Using random forest and multiple-regression models to predict changes in surface runoff and soil erosion after prescribed fire

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Abstract

Prescribed fire is a viable practice to reduce the wildfire risk in forests, but its application may lead to increased surface runoff and soil erosion. Several hydrological and erosive models have been proposed and evaluated to predict the changes in soil hydrology and erosion after prescribed fire. However, the prediction capacity of machine learning and Multiple-Regression models has scarcely been studied in sites treated with prescribed fire, despite of the usefulness of these tools for landscape planners. This study aims to evaluate how a Random Forest, RF, algorithm and Multiple-Regression, MR, and Partial Least Square Regression, PLS-R, equations can predict changes in surface runoff and soil erosion after prescribed fire. This prediction capacity has been quantified through the application of the models to 35 case studies reported in 18 academic papers selected from the international scientific literature. The model predictions have been evaluated using common statistics and indexes (e.g., the coefficient of Nash and Sutcliffe, NSE). The results show poor performance of the RF and PLS-R models in predicting runoff (NSE < 0 and < 0.31). However, the models' capacity to predict soil erosion was acceptable (NSE = 0.47 and 0.69, respectively). The predictions by the MR equation were also acceptable for runoff (NSE < 0.69) and good for erosion (NSE = 0.80). Furthermore, the MR equation offers a large applicability, since this simple model has been tested using a database of hydrological observations in environments with different characteristics. The performance of MR equations is encouraging when its broader use in runoff and erosion predictions in soils treated with prescribed fire.

Keywords Soil hydrology; wildfire risk; machine learning; regression analysis; hydrological modelling.

Introduction

Prescribed fire is an effective tool to reduce wildfire risk in rural areas (forests, pastures and croplands) and, as such, has been applied in several countries (Klimas et al. 2020). Prescribed fire treatments generally have a low severity and intensity, and the soil temperature is much lower compared to wildfires (Cawson et al. 2016). However, prescribed fire removes almost all litter cover and understory vegetation, leaving the soil exposed to rainfall erosivity (Hueso-González et al. 2018). Furthermore, the changes in some soil properties may be noticeable (e.g., reduction in organic matter content and thus hydraulic conductivity (Alcañiz et al. 2018)), and soil water repellency may occur or noticeably increase after a prescribed fire (Pierson et al. 2008; Cawson et al. 2016).

These impacts of prescribed fire on soil generally result in noticeable changes in runoff and erosion rates as well as alterations in the water quality of streams for some months after its application (Carrà et al. 2022; Beyene et al. 2023). For instance, Cawson et al. (2012) and Shakesby et al. (2015) report increases in runoff and erosion of one to two orders of magnitude when compared to unburned areas. These increases occur especially in the so-called 'window of disturbance', a period lasting some months from prescribed fire's application (Prosser and Williams 1998). In contrast, according to Coelho et al. (2004), and de Dios Benavides-Solorio and MacDonald (2005), prescribed fire generally results in minimal erosion. Furthermore, Keesstra et al. (2014) found lower erosion rates in sites burned with prescribed fire as compared to unburned forests. These contrasting results are mainly due to complex, highly dynamic and constantly changing hydrological processes in burned sites (Cao et al. 2022).

When they occur, the changes in soil hydrology after prescribed fire can induce severe flooding, erosion and landslides. To control and mitigate the associated risks, accurate predictions of post-fire runoff and erosion in sites treated with prescribed fire are essential (Morris et al. 2014). Computer-based models are generally able to predict the changes in hydrological and erosive variables resulting from complex natural processes and land management actions. These models may be of a different nature (e.g., empirical, physically-based and conceptual) and show different complexity and variable requirements of the input data (Merritt et al. 2003; Aksoy and Kavvas 2005). Therefore, choosing the most suitable model for a specific environment is difficult, and landscape managers and hydrologists need practical guidance to make this choice. Their planning and management tasks are complex, due to the large variability of environmental conditions.

Runoff and erosion in burned sites have been modelled using many prediction models in several environments (e.g., Rulli et al. 2013; Fernández and Vega 2016; Salis et al. 2019). Hydrological applications have tested empirical (e.g., SCS-CN and USLE-family models, Larsen and MacDonald 2007; Soulis 2018), semi-empirical (e.g., MMF, Hosseini et al. 2018; Vieira et al. 2018b), and more complex models (e.g., PESERA and WEPP models, Karamesouti et al. 2016; Fernández and Vega 2018) to predict the hydrological and erosive response of forest soils affected by wildfires. Studies showing modelling applications in sites treated with prescribed fire are much fewer (e.g., Lucas-Borja et al. 2020; Zema et al. 2022). To summarize, Lucas-Borja et al. (2020) applied linear regression equations and the SCS-CN model to predict surface runoff in the pine forests of Central-Eastern Spain. In three forest stands in Southern Italy, Carrà et al. (2021) found accurate predictions of runoff and soil loss using the SCS-CN and USLE-M models, while the simulations by Horton and MUSLE equations were poor. Despite the encouraging results from when using these models, these studies are limited in number, to common empirical models and also confined to specific environments. In contrast, at least to the authors' best knowledge, no evaluations of more complex models, such as machine learning algorithms or Multiple-Regression techniques, are available in areas treated with prescribed fire. Compared to the empirical models, these prediction tools may better capture the complexity of post-fire soil hydrology and offer larger applicability in environments with different climatic, soil and vegetation characteristics.

To fill this gap, this study aims to evaluate whether changes in surface runoff and soil erosion after prescribed fire can be predicted worldwide using Random Forest (a machine learning algorithm), and Multiple-Regression and Partial Least Square Regression models (two multivariate statistical models). To this aim, these three models have been applied to a dataset of 35 case studies found in the international scientific literature.

Materials and Methods

Paper selection

Comprehensive bibliographic research was carried out in late January2023 on Scopus®, Web of Science® and Google® Scholar® databases, to find academic papers, relevant to prescribed fire and soil hydrology, published between the year2000 and the present. The following individual keywords or combination of keywords were used:

‘prescribed fire’, ‘prescribed burning’, ‘water infiltration’, ‘soil hydraulic conductivity’, ‘surface runoff’, ‘soil loss’ and ‘water erosion’. This bibliographic research returned 41 articles with 89 case studies.

In order to identify the key drivers of the changes in surface runoff and erosion rates in burned soils, the following ‘environmental characteristics’ were identified according to the relevant literature (Neary et al. 1999; Certini 2005; Shakesby and Doerr 2006; Keeley 2009; Robichaud et al. 2010; Shakesby 2011; Moody et al. 2013; Alcañiz et al. 2018; Cole et al. 2020; Wagenbrenner et al. 2021; Agbeshie et al. 2022): (i) climate; (ii) soil slope; (iii) vegetation ; (iv) soil burn severity; and (v) soil texture.

Of the 41 academic papers previously selected, only 21 (totalling 35 case studies) reported surface runoff and/or soil erosion data in burned and unburned soils together with all the abovementioned environmental characteristics (Table 1).

Data collection

The 21 papers with the 35 case studies were carefully analysed, in order to compile a database in an Excel file. For each case study, this database reported the values of the environmental characteristics as well as those of the following quantitative variables: (i) rainfall depth (mm); (ii) water infiltration rate (mm/h); (iii) surface runoff volume (mm); and (iv) soil loss (tons/ha). Rainfall intensity, which is a key variable for erosion predictions (Wischmeier and Smith 1958; Liu et al. 2022), was excluded from the studied variables since the burned and unburned sites were subjected to very similar precipitation (the difference being lower than 5%).

Data processing

The specific soil’s hydrological response to prescribed fire was expressed quantitatively considering the four major processes (precipitation, infiltration, runoff, soil erosion and transport) of soil hydrology (Moody et al. 2013). In both unburned and burned state of each site, the hydrological and erosive variables (observations of water infiltration, surface runoff, and soil loss) and environmental characteristics of the experimental sites were extracted for the 35 case studies. In the case of burned sites this data was extracted at two dates: immediately after the prescribed fire (hereafter ‘short-term’) and at the end of the monitoring period in the relevant study (‘mid-term’). This separation in extraction dates was done to consider the different soil’s hydrological response to fire throughout the window of disturbance and the following period, when the pre-fire soil properties and vegetation cover are progressively recovering.

The site in unburned condition was assumed to be the ‘reference’ or ‘baseline’ value for each of the four investigated hydrological variables. For each case study, the so-called ‘effect size’ (e.g., Vieira et al. 2015; Girona-García et al. 2021) for the change between the burned and the unburned sites was calculated for both the short and mid-term. This effect size was estimated as the decimal logarithm (log) of the response ratio (Curtis and Wang 1998; Hedges et al. 1999) - hereafter ‘log response ratio’ (LRR) - using the following equation:

$$LRR = \log \frac{x_B}{x_{UB}} \qquad (1)$$

where 'x_B' is the mean value of the response variable measured in the site treated with prescribed fire (burned soil) and 'x_{UB}' is the corresponding value measured in the unburned condition at the same site. The value of the LRRs expresses the magnitude of the impact of prescribed fire on a given soil on a logarithmic scale (e.g., Kalies et al. 2010). More specifically, a positive LRR means that the related hydrological variable in the burned site is higher, and lower, if LRR is negative, as compared to the same variable at the unburned site. The exponent of LRR gives the order of magnitude of the change. The four calculated LRRs are hereafter indicated as 'LRR(RF)' (for rainfall), 'LRR(WI)' (for water infiltration), 'LRR(SR)' (for surface runoff), and 'lnRR(SE)' (for soil erosion).

The wide range of site conditions and experimental observations, and the different methods adopted to measure the studied variables do not impact the results of this analysis, since the calculation of the size effect was made in both unburned and burned sites under the same conditions and monitoring period in each study (Vieira et al. 2015; Girona-García et al. 2021).

The values of the environmental characteristics were grouped into classes to fix categorical variables, as follows:

(i) climate: continental; oceanic; temperate; semi-arid; tropical

(ii) soil slope (%): < 10; 10-20; 20-30; 30-40; 40-50; > 50

(iii) vegetation: grasses; shrubs; trees

(iv) soil burn severity: low; low to moderate; moderate; moderate to high; high

(v) soil texture: sandy; silty; clayey and combinations among these textural classes.

Short description of prediction methods

'Random Forests' or 'random decision forests' (hereafter 'RF') is a machine learning method used for the classification and/or regression of variables of different types. For regression, RF predicts a quantitative dependent variable based on: (i) independent quantitative and/or qualitative variables; (ii) continuous and discrete data.

The RF method creates a high number of so-called 'decision trees'. The latter is a structure, where each internal node represents a test on an attribute, each branch represents the test result, and each leaf represents a class label, that is a decision taken after computing all attributes. RF consists of a combination of several decision trees that incorporate multiple bootstrap samples from the observational data. Several input variables randomly participate in the construction of each tree. Using the bootstrap method, many samples from the initial observations are introduced. Then, a tree is expanded based on a bootstrap sample. Each tree produces a class prediction and the class obtaining more votes than others becomes the model's prediction. Once each whole tree is built, several trees are used as inputs to estimate the output variable. The average value of these estimates gives the final output of the model (Avand et al. 2019). More precisely, the outcome is a rank expressed in terms of mean decrease accuracy (or mean increase error, which is the sum of the squares) as a prediction error. A larger value of this error means that the importance of the related variable is higher for that model prediction (Mohammed et al. 2020).

A multiple-regression model (hereafter 'MR') builds a linear equation between a set of independent ('predictor' or 'explanatory') variables on one side, and one dependent (or 'response') variable. The coefficients of the independent variables are estimated by a regression method, for instance, the Minimum Least Square method. The MR method develops a prediction equation under the following form:

$$LRR(SR)\ \ or\ LRR(SE) = a + \sum_{i=1}^{N} b_i \cdot x_i \tag{2}$$

where:

- a = intercept
- b_i = model coefficients
- x_j = independent variables.

Partial Least Square Regression (hereafter 'PLS-R') is a regression method based on covariance, which is recommended when the explanatory variables are numerous and multi-collinearity among the variables is possible. PLS-R, having in general a non-linear structure, reduces the input variables to a smaller set of predictors ('component(s)'), which are used for regression.

A PLS-R method provides prediction equations under the following form:

$$LRR(SR)\ \ or\ LRR(SE) = a + \sum_{i=1}^{N} b_i \cdot x_i + \sum_{j=1}^{N}\sum_{k=1}^{N} c_i \cdot x_j \cdot x_k \tag{3}$$

where:

- a = intercept
- b_i and c_i = model coefficients
- x_j and x_k = independent variables ($x_j \cdot x_k$ representing the non-linear term).

Description of the case-studies

In the thirty-five case studies in the selected 21 papers reporting data of surface runoff and soil erosion, 22 values of runoff were related to the short-term observations (measured from immediately after the prescribed fire until 2-3 months later), and just as many to the mid-term observations (that is, at least one year after the prescribed fire). For erosion, 17 observations were related to the short term, and 25 to the mid-term. Some papers reported both short-term and mid-term observations, and many others both runoff and erosion values. All the categorical variables related to the environmental characteristics for the 35 case studies are reported in Table 1.

Table 1 Main characteristics of the case studies used for modelling surface runoff and soil erosion by the three prediction methods

Case study	First author (year)	Journal	Country	Climate	Vegetation	Soil burn severity	Soil slope class (%)	Soil texture
1	González-Pelayo et al. (2010)	Geomorphology	Spain	Semi-arid	Shrubs	Low	21-30	Sandy loam
2	Cawson et al. (2013)	Forest Ecology and Management	Australia	Temperate	Trees	Low	41-50	Silty clay loam
3	Vega et al. (2005)	Land Degradation and Development	Spain	Oceanic	Shrubs	Low	21-30	Sandy loam
4			Spain	Oceanic	Shrubs	Low	21-30	Sandy loam
5	Morales et al. (2000)	Forest Ecology and Management	Mexico	Temperate	Trees	Low	11-20	Sand
6			Mexico	Temperate	Trees	Low	11-20	Sand
7	Townsend and Douglas (2000)	Journal of Hydrology	Australia	Tropical	Trees	Low	< 10	Sandy loam
8			Australia	Tropical	Trees	High	< 10	Sandy loam
9	Carrà et al. (2022)	Ecological Engineering	Italy	Semi-arid	Trees	Low	11-20	Loamy sand
10			Italy	Semi-arid	Trees	Low	11-20	Loamy sand
11			Italy	Semi-arid	Trees	Low	21-30	Loamy sand
12	Lucas-Borja et al. (2019)	Science of the Total Environment	Spain	Semi-arid	Trees	Low	11-20	Clay
13	Cawson et al. (2016)	Geoderma	Australia	Semi-arid	Trees	Low	41-50	Silty clay loam

14	Fernández et al. (2012)	Journal of Environmental Management	Spain	Semi-arid	Shrubs	Low	< 10	Sandy loam
15			Spain	Oceanic	Shrubs	Low	31-40	Sandy loam
16	Robichaud (2000)	Journal of Hydrology	USA	Continental	Trees	Low	41-50	Loam
17			USA	Continental	Trees	Low	> 50	Loam
18	Pierson et al. (2008)	Earth Surface Processes and Landforms	USA	Continental	Shrubs	Moderate to high	41-50	Sandy loam
19			USA	Continental	Shrubs	Moderate to high	41-50	Sandy loam
20	Zavala et al. (2009)	Earth Surface Processes and Landforms	Spain	Semi-arid	Shrubs	Low	< 10	Sandy loam + clayey loam
21	Pierson et al. (2014)	Rangeland Ecology Management	USA	Semi-arid	Trees	Low to moderate	11-20	Sandy loam
22			USA	Semi-arid	Trees	Low to moderate	11-20	Sandy loam
23			USA	Semi-arid	Trees	Low to moderate	11-20	Sandy loam
24			USA	Semi-arid	Trees	Low to moderate	11-20	Sandy loam
25	Carrà et al. (2021)	Hydrology	Italy	Semi-arid	Trees	Low	11-20	Loamy sand
26			Italy	Semi-arid	Trees	Low	11-20	Loamy sand

27			Italy	Semi-arid	Trees	Low	21-30	Loamy sand
28	Shakesby et al. (2015)	Catena	Portugal	Oceanic	Shrubs	Low to moderate	31-40	Loamy sand
29	Singh et al. (2017)	Forests	USA	Continental	Trees	Low	11-20	Silty loam
30			USA	Continental	Trees	Low	21-30	Silty loam
31			USA	Continental	Trees	Low	21-30	Silty loam
32			USA	Continental	Trees	Low	21-30	Silty loam
33	de Koff et al. (2006)	Soil Science	USA	Semi-arid	Shrubs	Low	> 50	Loam
34	Lucas-Borja et al. (2022)	Journal of Environmental Management	Spain	Semi-arid	Trees	Low	21-30	Sandy loam
35			Spain	Semi-arid	Trees	High	21-30	Sandy loam

Application of prediction methods to the case studies

For all prediction methods, two response variables were set, namely LRR(SR) and LRR(SE). In the first case, the independent input parameters were the five categorical variables (climate, soil slope, soil burn severity, soil texture and vegetation) as well as two quantitative variables, that is LRR(RF) and LRR(WI). In the second case, predicting LRR(SE), the quantitative variable LRR(SR) was added to the set of independent categorical parameters.

The RF algorithm was applied using the 'random input with replacement' method with the 'Mtry' parameter set to 10 on the entire sample size (35 observations of surface runoff and just as many for soil erosion). The "bagging" method was used as a sample bootstrap, in order to train each tree on the different subsets of observations. The required number of trees in the forest was set to 100, which was equal to the number of trees built by the algorithm.

The MR analysis was applied selecting the most accurate set of independent variables as the best predictors. To select the best model, the maximum r^2 was adopted as an objective function, and the Least Mean Square method was used to calculate the model coefficients (a and b_i of equation 2).

PLS-R was applied to the case studies, adopting the 'Jack-and-Knife' cross-validation method. Table 3SI reports the variable importance in equation 3, as provided by this method. The algorithm selects a set of derivative variables ('Components') from the input parameters. We calculated the cumulated r^2_y and r^2_x, which measure the correlations between the explanatory (x) and dependent (y) variables with these components. The variable significance in the projections was also estimated, to identify the influence of each input parameter on the two response variables.

The three models were implemented using XLSTAT® software (release 2019).

Evaluation of the model's accuracy

The prediction accuracy of the three models was analysed for 'goodness-of-fit' against the corresponding observations adopting qualitative and quantitative approaches. The qualitative approach consisted of a visual comparison of pairs of 'observations' vs. 'predictions' of LRR(SR) and LRR(SE) using scatterplots. For the quantitative evaluation of model accuracy, we used the following indicators, commonly adopted in the literature (e.g., Willmott 1982; Loague and Green 1991; Legates and McCabe Jr 1999): (a) the main statistics (maximum, minimum, mean and standard deviation of observed and simulated values); (b) coefficient of determination (r^2); (c) coefficient of efficiency of Nash and Sutcliffe (NSE, (Nash and Sutcliffe 1970)); (d) Root Mean Square Error (RMSE); and (e) percentage bias (PBIAS). The studies by Van Liew and Garbrecht (2003), Krause et al. (2005) and Moriasi et al. (2007) report the equations used to calculate the quantitative indicators mentioned above, while the acceptance or optimal values are reported in Table 2. PBIAS, also known as the 'coefficient of residual mass (CRM)' (Loague and Green 1991), is positive, when a model underestimates the observations, and negative in the case of an overestimation (Gupta et al. 1999).

Table 2 Indexes, their range of variability and acceptance/optimal values to evaluate the prediction capacity of the three prediction models

Index	Range of variability	Acceptance limits or optimal values
r^2	0 to 1	$r^2 > 0.50$ (Santhi et al. 2001; Van Liew et al. 2003; Vieira et al. 2018b)
NSE	$-\infty$ to 1	Model accuracy: good, if NSE $\geq$ 0.75; satisfactory, if 0.36 $\leq$ NSE < 0.75; unsatisfactory, if NSE < 0.36 (Van Liew et al. 2003)
RMSE	0 to ∞	RMSE < 0.5 of observed SD (Singh et al. 2005)
PBIAS	$-\infty$ to ∞	Model accuracy: fair, if PBIAS is 25% (for runoff) and < 55% (for erosion) (Moriasi et al. 2007)

Notes: r^2 = coefficient of determination; NSE = coefficient of efficiency of Nash and Sutcliffe; RMSE = Root Mean Square Error; PBIAS = percentage bias.

Results

Characterization of changes in rainfall, infiltration, runoff and erosion in the case studies

LRR(RF) showed a very low variability in the selected case studies, from a minimum of -0.44 (case study 33, Table 1) to a maximum of 0.32 (case studies 34 and 35). LRR(WI) was in the range of -0.30 (case study 18) to 0.22 (case study 20). In six cases (of which three were in the short term), infiltration was lower in burned sites compared to unburned sites (shown by negative LRRs), while, in the mid-term, water infiltration recovered the pre-fire levels, with three exceptions (case studies 24, 25 and 27) (Table 1 and Fig. 1).

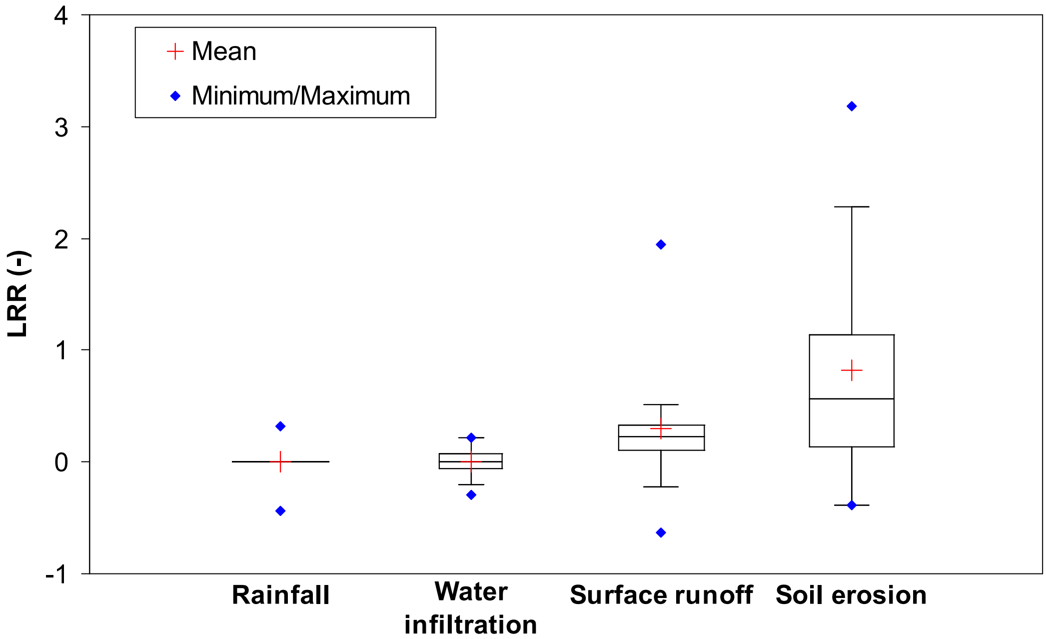


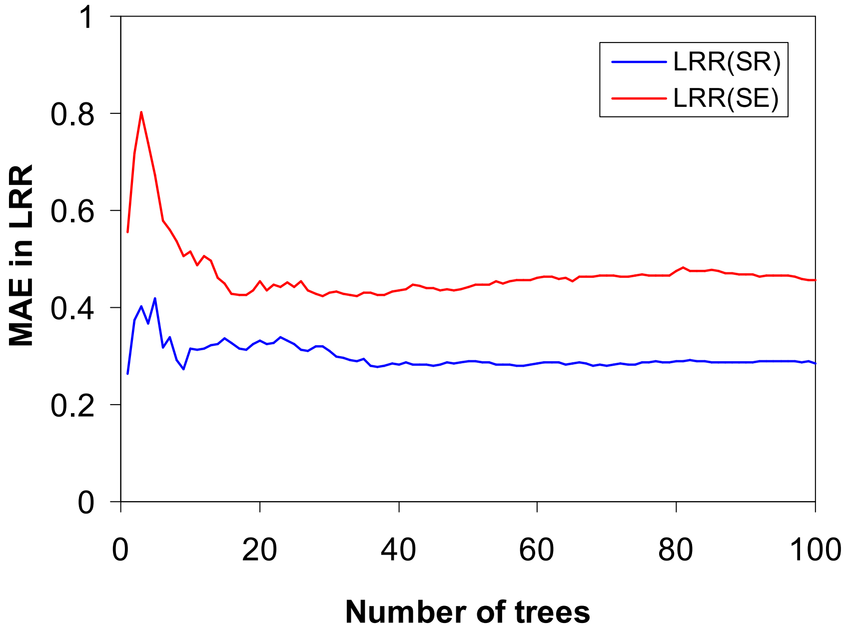
Fig. 1 Values of LRR (log response ratio) of rainfall, infiltration, runoff and erosion in the 35 case studies

The minimum LRR(SR) (-0.64) was found in case study 19, while case study 2 showed the maximum value (1.94). Surface runoff was always higher in burned sites compared to unburned sites in the short-term (positive LRRs), except in three case studies (13, 23 and 26). In the mid-term, surface runoff was generally lower in burned sites (case studies 18 to 20) (Fig. 1 and Table 1).

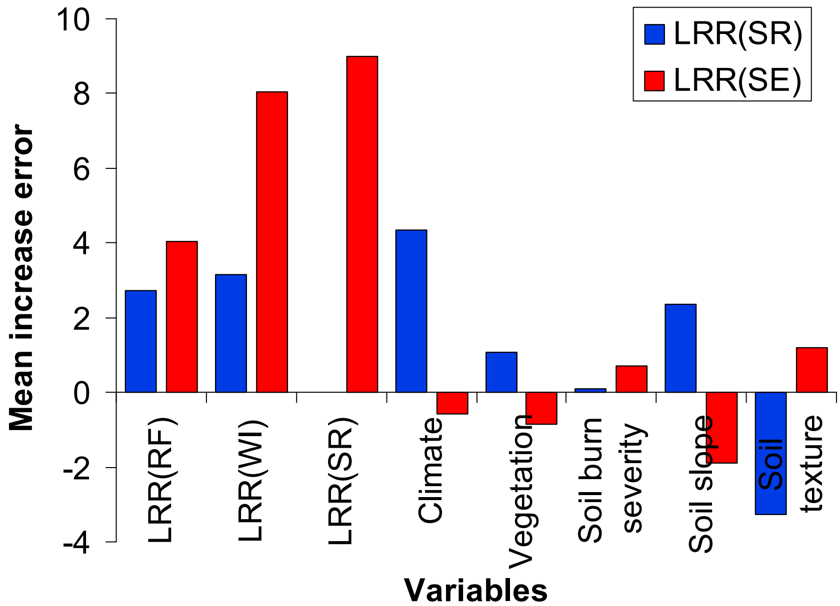
A similar pattern as that of the surface runoff was noticed in the short term for the changes in soil erosion. In more detail, LRR(SE) was always higher in burned sites compared to unburned sites (except for case study 23 in the short term and seven case studies in the mid-term). The lowest and highest values were found in the case studies 9 (-0.38) and 12 (3.19), respectively (Fig. 1 and Table 1).

Model running

Of the 100 decision trees built by the RF model, 45 trees for LRR(SR) and 42 for LRR(SE) were needed to get the lowest and steady value of the minimum absolute error (MAE), which was on average 0.286 in the first case and 0.462 in the second case (Fig. 2a).



(a)



(b)

Fig. 2 Variability of the Mean Absolute Error (MAE) with the number of trees (a) and mean increase error (b), expressing the importance of each input variable, in the Random Forest model applied to the case studies

For LRR(SR) predictions the most important input variables (identified using the highest mean increase errors) were climate, LRR(RF), LRR(WI) and soil slope, while all the numerical variables (LRR of rainfall, infiltration and runoff) were the most influential to predict LRR(SE) (Fig. 2b).

Regarding the MR analysis, a noticeable number of input variables were needed as best predictors of LRR(SR) and LRR(SE). In more detail, the highest values of r^2 (0.516 for runoff and 0.674 for erosion) were achieved using 11 variables (climate, vegetation and soil texture groups) and 16 variables (LRR(RF), LRR(WI), LRR(SR), climate, soil slope and soil texture), respectively (Table 3).

Table 3 Variability of the coefficient of determination (r^2) with input variables in Equation (2) of the Multiple-Regression models applied to the case studies

Number of variables	**Groups of variables**	**r^2**
	LRR(SR)	
10	Climate / Soil texture	0.250
11	**Climate / Vegetation / Soil texture**	**0.516**
12	LRR(WI) / Climate / Vegetation / Soil texture	0.507
13	LRR(RF) / LRR(WI) / Climate / Vegetation / Soil texture	0.491
14	LRR(RF) / LRR(WI) / Climate / Vegetation / Soil burn severity / Soil texture	0.474
18	LRR(RF) / LRR(WI) / Climate / Vegetation / Soil burn severity / Soil slope / Soil texture	0.451
	LRR(SE)	
6	LRR(SR) / Soil slope	0.514
11	LRR(SR) / Climate / Soil texture	0.598
12	LRR(RF) / LRR(SR) / Climate / Soil texture	0.651
15	LRR(RF) / LRR(SR) / Climate / Soil slope / Soil texture	0.671
16	**LRR(RF) / LRR(WI) / LRR(SR) / Climate / Soil slope / Soil texture**	**0.674**
17	LRR(RF) / LRR(WI) / LRR(SR) / Climate / Vegetation / Soil slope / Soil texture	0.666
19	LRR(RF) / LRR(WI) / LRR(SR) / Climate / Vegetation / Soil burn severity / Soil slope / Soil texture	0.659

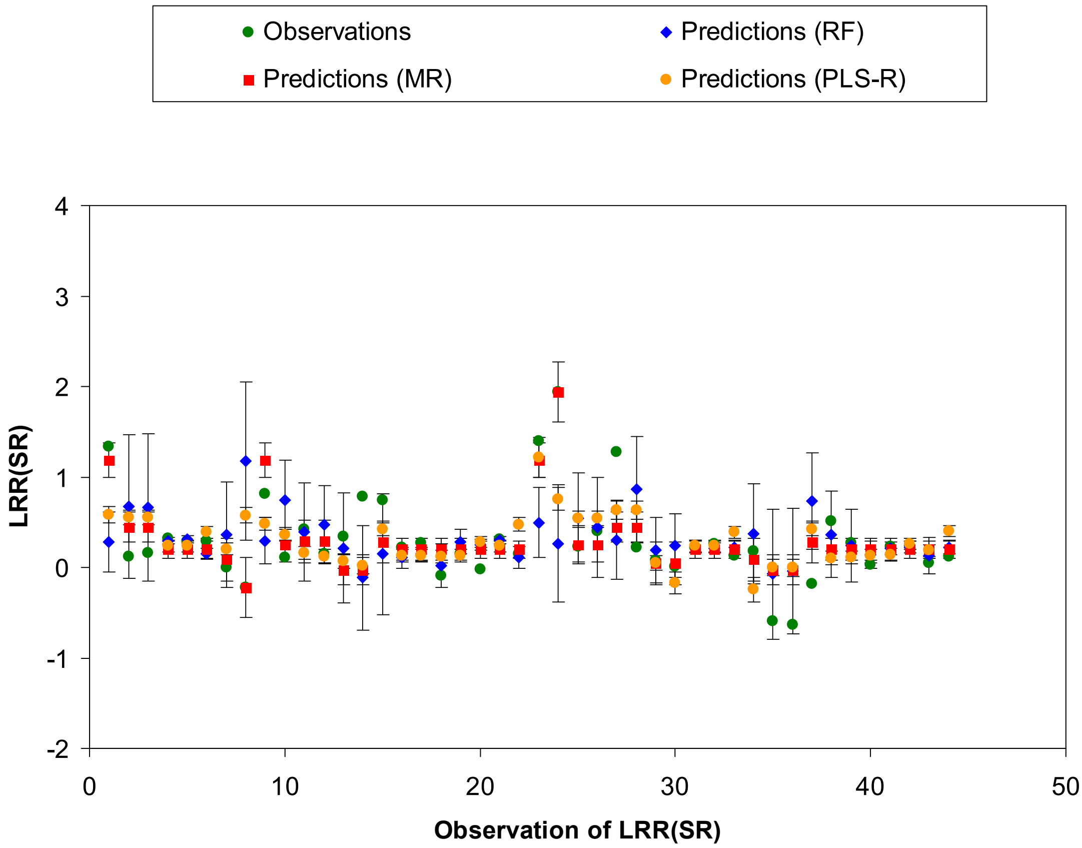
Note: the number in the first row indicates the total categorical or numeric variables of groups; the values in bold indicate the highest r^2 value with the selected input variables.

PLS-R selected only one derivative variable ('Component') from the selected dataset of input parameters. The cumulated r^2_y and r^2_x between the independent and dependent variables with this component were low for LRR(SR) (0.31 and 0.09, respectively), and higher (0.67 and 0.06) for LRR(SE).

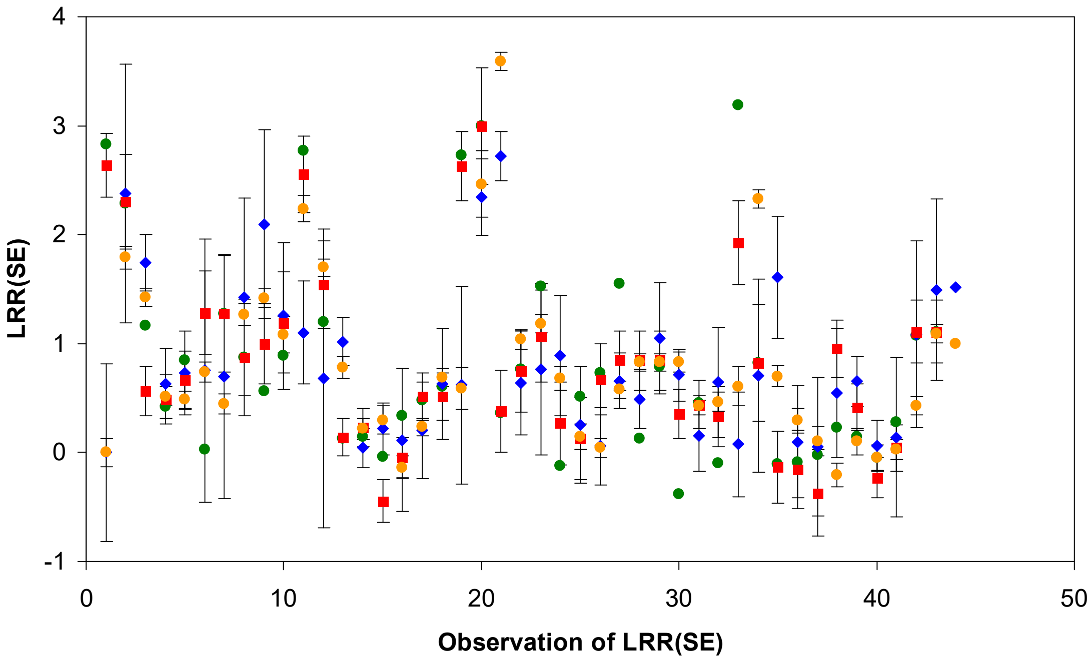
The coefficients of the two regression (MR and PLS-R) models found respectively in equations 2 and 3 are reported in Tables 1SI and 3SI, while Table 2SI shows the variable importance in predictions using the PLS-R model. It is worth noting that only the PLS-R models used quantitative variables as input parameters, namely LRR(RF), LRR(WI) and LRR(SR), while the MR analysis selected only categorical variables.

Prediction accuracy of the three models

Figs. 3a and 3b depict the predictions of LRR(SR) and LRR(SE) using the three models in comparison to the corresponding observations.



(a)

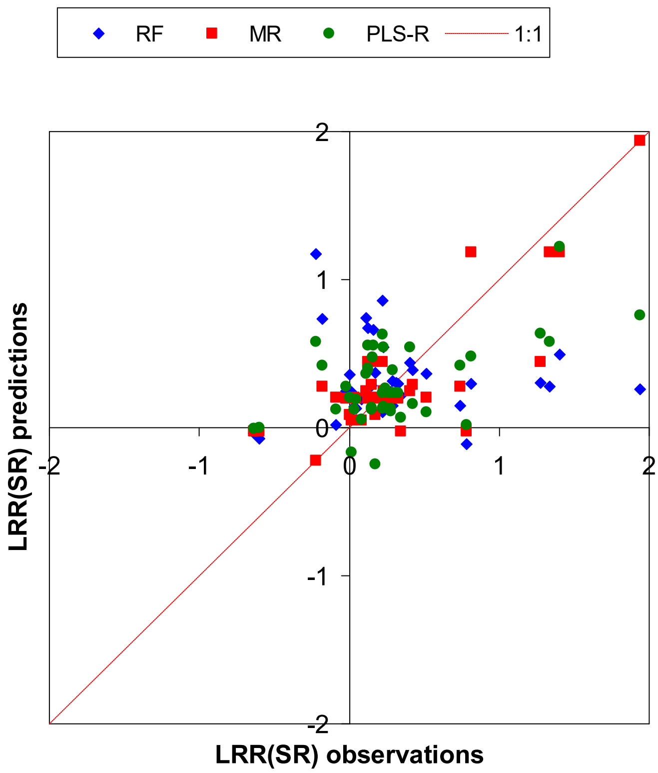


(b)

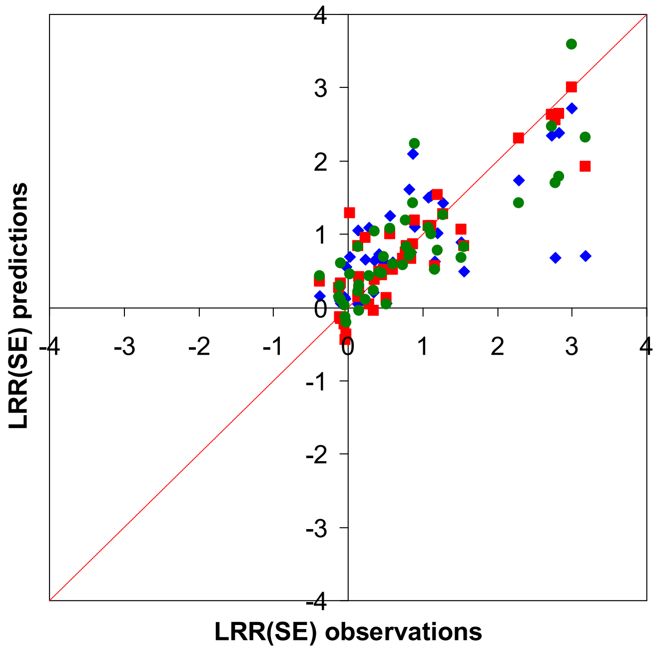
Fig. 3 Prediction of LRR(SR) (a) and LRR(SE) (b) (mean ± standard deviation) for each observation using three models (RF = Random forest; MR = Multiple-Regression; PLS-R = Partial Least Square Regression) applied to the case studies

The RF algorithm gave poor predictions of changes in surface runoff. This is shown not only by the large scattering of the ‘observation vs. prediction’ pairs along the line of perfect agreement (Fig. 4), but also by the poor values of the evaluation indexes. In more detail, r^2 was zero, NSE was negative, and RMSE was higher compared to half the observed standard deviation (Table 2). Therefore, all these indexes were far from the acceptable limits of Table 1. RF accurately predicted the mean LRR(SR) (difference of 5.6% compared to the observed value), while the errors in simulating the minimum and maximum LRRs were much higher (-82.3% and -39.5%). The algorithm showed a very slight tendency to overestimate the observations of runoff changes (PBIAS of -0.06) (Table 4).

The predictions of LRR(SE) given by the RF algorithm were more reliable than the estimations LRR(SR) and, in general, acceptable, although not good (r^2 and NSE equal to 0.47). There was no evidence of any model’s tendency towards overestimation or underestimation (PBIAS = -0.01) (Table 4). Overall, the model was more reliable in simulating LRRs of erosion (differences of 1.3%, mean, and -14.6%, maximum) compared to the runoff predictions.



(a)



(b)

Fig. 4 Scatterplot of observations vs. predictions of LRR(SR) (a) and LRR(SE) (b) using three models (RF = Random forest; MR = Multiple-Regression; PLS-R = Partial Least Square Regression) applied to the case studies

The MR equations reproduced the observed LRRs with a different accuracy for runoff and erosion. In more detail, the scatterplot of LRR(SR) predicted by Eq. (2) shows a limited agreement between observations and predictions for intermediate values, while the lowest and highest LRRs fall close to the line of perfect agreement (Fig. 4). While RMSE got unsatisfactory values (0.28), r^2 and NSE values were satisfactory but not good (0.64 for both indexes). PBIAS was zero, thus indicating no under- or over-estimation of LRRs. However, the differences in the mean and maximum observed and predicted LRR(SR) were high (78.7% and 53.7%, respectively) (Table 4). In contrast, the Multiple-Regression Eq. (2) showed a very good capacity to predict the post-fire changes in erosion rates. The highest LRR(SE) was very close to the line of perfect agreement, and the same was noticed for most of the intermediate values (Fig. 4). Both r^2 and NSE were very high (0.80), PBIAS was zero (no under- or over-estimation), and RMSE was relatively low (-0.42, < 0.5 std. dev. of observations) (Table 4). Moreover, the mean and maximum LRR(SE) difference was zero or very low (-5.8%).

Table 4 Indexes used to evaluate the LRR(SR) and LRR(SE) predictions using three models in the case studies

	LRR(SR)							
	Mean	*Minimum*	*Maximum*	*Standard deviation*	r^2	*E*	*PBIAS*	*RMSE*
	Random Forest							
Observation	0.297	-0.637	1.941	0.477	0.00	-0.29	-0.06	0.53
Prediction	0.314	-0.113	1.174	0.249				
	Multiple-Regression							
Observation	0.227	0.247	0.070	0.050	0.64	0.64	0.00	0.28
Prediction	0.405	0.247	0.108	0.050				
	Partial Least Square Regression							
Observation	0.297	-0.637	1.941	0.477	0.31	0.31	0.00	0.39
Prediction	0.297	-0.245	1.219	0.266				
	LRR(SE)							
	Random Forest							
Observation	0.821	-0.383	3.186	0.937	0.47	0.47	-0.01	0.68
Prediction	0.832	0.044	2.720	0.683				
	Multiple-Regression							
Observation	0.821	-0.383	3.186	0.937	0.80	0.80	0.00	0.42
Prediction	0.821	-0.446	3.000	0.838				
	Partial Least Square Regression							
Observation	0.821	-0.383	3.186	0.937	0.69	0.69	0.00	0.52
Prediction	0.821	-0.205	3.591	0.776				

Notes: r^2: coefficient of determination; NSE: coefficient of efficiency of Nash and Sutcliffe; RMSE: Root Mean Square Error; PBIAS: coefficient of residual mass.

The simulations of runoff changes by PLS-R models were only acceptable, while a good prediction capacity was noticed for LRR(SE). Regarding LRR(SR), r^2 and RMSE were poor (0.31 and 0.39, against a value of 0.48 of the observed std. dev.) and NSE was positive but low (0.31). PBIAS was zero, indicating no under- or over-estimation of LRRs, as also shown by the equal values of the observed and the predicted mean. In contrast, a noticeable overestimation was observed for the minimum and maximum LRR values (-61.5% and -37.2%, respectively, Table 4), as seen also in the related scatterplot (Fig. 4). The PLS-R model showed satisfactory predictions of LRR(SE), which is shown by the appreciable values of r^2 (0.69), NSE (0.69), PBIAS (0) and RMSE (0.52, very close to half observed std. dev.). However, while the predicted and observed values of mean and maximum LRR(SE) were equal or low, the predictions of the minimum LRR data showed a difference of -46.6% compared to the corresponding observations (Table 4).

4. Discussion

Prescribed fire noticeably alters the soil's hydrological and erosive response to the rainfall input (Cawson et al. 2012). However, the post-fire runoff and erosion rates are site-specific, since it depends on the peculiar climatic, soil and vegetal characteristics of the treated environment (Úbeda et al. 2018). This specificity is proved by the large variability in water infiltration as well as in runoff and erosion already present in the selected case studies. In more detail, water infiltration may decrease (as generally observed) but also increase (in a few case studies) after a prescribed fire. In the papers analysed, post-fire infiltration was up to 50% lower in some sites (Pierson et al. 2008) in the short term, but case studies with enhanced post-fire infiltration (up to +65%) are also reported (Zavala et al. 2009). The reduction in water infiltration is mainly due to the changes in the most important physical properties of soil, such as the aggregate stability (e.g., Fox et al. 2007; Arcenegui et al. 2008; Varela et al. 2010) and the occurrence of soil water repellency, which induces hydrophobicity (Letey 2001; Cawson et al. 2016).

In the selected case studies, surface runoff and erosion rates generally showed a dramatic increase of up to 87-fold (for runoff, Cawson et al. 2013) and 1500-fold (for erosion, Lucas-Borja et al. 2019) the values measured in the unburned sites. Only in a few case studies, post-fire runoff and erosion were lower in the burned sites compared to the unburned sites. The increase in the hydrological and erosive response of soil following the prescribed fire application is caused by several factors (Cawson et al. 2012; Vieira et al. 2018a). In addition to the changes in infiltration rates and hydrophobicity mentioned above, the almost total removal of vegetation and the noticeable modifications in some important physicochemical properties of soil due to burning noticeably influence post-fire runoff and erosion (Certini 2005; Shakesby 2011; Moody et al. 2013; Alcañiz et al. 2018; Agbeshie et al. 2022). Moreover, since these impacts are affected by high temporal variability, surface runoff and soil loss themselves are variable over time (Prosser and Williams 1998). In this regard, the selected case studies showed a general recovery of the pre-fire values some years after the fire, although in some case studies the mid-term runoff and erosion rates remained noticeably high, despite being a long time since the fire application.

The variability in soil hydrology after a prescribed fire, and the unsteady character of the soil's hydrological response over time make the simulation of post-fire surface runoff and erosion processes particularly challenging (Vieira et al. 2015; Lopes et al. 2021; Girona-García et al. 2021). This difficulty explains the contrasting prediction accuracy shown by the three models evaluated in the selected case studies, with the RF algorithm showing a low prediction accuracy, and regression models performing much better.

In more detail, one of the main advantages of RF algorithms is reproducibility and high transparency of feature importance (Wilder et al. 2021). However, the predictions of changes in runoff and erosion by the algorithms developed in this study were poor in reproducing the first case and acceptable (but not optimal) for the second variable. The poor RF performance in modelling post-fire runoff led to large overestimations of the measured variable. This inaccuracy may be explained by two reasons. First, the algorithm may have found severe problems in modelling such a high number of categorical variables (presumably the addition of a third quantitative variable smoothed this model's inaccuracy for erosion simulations). Second, the training dataset was limited. In contrast algorithms of artificial intelligence (AI) generally require many observations (Singh et al. 2016). Regarding previous applications of RF algorithms tools to predict surface runoff and erosion (Wilder et al. 2021) showed that two RF models better predicted the impacts of post-fire peak streamflow in small semi-arid watersheds compared to empiric methods, and these algorithms helped to identify critical watershed characteristics driving the flooding risk. Moreover, Ghosh and Maiti (2021) assessed the probability of severe erosion in sub-tropical watersheds using RF tools, showing its higher prediction accuracy compared to a logistic regression model. Furthermore, the results of the study by Mohammed et al. (2020) carried out in Mediterranean semi-arid hillslopes affected by severe erosion showed the higher prediction accuracy of RF algorithms compared to general linear models. RF models also performed better than other machine learning techniques in predicting soil erosion in tropical plots (Tarek et al. 2023) and k-Nearest Neighbor Classifiers in mapping gully erosion susceptibility in arid and semi-arid catchments (Avand et al. 2019). Past experiences of AI tools used to model post-fire soil hydrology were scarce. Only Folharini et al. (2022) used RF and Support Vector Machine algorithms for hydrological simulations in small burned catchments of Northern Portugal, and found a satisfactory prediction accuracy in modelling soil erosion (r^2 between 0.54 and 0.68). In a pine forest in Central-Eastern Spain, Zema et al. (2020) tested an Artificial Neural Network, which gave good predictions for both runoff and soil erosion (NSE > 0.90).

In this study, the prediction capacity of the MR and PLS-R models provided mixed results. In the case of runoff predictions, the two models were not able to reproduce the mean and maximum values. This is a poor result since the models are not able to estimate, as a minimum, the order of magnitude of changes in the runoff rates due to prescribed fire application in a specific environment. Moreover, both models were inaccurate in trying to simulate every log response ratio of runoff, and this limits the model transferability from one environment to another. These results contrast with those achieved by Lucas-Borja et al. (2020), who reported a NSE of 0.60 (in sites burned by prescribed fires) and 0.73 (in unburned soils) using MR linear equations to predict surface runoff in Mediterranean semi-arid forests. In contrast, the PLS-R performed reasonably well and the MR equation was very accurate in modelling the changes in post-fire erosion. The better prediction capacity shown by the two models for erosion simulations may be due to the addition of a third quantitative variable to the log response ratios of rainfall and infiltration used for runoff modelling. The worse performance of the PLS-R model compared to the MR equation could be explained by the loss of variance due to the need for the addition of non-linear terms in equation (3), which may have propagated measurement errors in the model. In contrast, the MR model retained several categorical variables (without any errors). In the latter model, it is worth mentioning the importance of some key variables that drive the runoff and soil loss generation mechanisms, such as the climate type and soil texture (for runoff and erosion) as well as the soil slope (for erosion).The patterns of precipitation that turn to surface runoff change with site climate (e.g., Molinié et al. 2012; Li et al. 2022) and soil texture (e.g., Cawson et al. 2012; Alcañiz et al. 2018). Climate governs rainfall erosivity (and thus an important share of erosion), which is higher in dry climates and lower in oceanic and continental areas (e.g., Capolongo et al. 2008; Nearing et al. 2017) Soil slope is influential on the processes of soil detachment and transport (e.g., Wischmeier and Smith (1978) and Lucas-Borja et al. 2020). However, in this analysis we must highlight the lack of measurements in many of the studies reviewed, which did not report a key variable for runoff and generation mechanisms in burned soils, such as the post-fire ground cover. Surface runoff and soil loss may result in very different rates between bare soils and sites covered by plants. Vegetation intercepts rainwater, increases evapo-transpiration, reduces rainsplash erosion, and slowdowns both overland and concentrated water flows (e.g., Shakesby and Doerr 2006; Zhang et al. 2023). This promotes the idea that this variable is essential for accurate predictions of both runoff and erosion. In other words, the accuracy of the evaluated models may increase, if the post-fire ground cover is considered as an input variable by the algorithms or regression equations. The good prediction capacity of erosion that was found for the MR model developed in this study agrees with the results of the study by Zema et al. (2022). These authors estimated runoff coefficients and sediment concentrations (from which soil loss can be estimated) using two multiple-regression models that adopted a limited set of input parameters related to ground cover (e.g., litter, shrub vegetation, ash, bare soil percentage) and 'dummy' categorical variables. The quantitative evaluation of the prediction capacity of the models gave NSE over 0.85 for runoff coefficients and 0.95 for soil losses, which are close to the values of the same index calculated in this study.

5. Conclusions

This study has evaluated three models (a Random Forest algorithm and two Multiple-Regression and Partial Least Square Regression equations) applied to case studies selected from the international scientific literature, to predict the changes in surface runoff and soil erosion in sites treated with prescribed fire under different environmental characteristics.

The Random Forest showed a poor performance in simulating runoff, but an acceptable capacity to predict soil loss. The prediction capacity to simulate runoff shown by the Multiple-Regression and Partial Least Square Regression equations was satisfactory but not optimal, while the performance in simulating erosion was good using the Multiple-Regression equation.

The Random Forest model proposed in this study is a novelty in its application to areas treated with prescribed fire, and the potentiality of this machine learning tool for hydrological predictions deserves more research. The limited number of case studies of the modelling exercise in this study may have influenced the RF's poor performance.

The good performance of the Multiple-Regression model in simulating erosion in soils treated with prescribed fire is encouraging. Although the applicability of Multiple-Regression models in burned environments has been tested previously, their adaptation to the case studies in this study has shown how the parameters of their equations may be used for modelling purposes in areas with similar climatic and geomorphological characteristics as the experimental sites.

Overall, considering the scarce applications of hydrological and/or erosive models in natural sites treated with prescribed fire that have been carried out on a global scale, this study helps land managers and hydrologists to select the most accurate prediction model to be adopted to control and mitigate the wildfire and hydrogeological risks in delicate environments, such as forest ecosystems.

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Supplementary Information

Table 1SI Values of the coefficients *a* and *b* in equation 2 of the Multiple-Regression model used to predict LRR(SR) and LRR(SE) in the case studies

Variables (x_i and x_j in equation 1)	**Model coefficients**	
	LRR(SR)	**LRR(SE)**
Intercept **(*a* in equation 1)**	-0.374	1.591
LRR(RF)	0	1.862
LRR(WI)	0	1.686
LRR(SR)	0	2.064
Climate(Continental)	-1.058	-0.819
Climate(Oceanic)	-0.784	-0.600
Climate(Semiarid)	0.153	-0.632
Climate(Temperate)	2.315	-3.373
Climate(Tropical)	0	0
Vegetation (Shrubs)	0.983	0
Vegetation(Trees)	0	0
Soil burn severity(Low)	0	0
Soil burn severity(Low to moderate)	0	0
Soil burn severity(Moderate to high)	0	0
Soil burn severity(High)	0	0
Soil slope(< 10%)	0	-1.110
Soil slope(11%-20%)	0	-0.783
Soil slope(21%-30%)	0	-0.608
Soil slope(31%-40%)	0	0.392
Soil slope(41%-50%)	0	0.731
Soil slope(> 50%)	0	0
Soil texture(Sand)	-1.495	0
Soil texture(Loam)	1.721	0
Soil texture(Clay)	0.309	1.065
Soil texture(Loamy sand)	0.419	-0.325
Soil texture(Sandy loam)	0.422	-0.517
Soil texture(Silty loam)	0	0

Soil texture(Silty clay loam)	0	0
Soil texture(Sandy loam + clayey loam)	-0.482	-0.213

Table 2SI Values of the coefficients *a*, *b* and *c* in equation 3 of the Partial Least Square Regression model used to predict LRR(SR) and LRR(SE) in the case studies

Variables (x_i and x_j in equation 1)	**Model coefficients**	
	LRR(SR)	**LRR(SE)**
Intercept **(*a* in equation 1)**	0.287	0.822
LRR(RF)	-0.036	0.025
LRR(WI)	-0.012	-0.030
LRR(SR)	0	0.164
Climate(Continental)	-0.103	0.003
Climate(Oceanic)	-0.022	0.081
Climate(Semiarid)	-0.011	-0.062
Climate(Temperate)	0.205	0.574
Climate(Tropical)	-0.106	-0.168
Vegetation(Shrubs)	0.055	0.133
Vegetation(Trees)	-0.055	-0.133
Soil burn severity(Low)	0.104	0.082
Soil burn severity(Low to moderate)	-0.048	-0.108
Soil burn severity(Moderate to high)	-0.145	0.012
Soil burn severity(High)	-0.117	-0.022
Soil slope(< 10%)	-0.002	-0.097
Soil slope(11%-20%)	-0.048	-0.146
Soil slope(21%-30%)	0.105	0.071
Soil slope(31%-40%)	-0.078	0.176
Soil slope(41%-50%)	-0.003	0.140
Soil slope(> 50%)	-0.060	0.001
Soil texture(Sand)	0.067	0.000
Soil texture(Loam)	-0.004	0.001
Soil texture(Clay)	-0.089	0.212
Soil texture(Loamy sand)	-0.056	-0.014
Soil texture(Sandy loam)	-0.002	-0.080

Soil texture(Silty loam)	-0.006	-0.006
Soil texture(Silty clay loam)	0.240	0.355
Soil texture(Sandy loam + clayey loam)	-0.007	-0.064
LRR(RF) • LRR(WI)	0.067	0
LRR(RF) • LRR(WI)	0.492	0
LRR(RF) • LRR(SR)	-0.457	0
LRR(RF) • Climate(Continental)	-0.058	0
LRR(RF) • Climate(Oceanic)	0.027	0
LRR(RF) • Climate(Semiarid)	0.030	0
LRR(RF) • Climate(Temperate)	-9.602	0
LRR(RF) • Climate(Tropical)	-0.504	0
LRR(RF) • Vegetation(Shrubs)	0.001	0
LRR(RF) • Vegetation(Trees)	0.077	0
LRR(RF) • Soil burn severity(Low)	0.021	0
LRR(RF) • Soil burn severity(Low to moderate)	0.032	0
LRR(RF) • Soil burn severity(Moderate to high)	-0.202	0
LRR(RF) • Soil burn severity(High)	0.026	0
LRR(RF) • Soil slope (< 10%)	-0.441	0
LRR(RF) • Soil slope(11%-20%)	0.605	0
LRR(RF) • Soil slope(21%-30%)	0.002	0
LRR(RF) • Soil slope(31%-40%)	0.026	0
LRR(RF) • Soil slope(41%-50%)	-2.307	0
LRR(RF) • Soil slope(> 50%)	0	0
LRR(RF) • Soil texture(Loam)	0	0
LRR(RF) • Soil texture(Clay)	0.553	0
LRR(RF) • Soil texture(Loamy sand)	0.028	0
LRR(RF) • Soil texture(Sandy loam)	-0.001	0
LRR(RF) • Soil texture(Silty loam)	0.099	0
LRR(RF) • Soil texture-Sandy loam + clayey loam	1.055	0
LRR(RF) • Soil texture(Silty clay loam)	-5.898	0

LRR(WI) • LRR(SR)	0.046	0
LRR(WI) • Climate(Continental)	-0.040	0
LRR(WI) • Climate(Oceanic)	0.063	0
LRR(WI) • Climate(Semiarid)	-0.026	0
LRR(WI) • Climate(Temperate)	0.000	0
LRR(WI) • Climate(Tropical)	0.000	0
LRR(WI) • Vegetation(Shrubs)	-0.029	0
LRR(WI) • Vegetation(Trees)	-0.036	0
LRR(WI) • Soil burn severity(Low)	-0.016	0
LRR(WI) • Soil burn severity(Low to moderate)	-0.036	0
LRR(WI) • Soil burn severity(Moderate to high)	-0.040	0
LRR(WI) • Soil burn severity(High)	0.000	0
LRR(WI) • Soil slope (< 10%)	-0.022	0
LRR(WI) • Soil slope(11%-20%)	-0.036	0
LRR(WI) • Soil slope(21%-30%)	0.000	0
LRR(WI) • Soil slope(31%-40%)	0.063	0
LRR(WI) • Soil slope(41%-50%)	-0.040	0
LRR(WI) • Soil slope(> 50%)	0.000	0
LRR(WI) • Soil texture(Clay)	0.000	0
LRR(WI) • Soil texture(Loam)	0.000	0
LRR(WI) • Soil texture(Loamy sand)	0.000	0
LRR(WI) • Soil texture(Sandy loam)	-0.033	0
LRR(WI) • Soil texture(Silty loam)	0.000	0
LRR(WI) • Soil texture(Silty clay loam)	0.000	0
LRR(WI) • Soil texture(Sandy loam + clayey loam)	-0.025	0
LRR(SR) • Climate(Continental)	0.161	0
LRR(SR) • Climate(Oceanic)	0.177	0
LRR(SR) • Climate(Semiarid)	0.170	0

Table 3SI Variable importance in predictions using equation 3 of the Partial Least Square Regression model used to predict LRR(SR) and LRR(SE) in the case studies

Variable	LRR(SR)	Variable	LRR(SE)
LRR(RF) • Vegetation(Shrubs)	**2.392**	LRR(SR)	**3.740**
Climate(Temperate)	**2.271**	LRR(RF) • LRR(SR)	**2.697**
Soil texture(Silty clay loam)	**1.739**	LRR(SR) • Climate(Semiarid)	**2.566**
Soil burn severity(Low)	**1.657**	LRR(RF) • Soil slope(11%-20%)	**2.479**
Soil burn severity(Moderate to high)	**1.451**	LRR(RF) • Soil texture(Clay)	**2.204**
Soil slope(21%-30%)	**1.407**	Climate(Temperate)	**2.000**
LRR(RF) • Climate(Semiarid)	**1.274**	LRR(RF) • Climate(Temperate)	**2.000**
LRR(RF)	**1.235**	LRR(RF) • Climate(Continental)	**1.736**
Climate(Continental)	**1.231**	Soil texture(Silty clay loam)	**1.731**
LRR(RF) • Climate(Continental)	**1.231**	LRR(RF) • Soil texture(Silty clay loam)	**1.725**
Soil texture(Loamy sand)	**0.865**	Soil slope(11%-20%)	**1.609**
Vegetation (Shrubs)	**0.853**	Vegetation(Shrubs)	**1.469**
Vegetation(Trees)	**0.853**	Vegetation(Trees)	**1.469**
Soil slope(11%-20%)	**0.834**	Soil slope(41%-50%)	**1.121**
Climate(Tropical)	0.769	LRR(RF) • Soil slope(41%-50%)	**1.114**
LRR(RF) • Climate(Tropical)	0.769	Soil burn severity(Low to moderate)	**1.054**
LRR(RF) • Climate(Temperate)	0.755	Soil slope(31%-40%)	**1.037**
Soil texture(Sand)	0.667	Soil texture(Clay)	**1.030**

Soil texture(Clay)	0.646	LRR(RF) • Vegetation(Trees)	**0.996**
Soil burn severity(Low to moderate)	0.643	Soil burn severity(Low)	**0.929**
Soil burn severity(High)	0.610	Soil texture(Sandy loam)	**0.918**
LRR(WI)	0.429	Climate(Tropical)	**0.819**
LRR(RF) • LRR(WI)	0.429	LRR(RF) • Climate(Tropical)	**0.819**
Soil slope(31%-40%)	0.404	LRR(WI) • LRR(SR)	0.779
Soil slope(> 50%)	0.314	Soil slope(21%-30%)	0.751
LRR(RF) • Vegetation(Trees)	0.210	LRR(RF) • Soil slope (< 10%)	0.742
Climate(Oceanic)	0.191	Soil slope(< 10%)	0.721
LRR(RF) • Climate(Oceanic)	0.191	Climate(Semiarid)	0.690
Climate(Semiarid)	0.187	LRR(WI) • LRR(SR)	0.679
Soil texture(Sandy loam + clayey loam)	0.053	LRR(WI)	0.679
Soil slope(41%-50%)	0.037	LRR(WI) • Climate(Continental)	0.635
Soil texture(Sandy loam)	0.035	LRR(WI) • Soil burn severity(Moderate)	0.635
Soil texture(Loam)	0.025	LRR(WI) • Soil slope(41%-50%)	0.635
Soil slope(< 10%)	0.017	LRR(WI) • Soil texture(Silty clay loam)	0.622
		LRR(WI) • Vegetation(Shrubs)	0.618
		Climate(Oceanic)	0.601
		LRR(RF)	0.582
		LRR(RF) • Climate(Semiarid)	0.558
		LRR(RF) • Soil burn severity(Low to moderate)	0.423
		LRR(WI) • Climate(Semiarid)	0.406

	LRR(RF) • Soil texture(Loamy sand)	0.382
	LRR(RF) • Climate(Oceanic)	0.356
	LRR(RF) • Soil slope(31%-40%)	0.349
	LRR(RF) • Soil burn severity(Low)	0.347
	LRR(SR) • Climate(Oceanic)	0.324
	Soil texture(Sandy loam + clayey loam)	0.310
	LRR(RF) • Soil texture(Sandy loam + clayey loam)	0.310
	LRR(WI) • Soil texture(Sandy loam + clayey loam)	0.310
	LRR(WI) • Soil slope (< 10%)	0.301
	LRR(WI) • Vegetation(Trees)	0.286
	LRR(WI) • Soil burn severity(Low to moderate)	0.286
	LRR(WI) • Soil slope(11%-20%)	0.286
	LRR(WI) • Climate(Oceanic)	0.238
	LRR(WI) • Soil slope(31%-40%)	0.238
	LRR(WI) • Soil burn severity(High)	0.231
	LRR(WI) • Soil burn severity(Low)	0.225
	Soil burn severity(High)	0.129
	Soil texture(Loamy sand)	0.126
	LRR(RF) • Soil burn severity(Moderate to high)	0.082
	Soil burn severity(Moderate to high)	0.082
	Soil texture(Silty loam)	0.040
	LRR(RF) • Soil texture(Silty loam)	0.040

	LRR(WI) • Climate(Continental)	0.031
	Climate(Continental)	0.031
	LRR(RF) • Soil slope(21%-30%)	0.023
	LRR(RF) • Vegetation(Shrubs)	0.019
	LRR(RF) • Soil texture(Sandy loam)	0.013
	Soil slope(> 50%)	0.003
	Soil texture(Loam)	0.003
	LRR(RF) • Soil slope(> 50%)	0.003
	LRR(RF) • Soil texture(Loam)	0.003
	LRR(WI) • Climate(Temperate)	0
	LRR(WI) • Climate(Tropical)	0
	LRR(WI) • Soil burn severity(High)	0
	LRR(WI) • Soil slope(21%-30%)	0
	LRR(WI) • Soil slope(> 50%)	0
	LRR(WI) • Soil texture(Clay)	0
	LRR(WI) • Soil texture(Loam)	0
	LRR(WI) • Soil texture(Loamy sand)	0
	LRR(WI) • Soil texture(Silty clay loam)	0
	LRR(WI) • Soil texture(Silty loam)	

Note: the values in bold indicate the highest values (over a limit of 0.80).