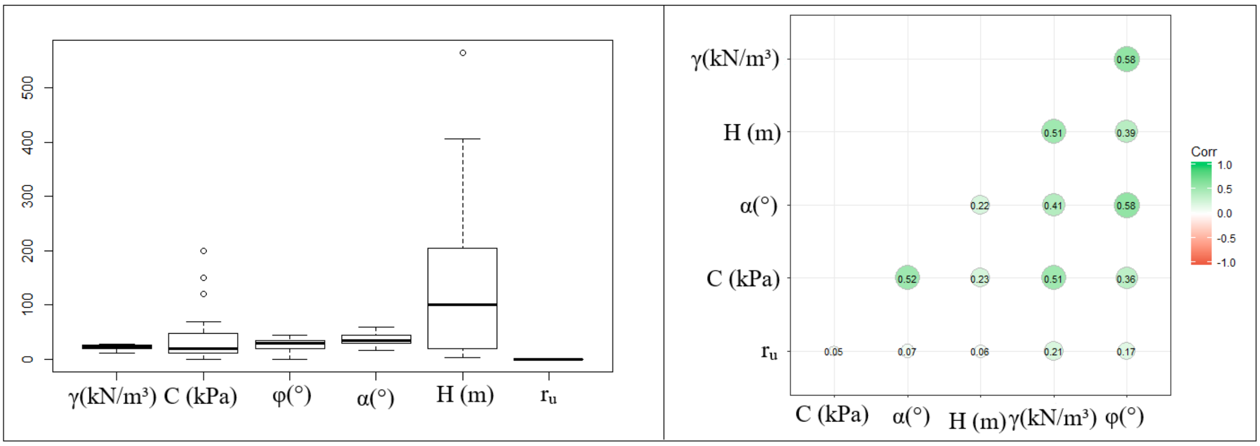
$$Error_1 = \frac{n_{21}}{n_{11} + n_{12} + n_{21} + n_{22}} \tag{3}$$

$$Error_2 = \frac{n_{12}}{n_{11} + n_{12} + n_{21} + n_{22}} \tag{4}$$

3 RESULTS AND DISCUSSIONS

For the analysis of the individual behavior of the variables the boxplot was done, which allows to evaluate the distribution of the values of the variables. From Figure 3 (a) it is possible to observe that the values of the variables under study follow a pattern. The only variable that presents a greater degree of scattering is the slope height variable, justified by the nature of the variable when compared to the others. Thus, in order to avoid the effect of the high variability of the variable height of the slope in the study, the determination of the main components was done by means of the correlation coefficient, which standardizes the variables eliminating any large influence by the variables with greater variability.

Figure 3 shows the correlogram, which was used to evaluate the correlation coefficients between the variables.



(a) (b)

Figure 3: (a) Boxplot of the variables; (b) correlogram of the variables.

In Figure 3(b), it is possible perceive consistency between the results of laboratory tests and the practices of building the slopes. High correlations between the variables specific weight and friction angle, cohesion and slope angle, specific weight and cohesion, friction angle and slope angle, specific weight with slope angle were verificated.

The high correlation between specific weight with friction angle and cohesion is justified by the fact that the specific weight represents the weight per unit of volume, that is, the larger the specific weight the more compact the grains, reflecting in a larger cohesion and friction angle between the particles.

Another point to be highlighted is that a soil that presents high cohesion and high friction angle admits higher values of slope angles. Therefore, the high correlations between slope angle with cohesion and friction angle were verified. Thus, the correlations between the variables in the database are justified.

The Bartlett sphericity test was applied in order to verify the existence of significant correlations among the variables, allowing the application of multivariate statistical techniques. Bartlett's sphericity test showed p-value less than 0.05, that is, with a 95% confidence level, it is possible to affirm that there are sufficient correlations for the application of the techniques and interpretation of the results (Table 2).

Table 2: Result of Bartlett's sphericity test.

Statistical parameter	Value
x_2	93.48
d_f	15
p-value	2.22×10^{-13}

Principal component analysis was applied in the database proposed by Feng, et al. (2018), generating 6 principal components. Table 3 presents the variability explained and accumulated by each principal component. It is possible to see that with only two components there is total variability explained of 63.2%.

Table 3: Variance explained by each component.

	1ª Comp.	2ª Comp.	3ª Comp.	4ª Comp.	5ª Comp.	6ª Comp.
Variability explained	46.4%	16.7%	14.7%	10.5%	7.0%	4.7%
Variability explained total	46.4%	63.2%	77.8%	88.3%	95.3%	100.0%

Figure 4 shows the screen plot of Catell (1966). Through it was possible to evaluate the sufficient number of components that can be retained based on the smoothing of eigenvector values. In addition, in the graph it was possible to apply the criterion of Kaiser (1958). Thus was are selected the components that have eigenvalues greater than 1, that is, maintaining the linear combinations that can explain at least the amount of variance of a standardized original variable.

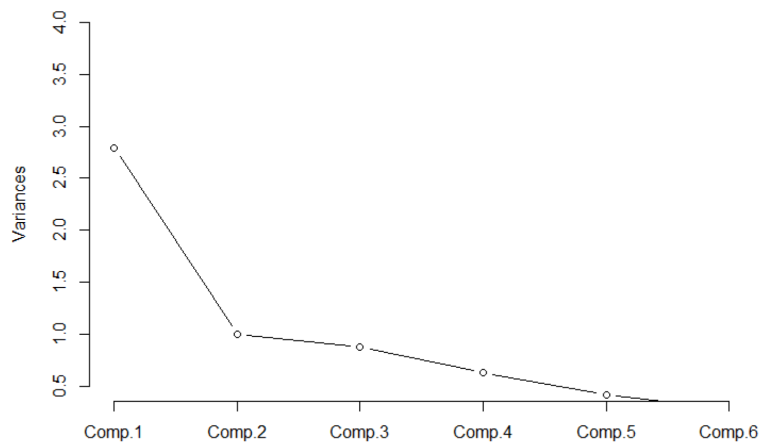


Figure 4: Screen-plot by Catell (1966).

From Figure 4 in conjunction with the explained variance analysis presented in Table 3, the number for principal component retention was 2 components. The first two main components together account for 63.2% of the total database variability and both have eigenvalues greater than 1.

In order to evaluate the retention of the two main components, the importance of the original variables in each component was analyzed from the loadings of the variables in each main component. Figure 5 shows the importance of the variables in the first and second principal components.

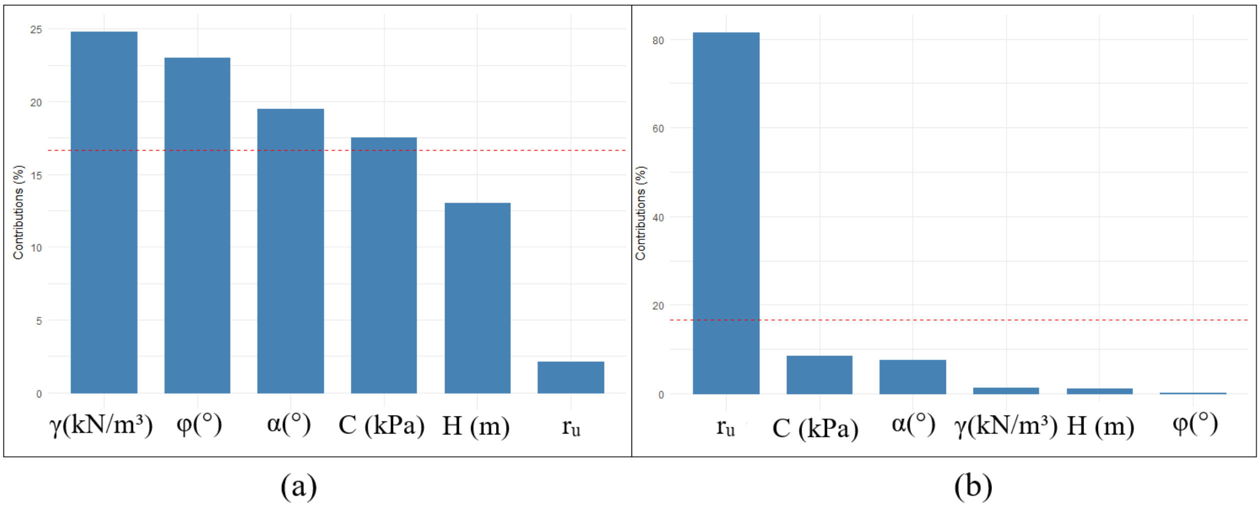


Figure 5: (a) Importance of variables in the 1ª Component; (b) Importance of variables in the 2ª Component.

The results of Figure 5 are related to the results of the correlogram in Figure 3. Still in Figure 5 it is possible to observe that the first component had representation of all variables, except for the pore pressure ratio (ru). The justification for choosing the second principal component, since the variable pore pressure ratio is highly related to this component balancing the choice of the two components. Thus, the choice of the first two principal components was based on the premise that all variables are represented in these components.

After the selection of the number of principal components, an analysis of the scores of the two components was performed. The multivariate normality test was performed and presented in Table 4, and it is possible to infer the multivariate non-normality of the two main components with a significance of 95%, due to the spreading of the data. The non-normality of the scores justifies the choice of Fisher's linear discriminant function.

Table 4: Result of the multivariate normality test (Royston test).

Statistical parameter	Value
H	17.21
p-value	0.0001823

Figure 6 shows the plot of the scores of the two main components, with slopes determinate by their stability conditions. The result of Figure 6 shows that the analysis of main components, through the selection of the first two components, was able to discriminate the slopes by their stability groups. Results similar to those found by Santos et al. (2018). From Figure 6 the choice of the discriminant analysis technique in the principal component analysis scores is justified.

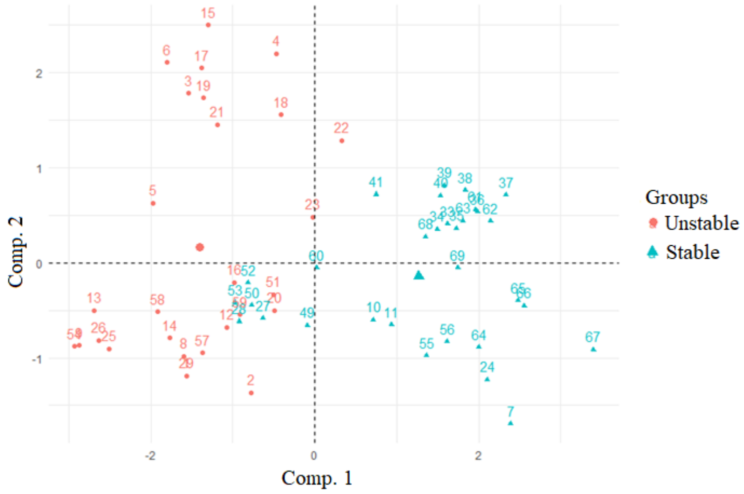


Figure 6: Scores for the first and second principal component.

In order to generate the discriminant function, the scores of PCA and the stability condition of the slopes, stable and unstable, were used according to Feng et al. (2018). Considering the multivariate normality test applied, the M box test was performed to verify if the data homocedasticity. Table 5 shows the result obtained the M box test.

Table 5: M Box test result.

Statistical parameter	Value
x_2	14.082
d_f	3
p-value	0.002796

From Table 5, it is verified that the p-value of the M Box test approached zero, in this case the null hypothesis is accepted and it is possible to affirm that there is no homoscedasticity in the data. Given this, the use of quadratic discriminant analysis would be adequate. However, the p-value of the multivariate normality test tends to zero indicating the absence of multivariate normality. Since quadratic discriminant analyzes assume normality, Fisher's canonical discriminant functions were used, based on the premise that the present study is focused only on the behavior of the discriminant boundary between the slope stability conditions.

Fisher's linear discriminant function was applied to the scores of the first two main components, resulting in Equation (5).

$$LD = 0.99Comp.1 - 0.32Comp.2 \tag{5}$$

The first validation applied in the discriminant function was the cross validation, which presented an overall probability of probability of success of 89.83%, classifying 53 slopes correctly. With this, the apparent error rate was 10.17%, classifying error 6 slopes. Table 6 presents the results of cross-validation.

Table 6: Cross-validation of the discriminant function.

Conditions	Stable (predicted condition)	Unstable (predicted condition)
Stable (real condition)	26	5

Unstable (real condition)	1	27

An analysis of the types of errors, error1 and error2 allowed to evaluate the discriminant function as a function with high safety rate, since error1 was only 3.5%, classifying only 1 unstable slope as stable. The largest contribution to the apparent error rate (AER) was in relation to error2, where stable slopes are classified as unstable slopes, with 5 slopes within this type of error, with a rate of 16.12%. Figure 7 shows a graph with the overall probability success (OPS), apparent error rate (TEA), error rate1 and error rate2.

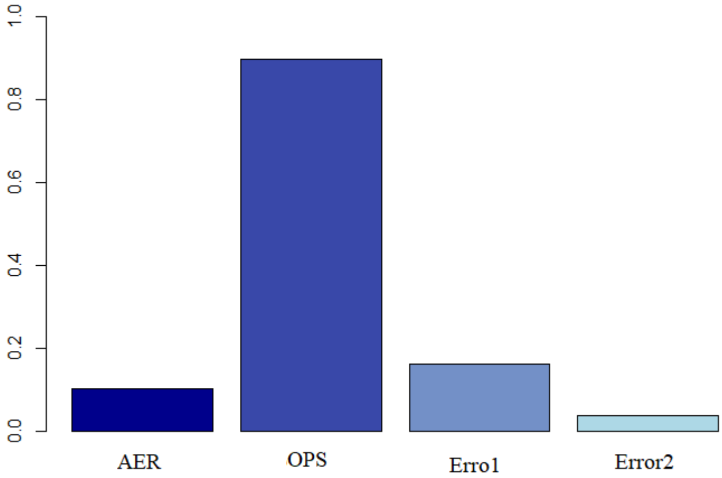


Figure 7: Cross-validation of the discriminant function.

External validation was applied with the validation database proposed by Feng et al. (2018), consisting of 12 new slopes. The overall probability of success was 66.66%, registering only errors regarding the classification of stable slopes in unstable (error2), as well as in the model created in this study. This result highlights the conservative behavior of the model. Table 7 summarizes the results in relation to the classifications.

Table 7: External validation.

Conditions	Stable (predicted condition)	Unstable (predicted condition)
Stable (real condition)	3	4
Unstable (real condition)	0	5

Table 8 presents the comparison of the results of the present study with the prediction models constructed by Feng et al. (2018) and Sah et al. (1994), in addition to the condition of the slopes under study, with their respective safety factor. Table 8 also shows the suitable threshold probability for classification. As there were only two classes studied by Feng et al. (2018), they proposed the slope cases with a conditional probability larger than the threshold probability (i.e., P (Stable|X) > 1/2) would be classified as "stable" slopes.

Table 8: Comparison with the results of Feng et al. (2018) and Sah et al. (1994).

Number of slope	Actual FoS		Predicted by Feng et al. (2018)		Empirical equation by Sah et al. (1994)	Present work
N°	Status	FS	Status	P(Stable)	Status	Status
1	Stable	1,84	Stable	58 %	Stable	Stable

2	Stable	1,49	Stable	54 %	Unstable	Unstable
3	Stable	1,43	Unstable	31 %	Unstable	Unstable
4	Stable	2,00	Stable	54 %	Stable	Unstable
5	Stable	2,31	Stable	54 %	Stable	Stable
6	Unstable	0,97	Unstable	27 %	Unstable	Unstable
7	Unstable	0,65	Unstable	20 %	Unstable	Unstable
8	Unstable	1,00	Unstable	27 %	Unstable	Unstable
9	Unstable	0,65	Unstable	20 %	Unstable	Unstable
10	Stable	1,12	Stable	54 %	Stable	Unstable
11	Unstable	0,99	Stable	50 %	Stable	Unstable
12	Stable	1,00	Stable	55 %	Unstable	Stable

Analyzing the two types of validations applied, it was observed that the linear discriminant function obtained can be used as a predictor of stability conditions. The calculated and obtained errors showed that the function is extremely conservative, presenting errors in favor of slope safety.

After the validations applied, the plot of the scores resulting from the analysis of principal components together with the linear discriminant function was constructed. Figure 8 shows the final result of the linear discriminant function, presented in Equation 5, which limits the two populations of stable and unstable slopes. From Figure 8 it is possible to visualize the adequacy of the discriminant function as limiting frontier in relation to the two stability conditions of the slopes in studies.

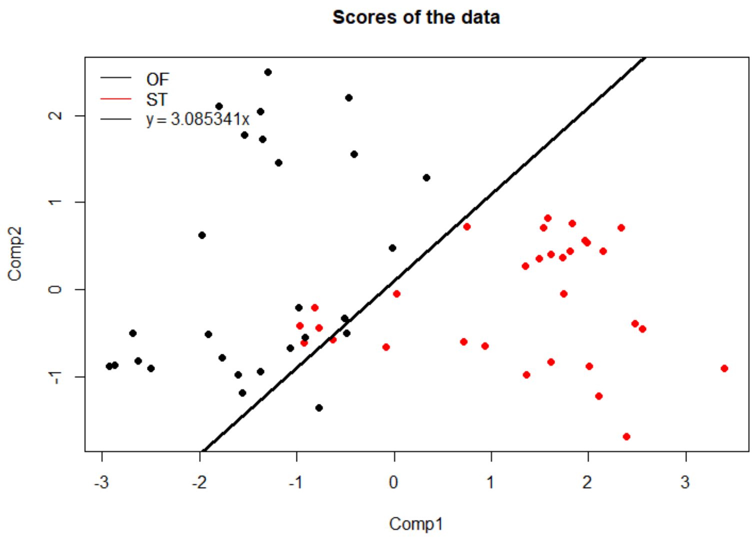


Figure 8: Frontier delimited by Fisher's discriminant function.

4 CONCLUSIONS

Nonparametric techniques for evaluating slope stability conditions are important for preliminary analyzes. These techniques should not replace analyzes such as Ordinary (Fellenius, 1936), Janbu (1954), simplified Bishop (1955), Morgenstren and Price (1965) and Spencer (1967), however these techniques can help in decision making in relation to a preliminary study approach.

The applied methodology is like that applied by Santos et al. (2018). The results are relevant showing that the methodology presents applicability not only on rock slopes, but also on slopes of soil. The applied methodology presented an overall probability of success of 89.83%, with error rates that favor slope safety, since the errors are related to the classification of stable slopes in unstable slopes. Although the methodology applied presented less overall probability of success when compared to the methodologies of Feng et al. 2018 and Sah et al. 1994, it is important to emphasize the basement of the applied techniques, in more precise studies in the relationships and structure of the variables based on statistical tests, analysis of variability and adequacy of variables.

Therefore, as in the research by Santos et al. (2018), that motivated this research, the model proposed here can be used to know the slope stability condition. Furthermore, the methodology is also capable of predicting the most hazardous situations not only in a group of rock slopes but also on in variable types of slopes.

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