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LANDSLIDE STABILITY ANALYSIS WITH THE USE OF THE DESIGN OF EXPERIMENTS METHOD – CASE STUDY OF SOUK AHRAS, ALGERIA

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Summary

In the northeast of Algeria, Souk Ahras area is known for the severity and spread of landslides, especially in Mechroha and Zaarouria municipalities. Stability analysis of landslides in these areas depends on the calculations of safety factor according to several parameters (physical, mechanical, geological…). The aim of this study is to investigate the parameters affecting the safety factor using the design of experiments (DOE) method, central composite design (CCD) and response surfaces methodology (RSM). These methods use parameter modeling and optimization to discuss a solution of landslide hazard by developing models of safety factor (*Fs*) considered as response. The other parameters adopted as input independent factors are geotechnical physical and mechanical parameters such as: the dry and wet unit weight (γ_d, γ_h), the water content (*w*), the plasticity and liquidity limits and the plasticity index (*WL*, *WP*, *IP*), the percentage of fine elements *Ff* (%) < 0.08 mm), the cohesion *C* and the internal friction angle (*Phi*). Obtained results show high correlations with a regression coefficient R^2 of 0.88 and 0.93 in the two cases study and the predicted factor of safety model fit best to those obtained in the analytical and numerical modeling procedure. The final model is applicable to give reliable results on the safety factor of landslides.

Keywords

landslides • Souk-Ahras region • numerical modeling • safety factor • geotechnical parameters • design of experiments DoE • response surface methodology RSM

1. Introduction

The development in the region of Souk Ahras (Algeria) is increasingly threatened by landslide mass movements […] These mass movements are varied in nature, generated by multiple factors that reflect the variability of the behavior of the geological materials in motion [Charef et al. 2019]. The present case studies are situated in Mechroha and Zaarouria municipalities. These areas are characterized by clayey and fine-grained soils, abundant with water resources and groundwater levels close to the surface (static level at 3 m depth). Unfortunately, the region has experienced many landslides, which result from the interaction between the geological, geomorphological, hydrological and mechanical parameters.

This research aims to use the concept of design of experiments (DOE) based on dataset of 99 samples collected, identified and tested in the public earthworks laboratory (Souk-Ahras unit) in order to study the safety factor of slope stability. The latter was calculated using the equilibrium limit in the Geoslope software in relation to two geometric models (Mechroha and Zaarouria) that include a substratum (marl) about 20 m deep, surmounted by clay marl at the base and marl clay on the surface. The obtained results of safety factors (*Fs*) varied from 0.8 to 1.7.

The design of experiments (DOE) method has been used in order to provide a practical way for studying, modeling and characterizing the influence of the mechanical and physical soil parameters in relation to the safety factor, which includes landslides hazards and slope stability. Indeed, the DOE method, which derives its principles from statistical and mathematical methods [Draper 1992, Tinsson 2010], has been successfully introduced in engineering, agriculture and research on industrial systems as well as in several other domains [Gurrala 2014, Murray 2016], and it has built. Essentially, this method is used to design new industrial products based on both a set of experimental trials and a statistical analysis in order to optimize the settings of a manufacturing process and improve its performance or to predict and characterize its behavioral model [Porter et al. 1997, Berrah et al. 2021, Guecioueur et al. 2022]. Based on a few experiments in a strictly closed study domain of input parameter variation, DOE appears as an alternative method for the evaluation of significant factors, the correlation between factors and their influence on the response of the system. To model any system using DOE, it is necessary to take into account a set of input variables that can modify a specific output variable determined by a response of the system, which leads to a mathematical model of factorial design of the response as a function of input factors that can vary in a bounded study area that limits the input parameter variations [Nearing 1999, Abdelouahhab et al. 2022].

In the present work, one can indicate the characterization, the predictive modeling of the safety factor Fs for a slope and landslide hazards by using the DOE technique. Fs has been considered in this study as an output response. The input parameters are mechanical and physical soil parameters, and the slope geometry.

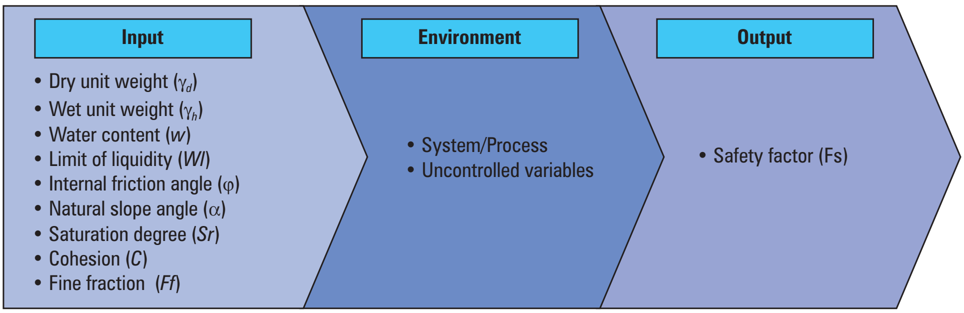

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Fig. 1. Diagram of application of the DOE method

The variables used as independent input parameters are: wet and dry unit weight (γ_h, γ_d), water content (*w*) plasticity index (I_P), degree of saturation (*Sr*), the fine fraction (*Ff*) in % < 80 μm, liquidity limit (*Wl*), cohesion (*C*), the angle of internal friction (φ) and the angle of the studied slopes (α).

2. Material and methods

In order to estimate the safety factor (*Fs*) as a function of different soil properties, 99 samples have been collected from hazardous areas in Mechroha and Zaarouria in wilaya of Souk Ahras, and analyzed specifically to study their geotechnical parameters, namely: wet unit weight (γ_h), dry unit weight (γ_d), water content (*w*) plasticity index (I_P), degree of saturation (*Sr*), the fine fraction (*Ff*) in % < 80 μm, liquidity limit (*Wl*), cohesive strength (*C*), the angle of internal friction (φ) and the angle of the studied slope (α). In this strategy, the experiments are conducted by simultaneously varying ten factors at two levels (low level and high level) so that they cover the practical range of the considered parameters, as shown in Table 1.

Table 1. Independent variables and their corresponding levels Mechroha (M) and Zaarouria (Z)

Factor	Name	Units	Min.	Max.	Coded low	Coded high	Mean	Std. Dev.
A	γ_d	(kN/m³)	13.20	18.80	−1 ↔ 13.20	+1 ↔ 18.80	16.85	1.17
B	γ_h	(kN/m³)	17.00	22.00	−1 ↔ 17.00	+1 ↔ 22.00	20.19	0.8820
C	*W*	%	12.50	38.80	−1 ↔ 12.50	+1 ↔ 38.80	20.10	4.67
D	*Sr*	%	62.00	100.00	−1 ↔ 62.00	+1 ↔ 100.00	89.22	10.41
E	*Ff* < 0.08 mm	%	22.48	100.00	−1 ↔ 22.48	+1 ↔ 100.00	84.49	16.65
F	*WL*	%	29.00	72.79	−1 ↔ 29.00	+1 ↔ 72.79	49.21	11.60
G	*IP*	%	10.00	39.00	−1 ↔ 10.00	+1 ↔ 39.00	24.87	7.61
H	φ	°	10.00	43.00	−1 ↔ 10.00	+1 ↔ 43.00	18.60	6.78
J	α(M)	%	18.55	30.00	−1 ↔ 18.55	+1 ↔ 30.00	27.89	3.18
J	α(Z)	%	24.94	30.38	−1 ↔ 24.94	+1 ↔ 30.38	29.18	1.31
K	*C*	kPa	3.00	140.00	−1 ↔ 3.00	+1 ↔ 140.00	37.72	33.30

The predictive mathematical model that links the response *y* to the factors *xi* using the DOE method is based on the linear regression model [Fisher 1935, Deming and Morgan 1996, Kostić et al. 2016, Turkane et al. 2022] as follows:

$$y = a_0 + \sum_{i=1}^{k} a_i x_i + \sum_{\substack{i,j=1 \\ i<j}}^{k} a_{ij} x_i x_j + \sum_{i=1}^{k} a_{ii} x_i^2 \tag{1}$$

Let x_i and x_j be the levels of the factors *i* and *j*, respectively (*i, j* = 1, 2, ..., *k* – number of factors).

a_0, a_i, a_{ij}, a_{ii} denote, respectively, the constant coefficient, the coefficients relative to the main effect of the factors, the coefficients representing the interactions between several factors, and the coefficients of the second-degree terms. They are calculated from the measurements taken in the trials.

2.1. The response surface methodology (RSM) application

Response surface methodology (RSM) in statistics explores the relationships between multiple explanatory variables and one or more response variable. The method was introduced by George Box and Wilson in 1951 [Draper 1992]. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. For that purpose, Box and Wilson propose the use of a second-degree polynomial. They acknowledge that this model is only an approximation, but they suggest it anyway, because such a model is easy to estimate and apply, even when little is known about the process [Box 1952]. Statistical approaches such as RSM can be employed to maximize the production of particular substances by optimizing operational factors. Recently, the RSM has become extensively used for formulation optimization with appropriate design of experiments (DOE) [Mir Mohammad Hosseini et al. 2019, Zangeneh et al. 2002]. In contrast to conventional methods, the interaction between process variables can be determined with statistical techniques.

Response surface methodology RSM is used in this work to investigate the effects of independent variables (wet and dry unit weight (γ_h), (γ_d), water content (*w*) plasticity index (I_P), degree of saturation (*Sr*), the fine fraction (*Ff*) in % < 80 μm, liquidity limit (*Wl*), cohesive strength (*C*), the angle of internal friction (φ) and the angle of the studied slope (α)) on response safety factor (*Fs*). The RSM design together with coded levels is presented in Table 1.

2.2. Experimental design DOE application

The standard deviation is a measure of the amount of variation or dispersion of a set of values [Bland 1996]. A low standard deviation indicates, that the values tend to be close to the mean (expected value) of the set, while a high standard deviation indicates that the values are spread out over a wider range. In the present design, the central composite design CCD (five levels) and the quadratic model were used to design this experiment, with 99 treatments (runs), including 76 non-center points and 23 center points, and randomized according to the CCD. Experimental data were statistically analyzed using the Design Expert 13 software, though different parameters (lack-of-fit, predicted, adjusted correlation coefficients and coefficient of variation) for different polynomial obtained models were compared to select the best fitting polynomial model.

3. Results and discussion

3.1. Fitting the model

Response surface methodology (RSM) in DOE is a best technique for model building in order to optimize the level of independent variables [Li 2016, Khuri and Cornell 2018]. The influence of independent variables (γ_d, γ_h, *w*, *Sr*, *Ff* < 0.08 mm, *WL*, *IP*, φ, α, *C*) on the safety factor (*Fs*) is shown in Table 2. The coefficients of polynomial equation were computed from experimental data to predict the best-fit values of the response variable.

Table 2. Experimental design for the safety factor (*Fs*) with independent variables, experimental and predicted values of responses (Mechroha)

Std	Run	F. 1 A: γ_d	F. 2 B: γ_h	F. 3 C: *w*	F. 4 D: *Sr*	F. 5 E: *Ff*	F. 6 F: *WL*	F. 7 G: *IP*	F. 8 H: φ	F. 9 J: α	F. 10 K: *C*	Response 1 *Fs*
81	1	15.4	19.6	27.27	97	50.2	57	31	19	28.68	4	0.538
43	2	17.3	20.3	17.34	84	62	47	23	22	26.25	7	0.822
53	3	16.8	20.4	21.42	95	96.8	59	31	26	25	7	0.919
50	4	17.5	21	20	79.48	100	56.77	28.16	12	21.07	7.1	0.795
27	5	16.7	19.2	14.97	68.09	100	56.42	29.59	10	29.52	33.8	1.243
64	6	17.6	20.9	18.75	97.6	100	59.03	33.52	10	30	52.9	1.663
91	7	16.2	19.8	21.6	89.62	100	39.29	16.45	22	25.77	7.4	0.76
5	8	18.2	19.7	13.09	89.82	100	39.38	16.42	23	28.56	7.3	0.772
80	9	13.2	17	28.78	74	65.5	50	27	14	30	60.9	2.015
31	10	16.4	19.8	20.73	84	89.4	38	17	18	26.84	24	1.334

3.2. Analysis of variance ANOVA for the quadratic model

For the two studied municipalities, Mechroha and Zaarouria, the results of analysis of variance ANOVA from DOE are presented in Table 3, where the response variable *Y* is a function of categorical predictor variables (so called factors). It has already been shown how such predictors can be applied in a linear regression model (Fig. 2 and Fig. 3). This means that analysis of variance can be seen as a special case of regression modeling which is worth studying separately. Analysis of variance and linear regression can be summarized under the concept of a linear model, in terms of the design of experiments method. The optimization of a response variable is only the covered topic.

Table 3. Experimental design for the safety factor (*Fs*) with independent variables, experimental and predicted values of responses (Zaarouria)

Std	Run	F. 1 A: γ_d	F. 2 B: γ_h	F. 3 C: *W*	F. 4 D: *Sr*	F. 5 E: *Ff*	F. 6 F: *WL*	F. 7 G: *IP*	F. 8 H: φ	F. 9 J: α	F. 10 K: *C*	Response 1 *Fs*
81	1	15.4	19.6	27.27	97	50.2	57	31	19	28.68	4	0.728
43	2	17.3	20.3	17.34	84	62	47	23	22	26.25	7	0.89
53	3	16.8	20.4	21.42	95	96.8	59	31	26	25	7	0.916
50	4	17.5	21	20	79.48	100	56.77	28.16	12	21.07	7.1	0.58
27	5	16.7	19.2	14.97	68.09	100	56.42	29.59	10	29.52	33.8	1.278
64	6	17.6	20.9	18.75	97.6	100	59.03	33.52	10	30	52.9	1.69
91	7	16.2	19.8	21.6	89.62	100	39.29	16.45	22	25.77	7.4	0.951
5	8	18.2	19.7	13.09	89.82	100	39.38	16.42	23	28.56	7.3	1.078
80	9	13.2	17	28.78	74	65.5	50	27	14	30	60.9	3.389
31	10	16.4	19.8	20.73	84	89.4	38	17	18	26.84	24	1.373

Note: There are 99 runs, and that makes the table too long, so we show just 10 runs as an example.

Fit Statistics: Statistical analysis of variance ANOVA results revealed that the experimental data could be well represented with a quadratic polynomial model with the coefficient of determination (R^2) values equal to 0.9278 for Mechroha municipality and 0.8883 for Zaarouria municipality, as shown in Table 4 and Table 5, respectively.

Table 4. Regression statistics adopted for the reduced quadratic model (Mechroha)

Std. Dev.	0.3588	R^2	0.9278
Mean	1.60	**Adjusted R^2**	0.7856
C.V. %	22.43	**Predicted R^2**	–20.2155
		Adeq Precision	10.7631

Table 5. Regression statistics adopted for the reduced quadratic model (Zaarouria)

Std. Dev.	0.5248	R^2	0.8883
Mean	1.70	**Adjusted R^2**	0.6684
C.V. %	30.94	**Predicted R^2**	–5.9054
		Adeq Precision	9.3555

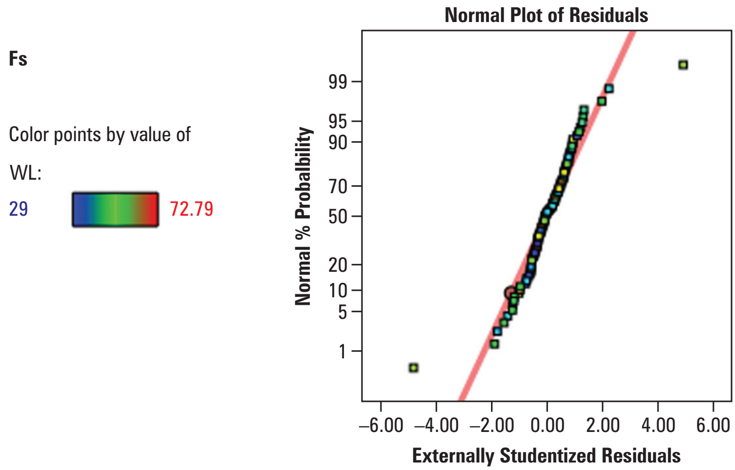

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Fig. 2. Normal Plot of Residuals (Mechroha)

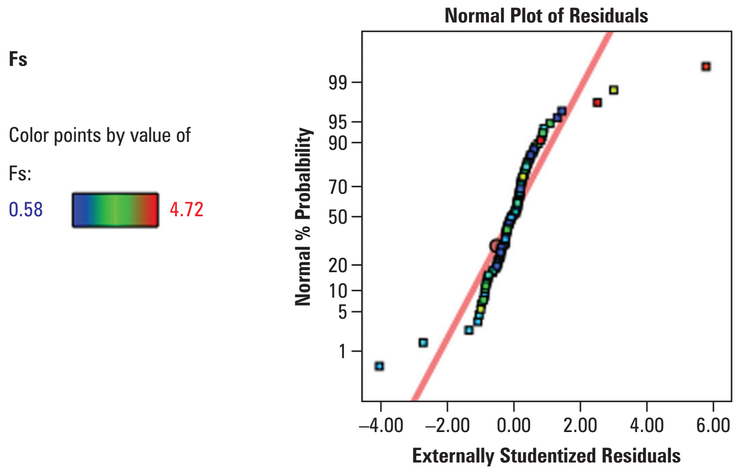

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Fig. 3. Normal Plot of Residuals (Zaarouria)

3.3. Effect of independent variables on response parameter

Various RSM computations were carried out for the current optimization study and a second-order statistical model, including interaction and polynomial terms, was generated for all the response variables. The general form of the model being as follows:

$$Fs = (\gamma d \cdot \gamma h \cdot w \cdot Ff \cdot Wl \cdot Ip \cdot Sr \cdot C \cdot \Phi \cdot \alpha) \tag{2}$$

Regression equations for each response variable allow obtaining the best-fit model using the response surface methodology, as shown in the following equation:

$$Fs = -0.08 - 0.24\gamma d + 0.2\gamma h - 0.03W - 0.002Sr - 0.001Ff + \\ + 0.05WL - 0.07IP + 0.02\varphi + 0.03\alpha + 0.02C \quad (3)$$

A minimum and a maximum level can be provided for each parameter including the weight assigned to each goal to adjust the shape of its particular desirability function.

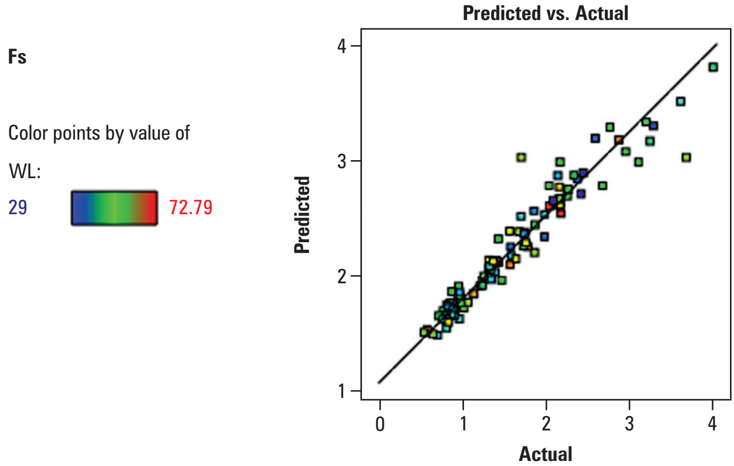

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Fig. 4. Predicted vs numerical plot (Mechroha)

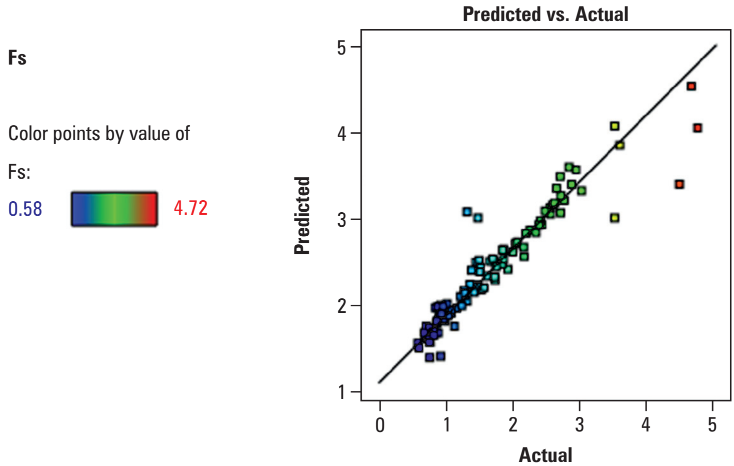

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Fig. 5. Predicted vs. numerical plot (Zaarouria)

The safety factor (*Fs*) was successfully calculated using the Morgenstern-Price method of limit equilibrium in the Geoslope program with (γ_h, C, Φ) as inputs and (α) for the model geometry. The effect of the independent variables on the safety factor can be represented by the safety factor parameter output from the numerical and predicted model. As shown in Figure 4 and Figure 5, the predicted safety factor versus the numerical model shows a strong and high correlation in the two case studies. The final best fit model can be used as a good indicator of the accuracy calculated by different programs that cover the stability factor of any slope in the region of Souk-Ahras.

3.4. Modeling and data analysis optimization

Models are used for prediction in order to generate response surface plots and contour plots. There are significant interactions between process factors. The response surface plots and contour plots as variations of the process conditions are shown in Figure 6 and Figure 7. Design of experiments modeling is a combination of the response surface method (RSM) and the process factors, which are capable of showing statistical effects and the dynamic nature of the process. The latter combines a mixture of factors (geotechnical soil parameters) to obtain a unique characteristic of the design of experiments modeling (a safety factor), which together with a process factor (a safety factor) depend on the dry and wet unit weight (kN/m^3) for this case study.

The response surfaces for the remaining measured responses are shown and plotted in analogy to the *Fs*, where the surface becomes 'hot' at higher response levels, the variation of *Fs* is between "the minimum value" 0,538 (blue) and "the maximum value" above 3,953 (red).

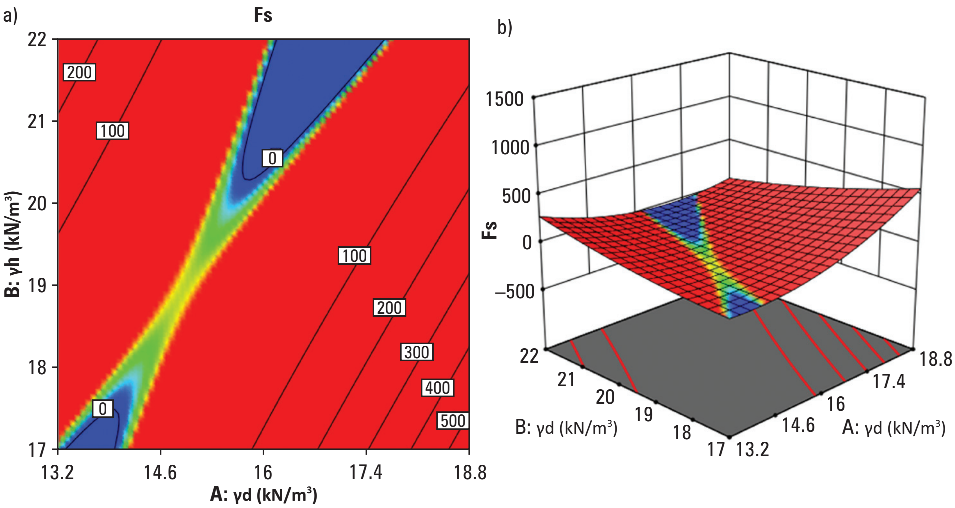

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Fig. 6. Contour and 3D plots, (a) and (b) representing the safety factor (*Fs*) dependence on the dry and wet unit weight (γ_d, γ_h (kN/m^3) for Mechroha sector

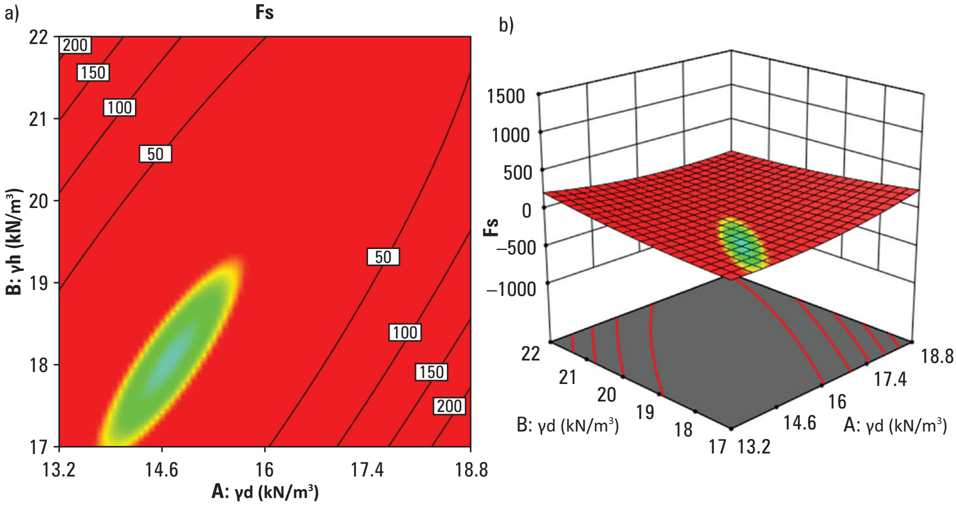

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Fig. 7. Contour and 3D plots, (a) and (b) representing the safety factor (*Fs*) dependence on the dry and wet unit weight (γ_d, γ_h (kN/m^3)) for Zaarouria sector

Contour, 3D surface, and perturbation plots of the desirability function at each optimum can be used to explore the function in the factor space. Any individual response can also be plotted to show the optimum point for both studied cases. The optimization of the safety factor (*Fs*) with respect to the different physical parameters in this study includes: wet and dry unit weight ($\gamma_{h,}$ γ_d), water content (*w*) plasticity index (*IP*), degree of saturation (*Sr*), the fine fraction *Ff* in % < 80 μm, liquidity limit (*Wl*), cohesive strength (*C*), the angle of internal friction (φ) and the angle of the studied slope (α).

In Figures 8 (a, b) and 9 (a, b) the ramp function combines individual graphs for ease of interpretation: the colored dot on each ramp represents the factor setting or response prediction for the desirable solution; the height of the dot shows the degree of desirability. The optimal solution represents the formulation that best maximizes the safety factor at the calculated target value by finding the point with the least error transmitted to the responses. The safety factor is maximized up to 4.01 for Mechroha and 4.84 for Zaarouria. This should therefore represent process conditions that are robust to small variations in the factor parameters.

4. Conclusion

In this work, different geotechnical data collected from two different sectors in northeast of Algeria (Mechroha and Zaarouria) have been analyzed using design of experiments (DOE) method. The response surfaces methodology (RSM) has been used to study and treat the solution through modeling and optimization of geotechnical parameters

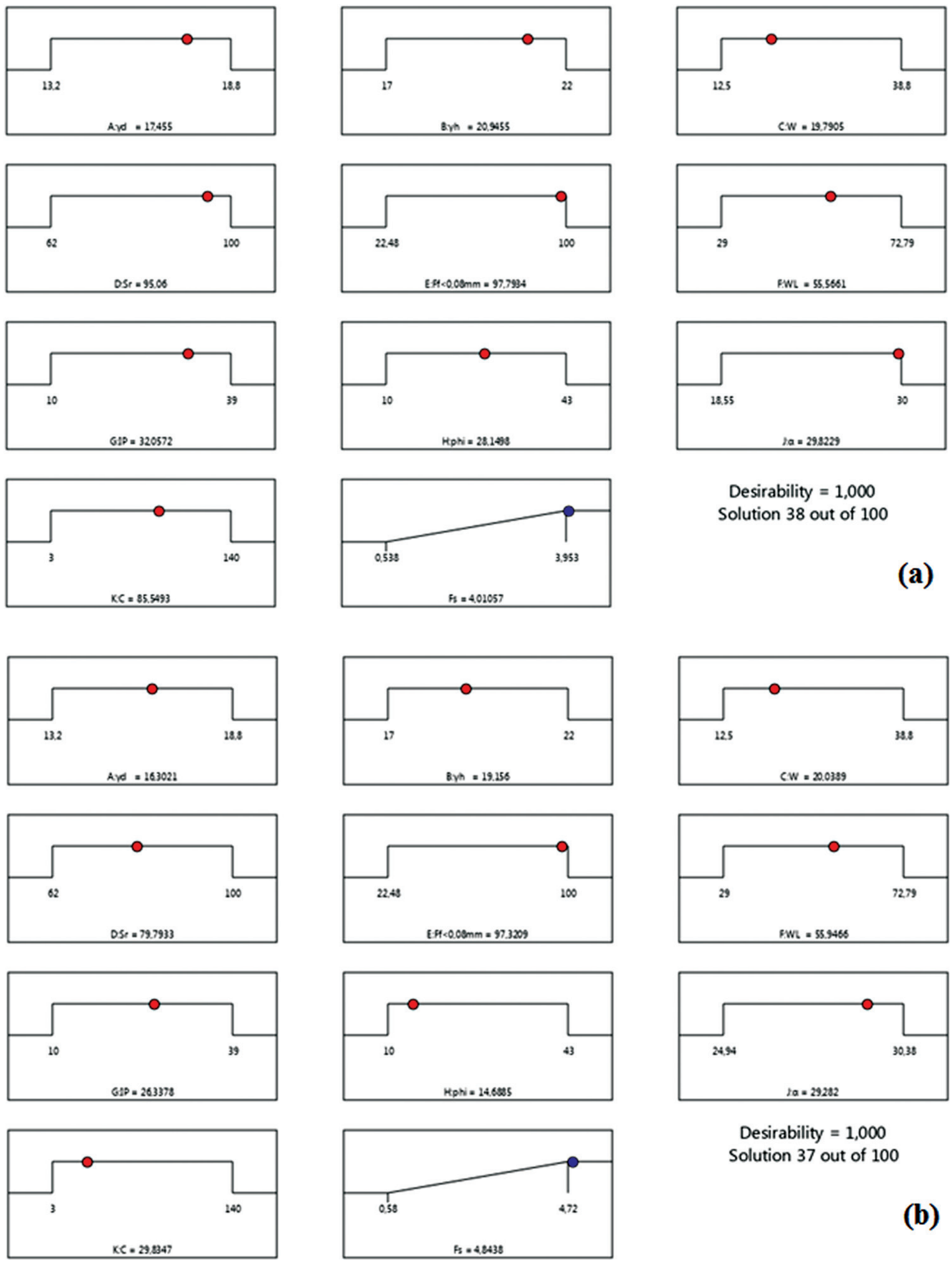

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Fig. 8. The maximization of the response (a) for Mechroha, (b) for Zaarouria

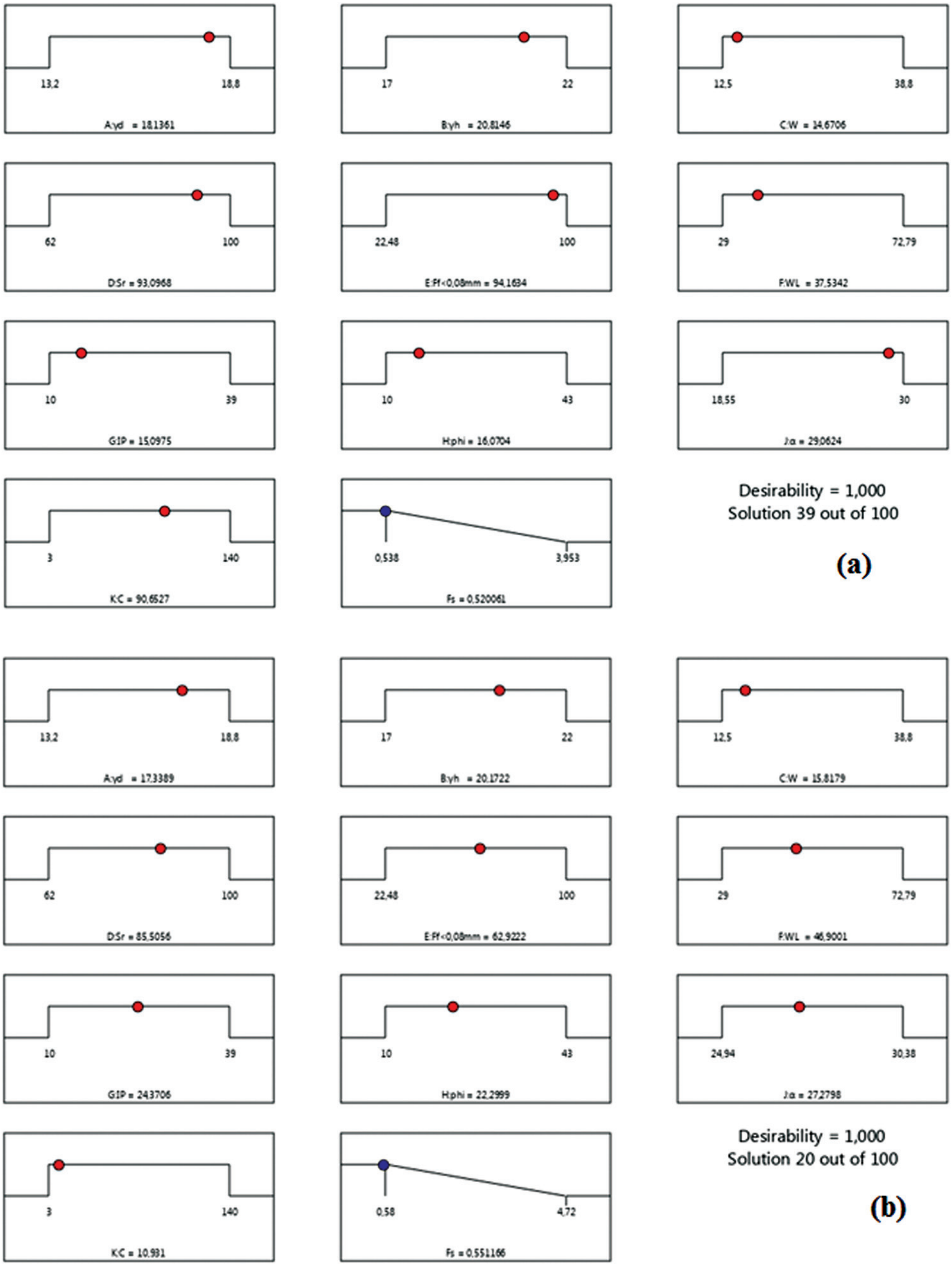

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Fig. 9. The minimization of the response (a) for Mechroha, (b) for Zaarouria

affecting problems related to landslides. Using multiple regression, the safety factor (*Fs*) model is developed by considering (*Fs*) as the response; the other independent parameters have been taken as input factors (dry and wet unit weight (γ_d (t/m^3), γ_h (t/m^3)), the water content w (%), the liquid limit and the plasticity index (*WL*%, IP%), the percentage of fine fraction *Ff* (%) < 0.08 mm), the cohesion *C* (bar) and the internal friction angle Phi (°)). The obtained correlations give a regression coefficient R^2 of 0.88 and 0.93 in Zaarouria and Mechroha respectively. The predicted factor of safety model best fits to those obtained in the analytical and numerical modeling procedure. The final model is applicable and provides reliable results of the safety factor of landslides. Presenting the design with the RSM and CCD function is suitable to optimize the solution given by the maximization or minimization of the Fs output response . It provides the parameters range that describe the slope stability sectors.

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