Acta Geophysica (2020) 68:505–517
https://doi.org/10.1007/s11600-020-00404-5

RESEARCH ARTICLE - HYDROLOGY

Multi-objective optimization of soil erosion parameters using response surface method (RSM) in the Emamzadeh watershed

Mojtaba Shirazi[1] · Ataallah Khademalrasoul[1] · Seyed Mohammad Safieddin Ardebili[2]

Received: 15 October 2019 / Accepted: 25 January 2020 / Published online: 3 February 2020

Abstract

Soil erosion is one of the most leading environmental and public health problems in the world which dislodges considerable volumes of soil annually. In order to control soil erosion, several soil factors should be taken into account. Regarding the importance of soil properties on erosion occurrence, it is necessary to focus on soil properties. The aim of this study is to evaluate the effect of physical parameters that consist of sand %, silt %, clay %, SP % and stone % along with hydraulic properties including theta *s*, theta *r*, alpha *n* and Ks (cm/day) on the amount of soil erosion in Emamzadeh watershed. The above-mentioned factors were optimized using response surface methodology. The soil texture in the study area is mostly silty clay loam, and the main soil orders are Entisols and Inceptisols. Moreover, the main land use in the study area is forest–rangeland. The results proved that both physical and hydraulic valuables illustrated a significant effect on all of the independent parameters. The optimized values of different physical parameters were 60.241 for sand, 14 for silt, 41.025 for clay, 58.729% for SP and 3.83% for stone. A theta *r* of 0.09, theta *s* of 0.457 alpha of 0.014, *n* of 1.3 and Ks of 46.01 were found to be optimal values. The results of this study indicated that at optimal studied parameters, the values of the soil erosion before and after application of management scenarios were found to be 11.537 and − 2.253, respectively. Results show that both physical and hydraulic parameters have significant effects at the 1% level on the soil erosion before and after application of management scenarios. The obtained results could assist policy-makers with decisions aimed at minimizing soil erosion in this watershed. In summary, using the simulation–optimization techniques helps to evaluate the effect of management scenarios, then select and apply the best one to minimize the soil erosion outcomes.

Keywords D-optimal design · Management scenarios · Optimization · Physical and hydraulic parameters · Response surface methodology (RSM)

Introduction

Soil as one of the most important sources of production has been demolished with population growth and industrialization of the world (Meliho et al. 2019). Land degradation through human activities such as deforestation, overgrazing, tillage operations, inappropriate agricultural practices and land-use changes has negative impacts on soil quality indices and soil healthy (Schole et al. 2018; IPBES 2018). Soil erosion by water, as the most prevailing factor of soil degradation, has several outcomes, including mitigation of agricultural productivity, water quality–quantity and environmental impacts (Park et al. 2011; Xu et al. 2013; Xiong et al. 2019). Therefore, effective planning and implementation of soil erosion monitoring program are needed for understanding and estimating of soil erosion severity (Mondal et al. 2017; Nasiri et al. 2017). Moreover, in order to decrease the risk of soil erosion should be considered convenient strategies in the management plan (Sherriff et al. 2018). However, despite widespread researches on soil erosion and conservation (Mhazo et al. 2016), still, there is not a precise technique for soil erosion assessment in the watersheds; this means that, given the importance of the occurrence of erosion processes and the complexity of their mechanisms, it is essential to use new software and techniques with the ability to monitoring complex processes (Diodato et al. 2012; Corella et al. 2019). A convenient tool

✉ Ataallah Khademalrasoul
a.khademalrasoul@scu.ac.ir; Ataalahsoil@gmail.com

[1] Soil Science Department, Faculty of Agriculture, Shahid Chamran University of Ahvaz, Ahvaz, Iran

[2] Biosystems Engineering Department, Faculty of Agriculture, Shahid Chamran University of Ahvaz, Ahvaz, Iran

to estimate soil erosion–deposition and to understand the relations between different effective parameters on soil erosion is the application of soil erosion models. Soil erosion models are beneficial tools for analyzing soil erosion processes in the watersheds (Laflen and Flanagan 2013). Qian et al. (2014) analyzed the relation between water and soil erosion using linear and quadratic regression models and concluded that the runoff rate had a significant linear relationship with the rate of sediment loss. The outputs of soil erosion models are efficient tools which ultimately can be used to provide different scenarios for selecting and implementing a best management practice (Argent et al. 2016). Well-developed and properly calibrated models provide reasonable estimations of soil erosion risks (Giannecchini 2006). Generally, using simulation–optimization techniques are effective tools for planners, managers and executive units which is convenient in achieving management goals. In this regard, should provide backgrounds and contexts for best application of these techniques in order to eventually adopt appropriate management scenarios (Batista et al. 2019).

Regarding the complexity of soil erosion mechanisms and due to deficiency of appropriate management strategies, it is necessary to apply new techniques for simulation and optimization of soil erosion processes (Kirkby et al. 2008; Arnold et al. 2015; Shojaei et al. 2019). Response surface methodology (RSM) is an appropriate technique for monitoring the complicated processes in the watersheds (Chandramohan et al. 2015). The main advantage of RSM is the reduction of experiments to evaluate multiple parameters and their interactions (). Another advantage of this technique is the simplification of complex processes, scrutinizing continuous variables, elimination of problems related to the one-factor and determination of response's sensitivity to each factor. The RSM is an efficient experimental strategy to run optimal conditions for multivariable systems (Long et al. 2019). Indeed, the RSM by providing response levels along with appropriate statistics and ultimately by optimizing them allows selection of the best set of input parameters based on the research objectives (Sharma et al. 2019). The RSM is a collection of useful statistical and mathematical techniques for developing, improving and optimizing processes. It also has essential applications in the design, development and formulation of new products, as well as in the improvement of the existing product designs (Tan et al. 2017). The primary purpose of the RSM is to optimize the response (output variable), which is influenced by several independent variables (input variable) (Kumar et al. 2016). Therefore, according to importance of soil against erosive forces, it is necessary to use RSM technique for optimization and ultimately selection of the best management practices. The specific objective of our study was to optimize soil erosion using response surface methodology based on soil physical and hydraulic parameters which are effective on soil erosion.

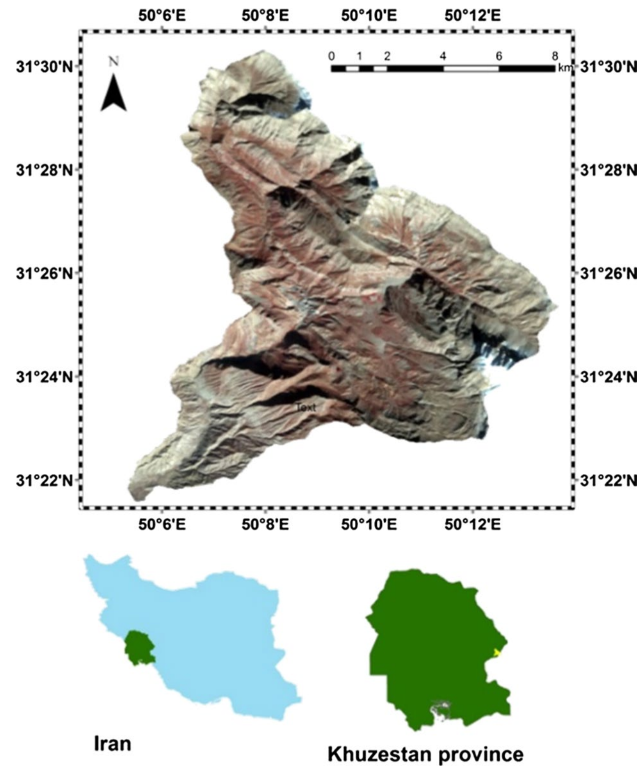

Fig. 1 Location of study area on true color composite of Landsat7 ETM^+ image acquired in March 2018

Methods and material

Location of the study area

The study area is placed in the northeast of Khuzestan Province, Iran country, with the geographical coordination of 31° 18′ to 31° 33′ N and 50° 5′ to 50° 13′ E (Fig. 1). The area of this watershed is approximately 104 km^2 including six hydrological parcels. In this area, the total annual precipitation is around 712 mm, and the average temperature is 23 °C. Furthermore, the soil texture in the study area is mostly silty clay loam (SiCL), and the main soil orders are Entisols and Inceptisols. The main land use in the study area is forest–rangeland.

Soil sampling, measurements and analysis

A composite sample (0–20 cm) was obtained by mixing soil from five separate sampling points in the watershed. Soil samples were air-dried at 20 °C in the laboratory. Afterward, soil texture was measured using hydrometric method. Regarding the heterogeneity of soil texture in different parts of study area, soil samples were collected and analyzed.

In order to measure stone (%) were collected all the stone, gravel and pebble in the 1×1 square meter area on the ground, then weighted. Using these 1×1 m^2 plots in different places, we calculated the average amount of stone on the ground in different parcels of watershed. Cation exchange capacity (CEC) and exchangeable bases were measured by the ammonium acetate method (pH = 7) (Thomas 1982). The soil organic matter (SOM) was measured using Walkley and Block method. Actually, soil organic matter is a key factor to prevent the soil against erosive factors. The saturation percentage (SP) is an index of soil texture; this parameter was measured based on the difference of the soil weight in the dry condition and the saturated condition. For all the soil samples, this parameter was measured three times to find an acceptable average. Albedo coefficient was calculated using the climate data, solar radiations and surface characteristics. This parameter depends on solar radiations and surface characteristics. For the white and flat surfaces, the Albedo coefficient has the highest amount. Compute theta *r*, theta *s*, alpha, *n* and K_S through RETC software.

Soil erosion simulation using the WEPP model

The Water Erosion Prediction Project (WEPP) model is based on surface water flow hydrology and erosion processes which provide the possibility of estimating the spatial and temporal patterns of soil erosion and sedimentation in the watersheds (Boll et al. 2015; Brooks et al. 2016). In the WEPP model, a watershed is defined as one or number of hillslopes, which have been drained into one or more channels (Flanagan and Nearing 1995; Flanagan et al. 2013). In this study, the climate simulation was performed using CLIGEN module (Kinnell et al. 2018; Anache et al. 2018) with data obtained from Izeh synoptic station. Moreover, soil, topography and management layers were defined for each hillslope (Schaap and Leij 2000; Tiwari et al. 2000). Ultimately, the studied watershed was simulated by hillslopes and the hydrographical network to run the model. In this study, in 17 hydrological units, the sediment load was converted to soil erosion values in ton/ha using the relationship between sediment load, sediment delivery ratio (SDR) and soil erosion described in PSIAC (1968) and modifications applied on PSIAC (MPSIAC) by Johnson and Gebhardt (1982). Sediment delivery ratio for each hydrological unit calculated based on the unit area (in mi^2) as above mentioned references (Table 1). Hydrological unit sediment production was obtained from the ministry of agriculture's hydrometric/sediment gauging stations (2009).

Response surface methodology

The second part of this study is the evaluation and optimization of physical and hydraulically parameters effective on soil erosion, which was performed using the RSM method. Design-Expert version 10 was utilized to generate a regression model and to perform the statistical analysis. The RSM shows the general form of the statistical model for predicting the response or dependent variable (*Y*) based on independent variables $(x_1, x_2, \dots, x_k)$ based on Eq. (1). The dependent variable is response, and independent variable acts as input factors (Muthusamy et al. 2019; Montgomery and Anderson-Cook 2009).

Table 1 The measured erosion, WEPP predicted and measured SDR for hydrological units

N	Overall SDR	Mean of predicted erosion (ton/ha)	Mean of predicted erosion (ton/ha)	Mean hydrological units SDR	Mean hydrological units area
17	30.68	23.04	29.27	61.98	6.15

$$y = f(x_1, x_2, \dots, x_k) + \varepsilon \quad (1)$$

f is the response function, which will be finally optimized by the software, while ε shows the variables (error) that are effective in y but are not included in *f* (Najafi et al. 2015). The general form of the quadratic polynomial model is expressed by Eq. 2:

$$Y = \alpha_0 + \sum_{j=1}^{k} \alpha_j x_j + \sum_{j=1}^{k} \alpha_{jj} x_j^2 + \sum_{j<1} \sum_{l=2}^{k} \alpha_{jl} x_j x_1 + \varepsilon \quad (2)$$

where *Y* is the response. α_0, α_j, α_{jj} and α_{jl} are regression coefficients for intercept, linear, quadratic and interaction coefficients, respectively ($k = 8$ levels for each factor). x_j and x_l are independent variables and ε unpredicted error (De Oliveira Faber and Ferreira-Leitão 2016).

Response surface methodology is a collection of mathematical and statistical techniques based on the fit of a polynomial equation to the experimental data, which predict the process and optimize the levels of independent variables to attain the best level of dependent variables (Keshtegar et al. 2016; Bezerra et al. 2008). The RSM includes three parts: designing, analysis and optimization (Pattanaik and Rayasam 2018). In the first section, were determined the independent and dependent variables in two levels (− 1 and + 1) for software, and in the next sections, data analysis and optimization were performed (Gao et al. 2016). In the analysis section, there is a possibility to choose PTF (pedotransfer function) for data analysis and a section dedicated to the analysis of variance called ANOVA[1] (Rao and Venkaiah 2015). Then, in the next section, the software shows

[1] Analysis of variance.

the relationship between independent and dependent variables in a way 2D and 3D graphs, contour graphs, one-factor graphs and interaction graphs (Podder and Majumder 2015). First, each parameter must be defined in the upper limit and lower limit for the software. Then, according to the nature of each parameter, the goal of optimization has been defined. Sometimes, the goal of optimization somehow was adjusted that optimization process doing out of this range. But generally, there are five goals in the optimization process, which include: maximize, minimize, target, in rang and equal to (Kumar et al. 2018). In the optimization section, there is a section called importance, which the value of each optimization parameters from 1 to 5 plus is determined according to the optimization goal. Another part of the optimization is related to the solutions step that desirability function shows the probability of reaching optimization paths to the whole goal of research (Dinarvand et al. 2017). Desirability is a goal function that ranges from zero to one at the goal. The numerical optimization finds a point that maximizes the desirability function. The characteristics of a goal may be shifted by regulating the weight or significance. For several responses and factors, all goals combine into one desirability function. Myers and Montgomery (Chabbi et al. 2017) explained a multiple response method called desirability. The method using an objective function, D(X), is called the desirability function. The desirable range for each response (di) is from zero to one. The concurrent objective function is a geometric mean of all converted responses (Eq. 3):

$$D = \left(d_1 \times d_2 \times \cdots \times d_n\right)^{\frac{1}{n}} = \left(\sum_{i=1}^{n} d_i\right)^{\frac{1}{n}} \tag{3}$$

n is the number of responses. If any of the responses was outside of their desirability range, the overall function becomes zero. For synchronic optimization, each response must have a low and high value specified to each goal. On the worksheet, the “goal” field for responses must be one of five choices: “none,” “maximum,” “minimum,” “target,” or “in range.” Factors will always be included in the optimization, at their design range by default, or as a maximum, minimum of target goal. For simultaneous optimization, all goals have been combined into a desirability function, which is expressed by Eq. (4).

$$D = \left((d_1)^{P_1}(d_2)^{P_2}\ldots(d_n)^{P_n}\right)^{\frac{1}{\Sigma Pi}} = \left(\prod_{i=1}^{n} d_i^{Pi}\right)^{\frac{1}{\Sigma Pi}}. \tag{4}$$

The goals of minimum and maximum for defining desirability (di) were obtained using Eqs. (5) and (6), respectively.

$$d = \begin{cases} 0 & \text{if:} \quad y_i \le y_i^{\min} \\ \left(\frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}}\right)^{w_i} & \text{if:} \quad y_i^{\min} \le y_i \le y_i^{\max} \\ 1 & \text{if:} \quad y_i \ge y_i^{\max} \end{cases} \tag{5}$$

$$d = \begin{cases} 1 & \text{if:} \quad y_i \le y_i^{\min} \\ \left(\frac{y_i^{\min} - y_i}{y_i^{\max} - y_i^{\min}}\right)^{w_i} & \text{if:} \quad y_i^{\min} \le y_i \le y_i^{\max} \\ 0 & \text{if:} \quad y_i \ge y_i^{\max}. \end{cases} \tag{6}$$

RSM for soil erosion modeling and optimization

The simulation and optimization processes using RSM consist of six consecutive steps (Fig. 2): (1) screening of independent factors and defining dependent factors, (2) selecting the strategy for experimental design, (3) running the experiments and measuring the results, (4) fitting and diagnosing mathematical model, (5) confirming the model using ANOVA and graphs and (6) determination of optimal conditions (Karimifard and Moghaddam 2018). In this study, ten parameters (independent variables) were defined at minimum (− 1) and maximum (+ 1) levels for software (Table 2). Two responses in the output template (R_1 = amount of soil erosion and R_2 = soil erosion amount after management) were determined. The type of applied management scenario was a revision of crop cover and exclosure in the watershed. In the first step, a design for processing was selected. Then, the amounts of each input parameter (independent variables) were defined at minimum (− 1) and maximum (+ 1) levels. In the next step, the processing was begun after selecting the PTF and process order or regression models (mean, linear, 2FI, quadratic and cubic). In the last section of this stage, the software was shown the relationships between parameters as individually and interacting effect on the dependent variable (soil erosion) in the form of 2D and 3D graphs. In the optimization section, the optimization process was accomplished for both of the responses in two ways numerical and graphical that different stages of optimization and response parameters using RSM are shown (Fig. 2).

Results and discussion

Statistical analysis of RSM parameters and model selection

Our results illustrated a significant relationship between all evaluated parameters and soil erosion, before and after application of management scenarios. Regarding the possibility of RSM technique to select the best model among all assessed models using statistical parameters, the quadratic

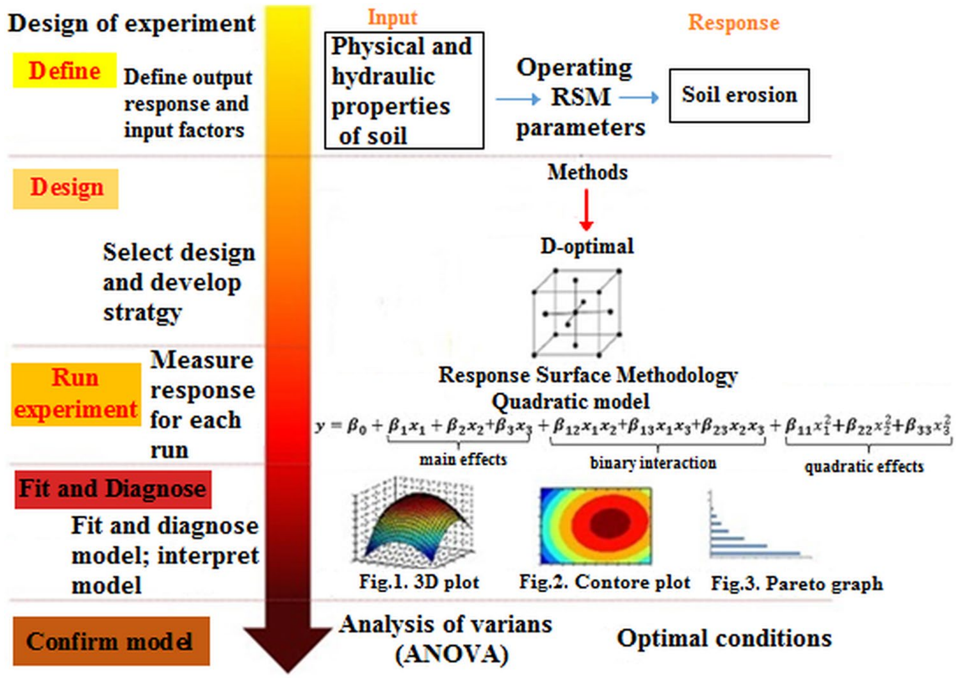

Fig. 2 Steps of experimental design in the response surface methodology

Table 2 The D-optimal design of the independent variables

Parameters	Coded values	
	Min (− 1)	Max (+ 1)
Physical		
Sand	− 1.000 = 6.0000	1.000 = 64.0000
Silt	− 1.000 = 14.0000	1.000 = 76.0000
Clay	− 1.000 = 6.0000	1.000 = 46.0000
SP	− 1.000 = 31.6000	1.000 = 68.1000
Stone	− 1.000 = 0.0900	1.000 = 5.2000
Hydraulic		
Theta *r*	− 1.000 = 0.0339	1.000 = 0.0974
Theta *s*	− 1.000 = 0.3856	1.000 = 0.4874
Alpha	− 1.000 = 0.0052	1.000 = 0.0291
n	− 1.000 = 1.2767	1.000 = 1.6799
K_S	− 1.000 = 6.8400	1.000 = 46.0100

model was suggested as the best model (Table 3) (select the highest-order polynomial where the additional terms are significant and the model is not aliased). Based on the statistical analysis, the quadratic model was selected as the best model; therefore in the ANOVA section, all analyses were performed with this selected model. The value of "Prob[2] > *F*" was smaller than 0.05, which defined as the α value of the test with a confidence interval of 95% (Table 4). This means that the quadratic model is significant and independent variables (physical and hydraulic properties of soil) influenced soil erosion. Also, the *F*-value of 99.30 implies that the model is significant. The values of "Prob > *F*" less than 0.05 indicate that our model is significant, whereas the values more than 0.10 stated that the model is not significant. Moreover, the *R*-square of the model with *df* equal to 65 ($df = n - 1$) was greater than 0.99, and the difference between *R*-square and adjusted *R*-square was smaller than 0.01, which illustrated the high accuracy of the obtained model. The "Adeq[3] Precision" measures the signal to noise ratio, and a ratio greater than 4 is desirable (Stat-Ease., 1998). Our results showed that this ratio was 23.73 which confirmed an adequate signal; therefore, this model can be used to navigate the design space. Ultimately based on all above mentioned statistical parameters, the optimization of effective parameters on soil erosion was performed using the quadratic model that suggested with the RSM. Therefore, using the RSM technique (Bezerra et al. 2008), the best model with the highest accuracy for simulation–optimization process was selected.

Interactive effects of sand and clay on soil erosion using RSM

The range of clay content was from 6 to 46%, and for sand content was 4 to 64%; therefore, results illustrated that minimum amount of soil erosion occurred in the maximum levels of both clay and sand contents which soil erosion was equal to 15.4 ton/ha (Fig. 3a). Also, the maximum amount

[2] Probability.

[3] Adequate.

Table 3 Statistical parameters of different regression models based on dependents variables (including R_1 and R_2)

Source	SDEV		R-square		Adjusted R-square		
Response	R_1	R_2	R_1	R_2	R_1	R_2	
Linear	4.740	2.030	0.2789	0.0911	0.1587	−0.0604	
2FI	3.990	2.100	0.8720	0.7560	0.4027	−0.1389	
Quadratic	0.540	0.260	0.9992	0.9988	0.9892	0.9826	Suggested
Cubic	0	0	1	1	1	1	Aliased

Additionally, mean ± standard deviation (SDEV) is shown (n = 66)

Table 4 The ANOVA analysis for response surface quadratic model

ANOVA for response surface quadratic model											
Source	Sum of squares		*df*		Mean square		F-value		p value prob > f		
Response	R_1	R_2	R_1	R_2	R_1	R_2	R_1	R_2	R_1	R_2	
Model	1865.41	270.71	65	65	28.70	4.16	99.30	61.94	< 0.0001	< 0.0001	Significant

of soil erosion (equal to 24 ton/ha) was at the minimum level of clay content and the sand content between 40 and 50% (Fig. 3c). According to the high amount of sand and increasing clay content (Fig. 3a), it was expected that soil erosion was reduced from 22.8 to 15.4 ton/ha. The main reason for this result is the meaningful effect of clay and associated organic matter content on soil aggregation compared to silt and sand particles (Kumar et al. 2016; Mangalassery et al. 2019). Therefore, in the soil conservation plan, one of the most important parts is the soil properties.

Moreover, according to Russell's theory, clay particles owing to small size with high cation exchange capacity and high specific surface area, therefore, enhance soil aggregation and diminish the soil erosion potential (Shaikh et al. 2017; Spagnoli and Shimobe 2019). However, based on the existing management situations in the studied watershed and the interaction effects of sand and clay content, the soil erosion was around 15 ton/ha. To evaluate the effectiveness of management scenarios using WEPP model, the effect of the applied management strategies including revision of crop cover (RC) and exclosure (EX) was assessed as response 2 (R_2) using RSM. Results showed that after the application of management scenarios as R_2, the soil erosion was significantly decreased to around 1–2 ton/ha (Fig. 3b). This meaningful declining of soil erosion clearly confirmed the positive effects of convenient management strategies on soil preserving against erosive forces. Feng et al. (2006) showed that the establishment of a vegetation riparian buffer regarding the crop cover revision is an effective scenario to reduce the on-site and off-site effects of soil erosion. Indeed, the riparian buffer is a permanent vegetation cover which is located between erosion site and water bodies with numerous capabilities to mitigate soil erosion potential. Also, as Fig. 3b illustrates regarding the effectiveness of the applied management scenarios, the amount of deposited soil was −0.06 ton/ha, which means the dramatical effects of the applied management scenarios on soil erosion controlling in the watershed. Results confirmed that the application of convenient management scenarios is able to conserve soil against erosive agents, therefore to mitigate on-site and off-site effects of soil erosion. The evaluated management strategies in our study were non-structural management scenarios which covered the purposes of sustainable management.

Interactive effects of sand and Ks on soil erosion using RSM

Our results depicted that by increasing the sand content and saturated hydraulic conductivity (Ks), the soil erosion was at the minimum level, which was equal to 21.7 ton/ha (Fig. 4a). As Fig. 4a shows by decreasing of sand content and Ks, the soil erosion potential was enhanced to 26 ton/ha while when the Ks was between 10 and 25 cm/day, the soil erosion was at the lowest amount (22 ton/ha) (Fig. 4c). As our results illustrated the hydraulic conductivity and sand content both are effective on soil erosion occurrence and this is an interactive effect. Soil erosion as a dynamic phenomenon is a function of different factors; therefore, despite the increasing of hydraulic conductivity, this parameter is not sufficient to enhance the resistance of soil aggregates against erosive factors (Jarzyna et al. 2019; Barman et al. 2019). Considering the complexity of the soil erosion process, the RSM technique provides an advanced infrastructural analysis to evaluate the interaction effects of different parameters on soil erosion. Utilizing the interactive effects of several parameters on soil erosion is a suitable tool to select and apply the best management practice in the critical area.

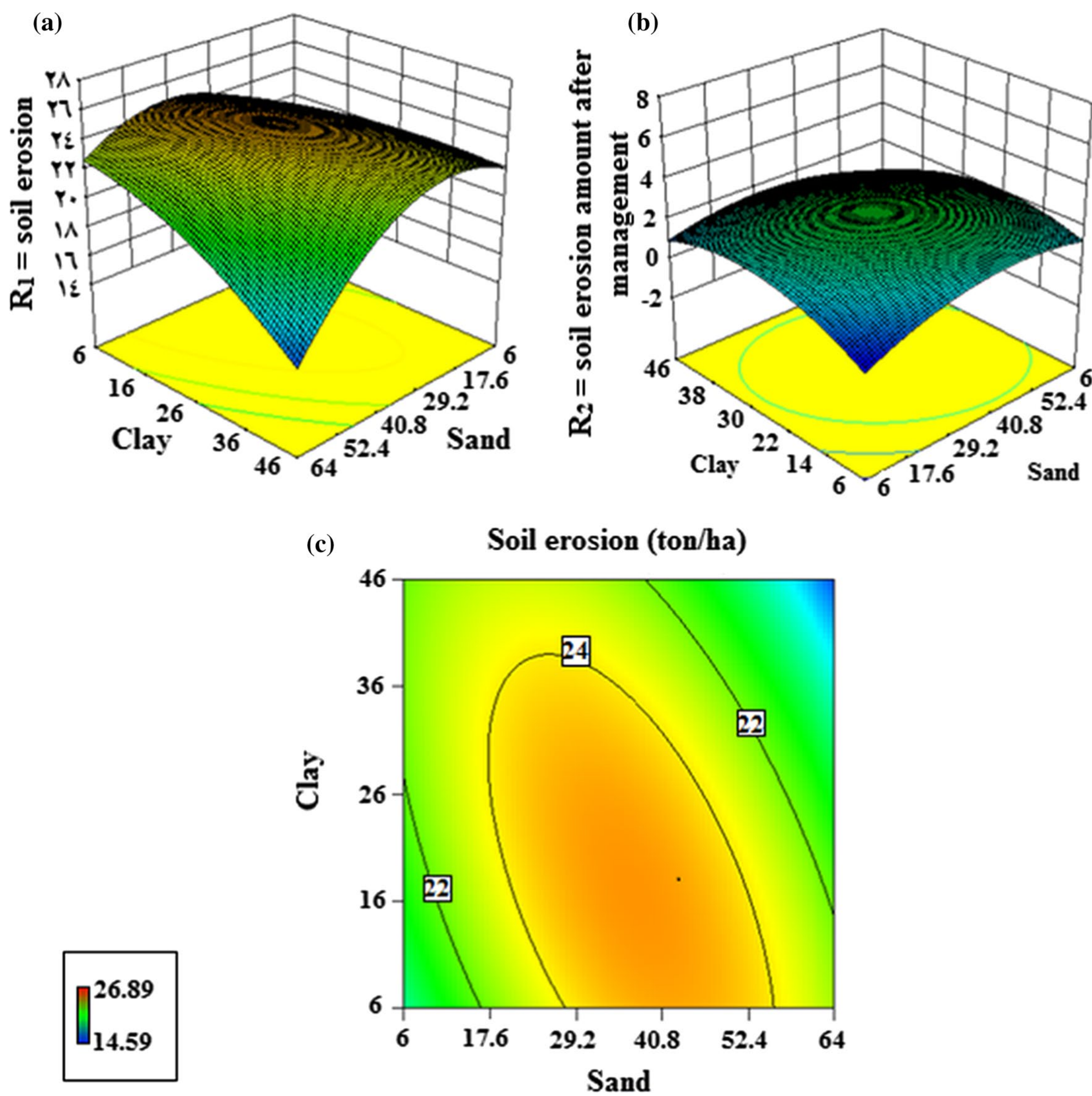

Fig. 3 The 3D diagram of clay and sand effects on the soil erosion. **a** Before application of management scenarios and **b** after application of management scenarios. The contour plot of clay and sand content (**c**)

Also, investigation of interactive factors presents a real situation of soil erosion occurrence in the watershed.

Results of management scenarios applications on soil erosion outcomes illustrated the significant effects of management strategies on soil erosion controlling and diminishing to 1.7–3 ton/ha (Fig. 4b). Actually, this mitigation of soil erosion (at the maximum level, 3 ton/ha) is significantly effective on different parts of conservational plan and reduces the costs of soil preserving. This result confirms the meaningful effects of land use and the type of management operations on soil erosion occurrence.

Interactive effects of clay and theta *r* on soil erosion using RSM

The relation between clay and residual moisture (theta *r*), which is associated with clay content increasing and the theta *r* decreasing, is shown (Fig. 5a). As Fig. 5a shows, by reducing theta *r* and clay content, the soil erosion was at the maximum level (equal to 25.7 ton/ha), whereas by increasing clay content the soil erosion was decreased and illustrated the minimum level (equal to 21.7 ton/ha). The clay particles have an essential role in soil aggregation processes and meaningfully are effective on aggregate stability; therefore, with changing the soil clay content, the magnitude of soil erosion was varied (Arthur et al. 2019). The theta *r* as

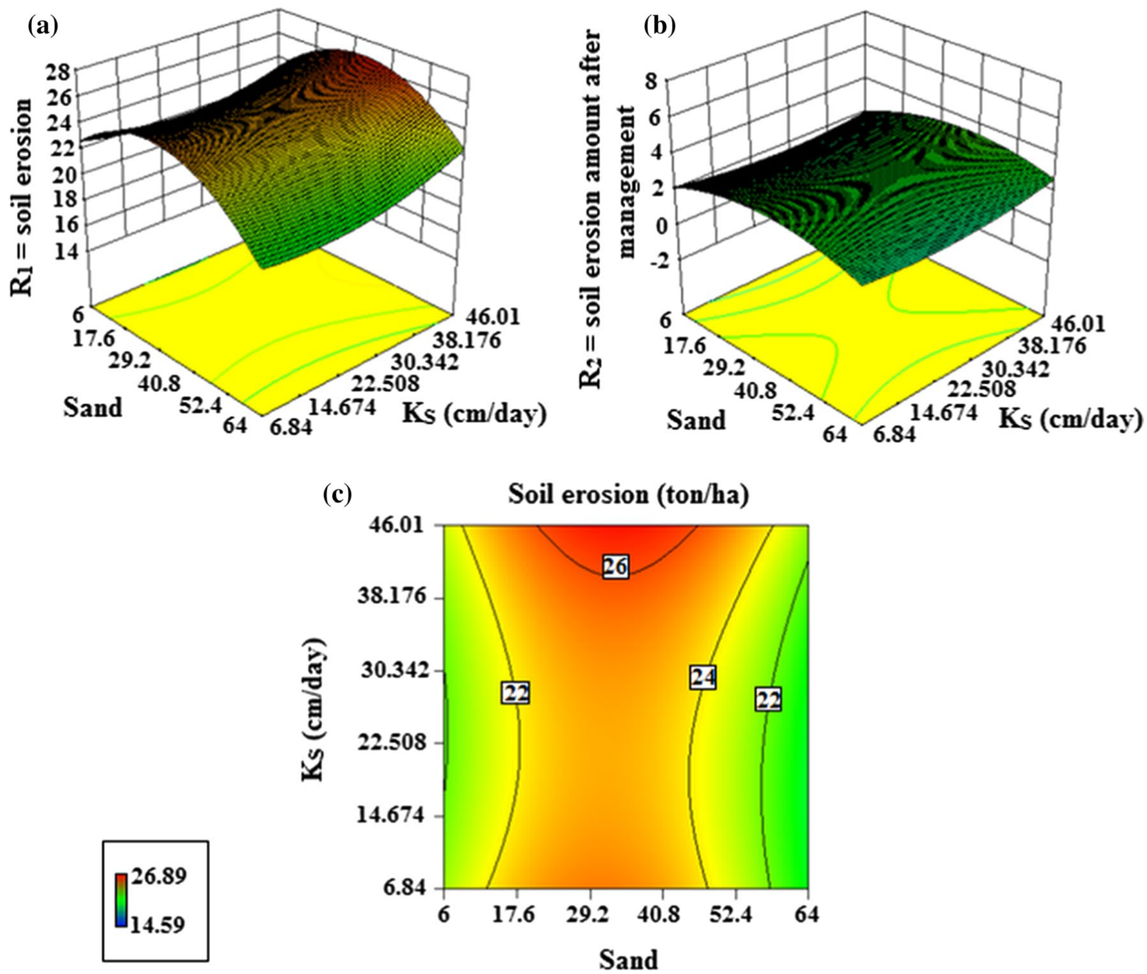

Fig. 4 The 3D diagram of sand content and saturated hydraulic conductivity (Ks) on the soil erosion. **a** Before application of management scenarios and **b** after application of management scenarios. The contour plot of sand content and saturated hydraulic conductivity (**c**)

hydraulic parameter depends on soil porosity, and the heavy textured soils have higher theta *r* values. Our results show that the theta *r* is equal to 0.03393 for silty soils (Fig. 5a) and regarding the structural properties of silt particles, the existence of silt particles in the soil enhanced the soil erosion potential. Also, the interaction between sand particles and theta *r* is same as the interaction between clay particles and theta *r*, because both of them can control the soil erosion occurrence (Wee and Yap 2019). Besides, sand particles reduced the soil erosion by increasing permeability and saturated hydraulic conductivity (Ks) in the critical soils, therefore reduce the runoff potential. Based on the modeling results, the critical area was recognized; then for those areas, the specific management scenarios were defined.

Regarding the effectiveness of those management strategies (R_2 in the RSM), the soil erosion was decreased to 1.6–3.5 ton/ha (Fig. 5b). This significant decreasing in soil erosion confirmed the positive feedbacks of appropriate management scenarios to reduced soil erosion and the off-site effects of erosion. Dybkjær et al. (2012) showed the significant effects of plant cover properties that consist of density, length and width on soil erosion controlling; therefore, the plant operations in the form of management strategies are effective on soil erosional behaviors. Application of RSM technique with responses (mainly R_2) clearly showed the positive impacts of clay particles and management scenarios on soil erosion controlling in the watershed (Fig. 5b). Soil aggregation mainly depends on clay content, and beside the soil clay content, land use (the applied management scenarios) significantly determine the soil status against erosive forces.

Interactive effect of clay and theta *s* on soil erosion using RSM

The interaction effects of soil clay content and saturation moisture (theta *s*) are shown (Fig. 6a). As Fig. 6a illustrates, the minimum level of soil erosion was at the maximum level of clay content and the minimum amount

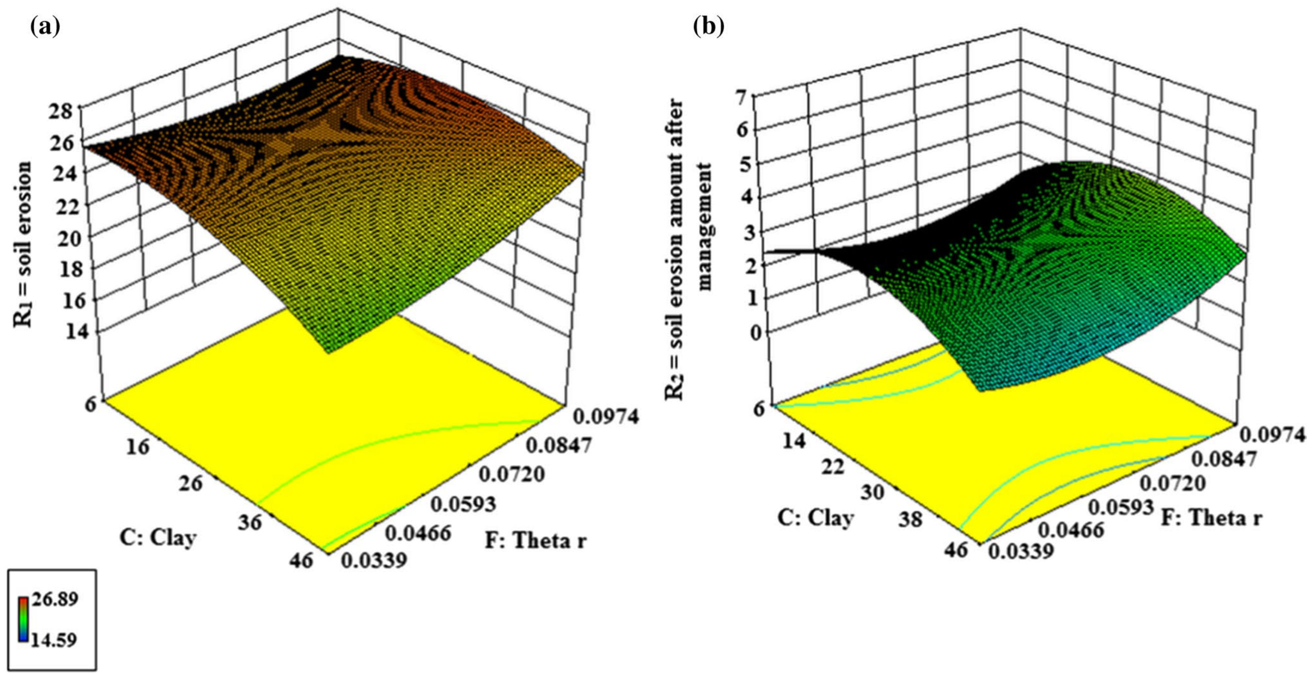

Fig. 5 The 3D diagram of clay content and moisture residual (theta *r*) on the soil erosion. **a** Before application of management scenarios and **b** after application of management scenarios

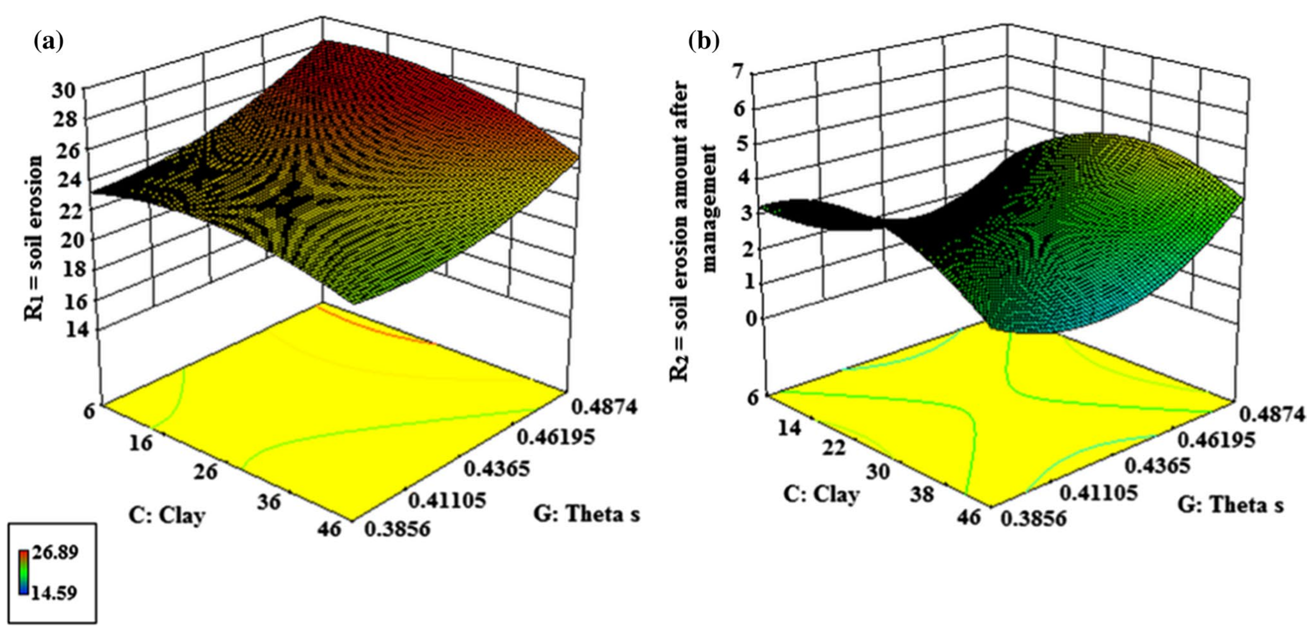

Fig. 6 The 3D diagram of clay and saturation moisture (theta *s*) on the soil erosion. **a** Before application of management scenarios and **b** after application of management scenarios

of theta *s*. As mentioned in other sections of the paper, clay particles are capable of creating and increasing the binding in the soil matrix; therefore by increasing the clay content individually, the soil erosion was decreased (Chen et al. 2014). Our results showed that the theta *s* was equal to 0.38, which means the soil texture could be sandy clay and clay, because theta *s* is an index of soil texture therefore could represent the soil hydrological

Table 5 The ANOVA result of quadratic model for responses (R_1 and R_2)

Response	R_1	R_2	Response	R_1	R_2
SDEV	0.54	0.26	R-square	0.9992	0.9988
Mean	20.76	1.48	C.V. %	2.59	17.52

Table 6 The range of input parameters and responses for optimization using RSM

Parameters	Unit	Goal	Lower limit	Upper limit	Importance
A[a]: Sand	%	Is in range	6.0000	64.0000	***[b]
B: Silt	%	Minimize	14.0000	76.0000	****[b]
C: Clay	%	Is in range	6.0000	46.0000	***
D: SP	%	Is in range	31.6000	68.1000	***
E: Stone	%	Is in range	0.0900	5.2000	***
F: Theta *r*	–	Is in range	0.0339	0.0974	***
G: Theta *s*	–	Is in range	0.3856	0.4874	***
H: Alpha	–	Is in range	0.0052	0.0291	***
J: *n*	–	Is in range	1.2767	1.6799	***
K: Ks	cm/day	Maximize	6.8400	46.0100	****
R_1	ton/ha	Minimize	14.5900	26.8900	*****[b]
R_2	ton/ha	Minimize	0.0900	6.0100	*****

[a]The codes of independent variables

[b]The importance values

group. These results confirmed the relation and interaction effects of clay content and the hydraulic properties. Application of RSM technique in the form of R_2 (Fig. 6b), to evaluate the interaction effects of clay content theta *s* and the management strategies, illustrated the positive effects of management scenarios to reduced soil erosion. Generally, the application of convenient and adaptive management programs in the watershed plays an effective role to diminish soil erosion and deposition. This is a milestone of RSM that based on response 2 (R_2) clearly presents the effectiveness of convenient management operations and is applicable for selecting the best management practice in the watershed. Generally, interactive effects of soil texture components, hydraulic characteristics and land use are effective on soil erosion occurrence (Table 5).

Table 7 The optimal values of input parameters and responses

Parameters	Unit	Goal	Optimum values
A: Sand	%	Is in range	60.241
B: Silt	%	Minimize	14.000
C: Clay	%	Is in range	41.025
D: SP	%	Is in range	58.729
E: Stone	%	Is in range	3.830
F: Theta *r*	–	Is in range	0.090
J: Theta *s*	–	Is in range	0.457
H: Alpha	–	Is in range	0.014
J: n	–	Is in range	1.300
K: Ks	cm/day	Maximize	46.010
R_1	ton/ha	Minimize	11.537
R_2	ton/ha	Minimize	−2.253
Desirability	–	–	1

Optimization of effective factors on erosion using RSM

The design factors, model responses and optimized values are shown (Tables 6, 7). In the optimization phase, the purpose is finding the optimal value of the independent and dependent parameters shown in Table 7. In the present study, the desirability function was used for the optimization (Ardebili et al. 2019). All parameters were weighted equally 1:1 with an importance of 3 for each of them other than silt and K_S parameters that were set in 4. Also, the importance of dependent variables was 5. The bar graph is used to display desirability of the results and is shown as being a variable from to 1 denoting the vicinity of the output. The optimal solution for the problem is achieved with the following design parameters, and the entire results of the model are close to maximum anticipation set for the model (Fig. 7). Finally, the optimal blend was selected based on the result of the desirability function that so equals 1. This technique shows that by defining the K_S parameter in the maximum of goal, silt and dependent variables in the minimum of goal, the R_1 value is 11.54 ton/ha and R_2 is equal −2.25 ton/ha. Thus, the bar graph shows how each design factor is optimally set to get requirements, and total desirability equal 1 is excellent attainment (Fig. 8) (Pour et al. 2018). Therefore, using the RSM technique for selected parameters and the real situation in the studied watershed, the statistical parameters were obtained to apply the best one in the watershed.

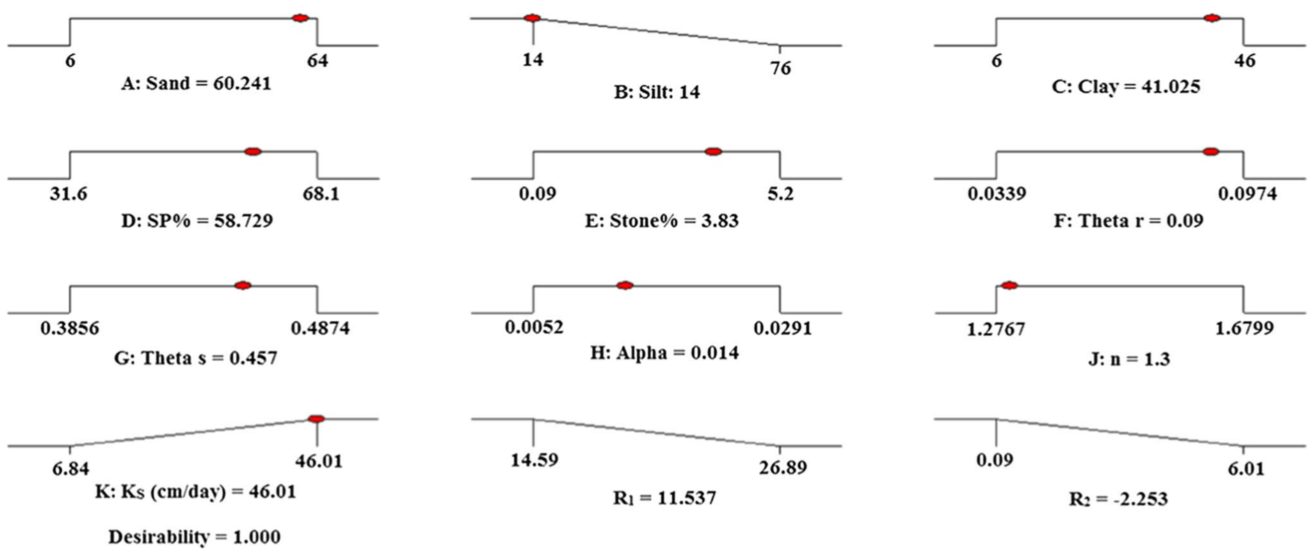

Fig. 7 The ramp graph of optimization using RSM technique

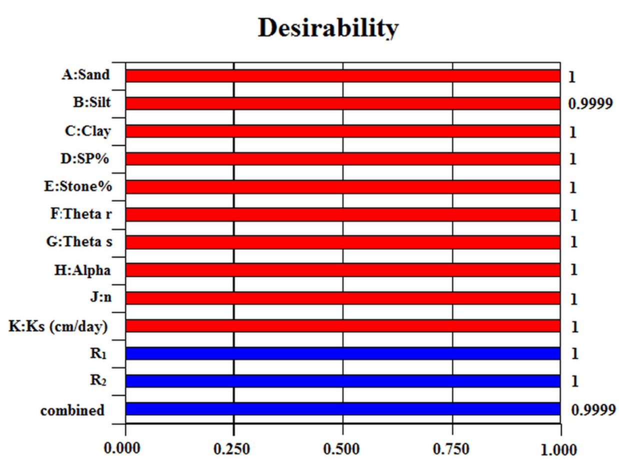

Fig. 8 The bar graph of desirability

Conclusion

RSM as a powerful methodology has high potential and optimizes modeling that can gain in more significant and comprehensive outcomes. Today, using of response surface methodology in optimization processes and analytical methods is expanding because of its benefits as one-variable-a-time and providing large amounts of information from a small number of experiments. Presentation of several optimization scenarios could be ideal for future studies to fully to establish the process of optimization in different and diverse scopes which could result in a better understanding of the process and applicability of the optimization. The purpose of this study was to optimize the physical and hydraulic properties of soil, providing the best management practices according to optimization results. The results showed that changes in physical and hydraulic parameters of soil have a significant effect on soil erosion. Also, the effect of the physical/hydraulic parameters on response variables was discussed using ANOVA results of suggested models. According to ANOVA results, it was found that all of the suggested models were significant at 1% level and the *p* value of model is equal to 0.0001. The optimized values of different physical parameters were 60.241 for sand, 14 for silt, 41.025 for clay, 58.729% for SP and 3.83% for stone. A theta *r* of 0.09, theta *s* of 0.457, alpha of 0.014, *n* of 1.3 and Ks of 46.01 were found to be optimal values. The results of this study indicated that at optimal studied parameters the values of the soil erosion before and after management scenarios were found to be 11.537 and −2.253, respectively. Results show that both physical and hydraulic parameters have significant effects at the 1% level on the soil erosion. The obtained results could assist policy-makers with decisions aimed at minimizing soil erosion in this watershed.

References

Anache JA, Flanagan DC, Srivastava A, Wendland EC (2018) Land use and climate change impacts on runoff and soil erosion at the hillslope scale in the Brazilian Cerrado. Sci Total Environ 622:140–151

Ardebili SMS, Solmaz H, Mostafaei M (2019) Optimization of fuel oil–Gasoline blend ratio to enhance the performance and reduce emissions. Appl Therm Eng 148:1334–1345

Argent RM, Sojda RS, Giupponi C, McIntosh B, Voinov AA, Maier HR (2016) Best practices for conceptual modelling in environmental planning and management. Environ Model Softw 80:113–121

Arnold JG, Youssef MA, Yen H, White MJ, Sheshukov AY, Sadeghi AM, Haney EB (2015) Hydrological processes and model representation: impact of soft data on calibration. Trans ASABE 58(6):1637–1660

Arthur E, Tuller M, Norgaard T, Moldrup P, de Jonge LW (2019) Improved estimation of clay content from water content for soils rich in smectite and kaolinite. Geoderma 350:40–45

Barman B, Kumar B, Sarma AK (2019) Impact of sand mining on alluvial channel flow characteristics. Ecol Eng 135:36–44

Batista PV, Davies J, Silva ML, Quinton JN (2019) On the evaluation of soil erosion models: Are we doing enough? Earth Sci Rev 102898

Bezerra MA, Santelli RE, Oliveira EP, Villar LS, Escaleira LA (2008) Response surface methodology (RSM) as a tool for optimization in analytical chemistry. Talanta 76(5):965–977

Boll J, Brooks ES, Crabtree B, Dun S, Steenhuis TS (2015) Variable source area hydrology modelling with the water erosion prediction project model. JAWRA J Am Water Resources Assoc 51(2):330–342

Brooks ES, Dobre M, Elliot WJ, Wu JQ, Boll J (2016) Watershed-scale evaluation of the Water Erosion Prediction Project (WEPP) model in the Lake Tahoe basin. J Hydrol 533:389–402

Chabbi A, Yallese MA, Meddour I, Nouioua M, Mabrouki T, Girardin F (2017) Predictive modelling and multi-response optimization of technological parameters in turning of Polyoxymethylene polymer (POM C) using RSM and desirability function. Measurement 95:99–115

Chandramohan T, Venkatesh B, Balchand AN (2015) Evaluation of three soil erosion models for small watersheds. Aquatic Procedia 4:1227–1234

Chen C, Ren T, Hu K, Li B, Wang Y (2014) Estimation of soil clay content using hygroscopic water content at an arbitrary humidity. Soil Sci Soc Am J 78(1):119–124

Corella JP, Benito G, Wilhelm B, Montoya E, Rull V, Vegas T, Valero-Garcés BL (2019) A millennium-long perspective of flood-related seasonal sediment yield in Mediterranean watersheds. Glob Planet Change 177:127–140

De Oliveira Faber M, Ferreira-Leitão VS (2016) Optimization of biohydrogen yield produced by bacterial consortia using residual glycerin from biodiesel production. Biores Technol 219:365–370

Dinarvand M, Rezaee M, Foroughi M (2017) Optimizing culture conditions for the production of intra and extracellular inulinase and invertase from Aspergillus Niger ATCC 20611 by response surface methodology (RSM). Braz J Microbiol 48(3):427–441

Diodato N, Gericke A, Bellocchi G (2012) Modelling the inter-annual variability of sediment yields: a case study for the upper Lech River. Catena 97:12–19

Dybkjær JB, Baattrup-Pedersen A, Kronvang B, Thodsen H (2012) Diversity and distribution of riparian plant communities in relation to stream size and eutrophication. J Environ Qual 41(2):348–354

Feng H, Kurkalova LA, Kling CL, Gassman PW (2006) Environmental conservation in agriculture: land retirement vs. changing practices on working land. J Environ Econ Manag 52(2):600–614

Flanagan DC, Nearing MA (1995) USDA-Water Erosion Prediction Project: Hillslope profile and watershed model documentation, vol 10, pp 1603–1612. NSERL report

Flanagan DC, Frankenberger JR, Cochrane TA, Renschler CS, Elliot WJ (2013) Geospatial application of the water erosion prediction project (WEPP) model. Trans ASABE 56(2):591–601

Gao Y, Xu J, Luo X, Zhu J, Nie L (2016) Experiment research on mix design and early mechanical performance of alkali-activated slag using response surface methodology (RSM). Ceram Int 42(10):11666–11673

Giannecchini R (2006) Relationship between rainfall and shallow landslides in the southern Apuan Alps (Italy). Nat Hazards Earth Syst Sci 6(3):357–364

IPBES (2018) In: Scholes R, Montanarella L, Brainich A, Barger N, ten Brink B, Cantele M, Erasmus B, Fisher J, Gardner T, Holland TG, Kohler F, Kotiaho JS, Von Maltitz G, Nangendo G, Pandit R, Parrotta J, Potts MD, Prince S, Sankaran M, Willemen L (eds) Summary for policymakers of the assessment report on land degradation and restoration of the Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services. IPBES Secretariat, Bonn

Jarzyna JA, Puskarczyk E, Motyka J (2019) Estimating porosity and hydraulic conductivity for hydrogeology on the basis of reservoir and elastic petrophysical parameters. J Appl Geophys 167:11–18

Johnson CW, Gebhardt KA (1982) Predicting sediment yields from sagebrush rangelands [Pacific Southwest Inter-Agency Committee prediction procedure, southwest Idaho]. Agric Rev Manuals

Karimifard S, Moghaddam MRA (2018) Application of response surface methodology in physicochemical removal of dyes from wastewater: a critical review. Sci Total Environ 640:772–797

Keshtegar B, Allawi MF, Afan HA, El-Shafie A (2016) Optimized river stream-flow forecasting model utilizing high-order response surface method. Water Resour Manag 30(11):3899–3914

Kinnell PIA, Wang J, Zheng F (2018) Comparison of the abilities of WEPP and the USLE-M to predict event soil loss on steep loessal slopes in China. Catena 171:99–106

Kirkby MJ, Irvine BJ, Jones RJ, Govers G, PESERA team (2008) The PESERA coarse scale erosion model for Europe. I.–Model rationale and implementation. Eur J Soil Sci 59(6):1293–1306

Kumar AK, Kalaiselvi B, Sujata K, Nair KM, Singh SK (2016) Characterization of red and lateritic soils formed under varied climates and their management. Clay Res 35(1):43–53

Kumar M, Singh G, Arya SK, Bhatti JS, Sharma P (2018) Artificial Neuro-Fuzzy Inference System (ANFIS) based validation of laccase production using RSM model. Biocatal Agric Biotechnol 14:235–240

Laflen JM, Flanagan DC (2013) The development of US soil erosion prediction and modeling. Int Soil Water Conserv Res 1(2):1–11

Long X, Cai L, Li W (2019) RSM-based assessment of pavement concrete mechanical properties under joint action of corrosion, fatigue, and fiber content. Constr Build Mater 197:406–420

Mangalassery S, Kalaivanan D, Philip PS (2019) Effect of inorganic fertilizers and organic amendments on soil aggregation and biochemical characteristics in a weathered tropical soil. Soil Tillage Res 187:144–151

Meliho M, Nouira A, Benmansour M, Boulmane M, Khattabi A, Mhammdi N, Benkdad A (2019) Assessment of soil erosion rates in a Mediterranean cultivated and uncultivated soils using fallout 137Cs. J Environ Radioact 208:106021

Mhazo N, Chivenge P, Chaplot V (2016) Tillage impact on soil erosion by water: discrepancies due to climate and soil characteristics. Agric Ecosyst Environ 230:231–241

Mondal A, Khare D, Kundu S, Mukherjee S, Mukhopadhyay A, Mondal S (2017) Uncertainty of soil erosion modeling using open source high resolution and aggregated DEMs. Geosci Front 8(3):425–436

Montgomery DC, Anderson-Cook CM (2009) Response surface methodology: process and product optimization using designed experiments. Wiley, New York

Muthusamy S, Manickam LP, Murugesan V, Muthukumaran C, Pugazhendhi A (2019) Pectin extraction from Helianthus annuus (sunflower) heads using RSM and ANN modelling by a genetic algorithm approach. Int J Biol Macromol 124:750–758

Najafi G, Ghobadian B, Yusaf T, Ardebili SMS, Mamat R (2015) Optimization of performance and exhaust emission parameters of a SI (spark ignition) engine with gasoline-ethanol blended fuels using response surface methodology. Energy 90:1815–1829

Nasiri A, Shirokova V, Zareie S, Shojaei S (2017) Assessment of the statue and intensity of water erosion in the river basin Delichai

(Iranian territory) using GIS model. In: International multidisciplinary scientific Geoconference: SGEM: surveying geology and mining ecology management, vol 17, pp 89–96
Park S, Oh C, Jeon S, Jung H, Choi C (2011) Soil erosion risk in Korean watersheds, assessed using the revised universal soil loss equation. J Hydrol 399(3–4):263–273
Pattanaik A, Rayasam V (2018) Analysis of reverse cationic iron ore fines flotation using RSM-D-optimal design–An approach towards sustainability. Adv Powder Technol 29(12):3404–3414
Podder MS, Majumder CB (2015) Modeling of optimum conditions for bioaccumulation of As (III) and As (V) by response surface methodology (RSM). J Environ Chem Eng 3(3):1986–2001
Pour AH, Ardebili SMS, Sheikhdavoodi MJ (2018) Multi-objective optimization of diesel engine performance and emissions fueled with diesel-biodiesel-fusel oil blends using response surface method. Environ Sci Pollut Res 25(35):35429–35439
Qian F, Cheng D, Liu J (2014) Analysis of the water and soil erosion and infiltration characteristic in Ziquejie Terrace. IERI Procedia 9:13–19
Rao MS, Venkaiah N (2015) Parametric optimization in machining of Nimonic-263 alloy using RSM and particle swarm optimization. Procedia Mater Sci 10:70–79
Schaap MG, Leij FJ (2000) Improved prediction of unsaturated hydraulic conductivity with the Mualem-van Genuchten model. Soil Sci Soc Am J 64(3):843–851
Schole RJ, Kanter DR, Musumba M, Wood SL, Palm C, Antle J, Balvanera P, Thornton P (2018) Evaluating agricultural trade-offs in the age of sustainable development. Agric Syst 163:73–88
Shaikh SM, Nasser MS, Hussein I, Benamor A, Onaizi SA, Qiblawey H (2017) Influence of polyelectrolytes and other polymer complexes on the flocculation and rheological behaviors of clay minerals: a comprehensive review. Sep Purif Technol 187:137–161
Sharma AK, Kaith BS, Tanwar V, Bhatia JK, Sharma N, Bajaj S, Panchal S (2019) RSM-CCD optimized sodium alginate/gelatin based ZnS-nanocomposite hydrogel for the effective removal of biebrich scarlet and crystal violet dyes. Int J Biol Macromol 129:214–226
Sherriff SC, Rowan JS, Fenton O, Jordan P (2018) Sediment fingerprinting as a tool to identify temporal and spatial variability of sediment sources and transport pathways in agricultural catchments. Agric Ecosyst Environ 267:188–200
Shojaei S, Ardakani MAH, Sodaiezadeh H (2019) Optimization of parameters affecting organic mulch test to control erosion. J Environ Manag 249:109414
Spagnoli G, Shimobe S (2019) A statistical reappraisal of the relationship between liquid limit and specific surface area, cation exchange capacity and activity of clays. J Rock Mech Geotech Eng 11:874–881
Tan YH, Abdullah MO, Nolasco-Hipolito C, Zauzi NSA (2017) Application of RSM and Taguchi methods for optimizing the transesterification of waste cooking oil catalyzed by a solid ostrich and chicken-eggshell derived CaO. Renew Energy 114:437–447
Thomas GW (1982) Exchangeable cations. In: Page AL (ed) Methods of soil analysis, Part 2, Chemical and microbiological properties, 2nd edn. Agronomy, No. 9, Part 2. American Society of Agronomy, Soil Science Society of America, Madison, WL, pp 159–165
Tiwari AK, Risse LM, Nearing MA (2000) Evaluation of WEPP and its comparison with USLE and RUSLE. Trans ASAE 43(5):1129
Wee SK, Yap YJ (2019) CFD study of sand erosion in pipeline. J Petrol Sci Eng 176:269–278
Xiong M, Sun R, Chen L (2019) A global comparison of soil erosion associated with land use and climate type. Geoderma 343:31–39
Xu L, Xu X, Meng X (2013) Risk assessment of soil erosion in different rainfall scenarios by RUSLE model coupled with Information Diffusion Model: a case study of Bohai Rim, China. Catena 100:74–82