Exploring the accuracy of Random Forest and Multiple Regression models to predict rill detachment in soils under different plant species and soil treatments in deforested lands

This is the peer reviewed version of the following article:

Parhizkar, M., Lucas-Borja, M. E., & Zema, D. A. (2024). Exploring the accuracy of Random Forest and Multiple Regression models to predict rill detachment in soils under different plant species and soil treatments in deforested lands. *Modeling Earth Systems and Environment*, *10*(2), 2533-2546.

which has been published in final doi

10.1007/s40808-023-01919-8

(https://link.springer.com/article/10.1007/s40808-023-01919-8#citeas)

Exploring the accuracy of Random Forest and Multiple Regression models to predict rill detachment in soils under different plant species and soil treatments in deforested lands

Abstract

Rill detachment capacity (D_c) is a key factor of the overall erosion process on steep and long hillslopes of deforested areas. Accurate predictions of this factor are essential for land managers, in order to adopt the most effective soil conservation techniques against erosion. However, no previous studies have evaluated how much machine learning algorithms (such as Random Forest, RF) and multiple regression models (such as Multiple Linear Regression, MLR, and Partial Least Square Regression, PLS-R) are accurate to predict D_c in forest and deforested sites and with or without application of treatments for soil conservation. This study evaluates the D_c prediction capacity of RF, MLR or PLS-R algorithms in forestlands of Northern Iran. The models have been applied to 250 observations of the changes in D_c between sites covered by natural tree species or subjected to reforestation and five soil treatments, and deforested sites can be predicted using. The results of model applications showed that: (i) in natural and planted forests, both MLR and PLS-R gave accurate predictions of changes in D_c (coefficient of efficiency of Nash and Sutcliffe, NSE, over 0.80); (ii) in the same sites, the RF algorithm was much less accurate when applied to natural forests (NSE = 0.46), and its performance was poor (NSE = -0.51) in reforested sites; (iii) in deforested and treated sites, the D_c predictions by both MLR and PLS-R were poor (NSE < 0), while the RF algorithm was more accurate (NSE = 0.49), but not its prediction capacity was not optimal. Since both MLR and PLS-R are accurate in predicting rill erosion in natural and planted forests, the use of these models may be suggested to landscape managers, in order to estimate the changes in rill erodibility due to deforestation or reforestation works. Moreover, modelers may adopt the parameters of the linear regression equations setup in this study for predictions of rill erosion in deforested areas with similar characteristics as the experimental sites. The low reliability of all tested models for D_c predictions in sites deforested and treated with soil conservation techniques suggests more research, for instance testing the accuracy of Artificial Neural Networks or multiple regression algorithms with different mathematical structure under those conditions.

Keywords Soil hydrology; log response ratio; soil properties; soil hydrology; hydrological modelling.

1. Introduction

Deforestation is one of the most severe degradation factors in forest ecosystems (van Lierop et al. 2015; Watson et al. 2018). Removal of vegetation results in biodiversity loss and leaves the soil exposed to detachment of soil particles due to rainsplash erosion and surface runoff (Polyakov and Nearing 2003; Cantón et al. 2011). Soil erosion due to the overland flow often forms rills with depth and width increasing downstream of eroded channels (Ellison 1947; Wang et al. 2014; Li et al. 2019). Rill detachment, whose maximum value is defined as "rill detachment capacity" (hereafter indicated as D_c), is the most important erosive process on steep and long slopes (Owoputi and Stolte 1995; Wang et al. 2014). This process may be noticeably different between low and high flow rates of the surface water stream (Zhang et al. 2002). An accurate estimation of rill erosion is essential in deforested ecosystems, when process-based hydrological models must be used to predict the erosion rates (Nearing et al. 1989; Wang et al. 2016) and anti-erosive actions must be adopted (Alewell et al. 2019; Lopes et al. 2021). However, the performance of the common erosion models is different across the large variety of environments on the global scale (Batista et al. 2019; Fan et al. 2019). With specific focus on rill detachment, D_c shows a large variability depending on land use, soil and vegetation characteristics, and anthropogenic actions (García-Ruiz 2010; Parhizkar et al. 2020). Different vegetation species may also have a significant influence on rill erosion (Parhizkar et al. 2021). Moreover, for specific land uses and vegetation species, D_c depends on hydraulic parameters and soil properties (Nearing et al. 1991). With regard to the hydraulic parameters, the shear stress and stream power are the most commonly characteristics of water flow to predict D_c (Nearing et al. 1991; Hairsine and Rose 1992; Foster et al. 1995). Among the soil and vegetation properties, bulk density and cohesion, aggregate median diameter, and plant root density are among the best predictors of D_c (Zhang et al. 2008; Li et al. 2015). Often the combination of both water characteristics and soil properties is a suitable set of input parameters to predict D_c using hydrological models (De Baets et al. 2006; Li et al. 2015).

Reforestation and soil conservation treatments in deforested areas can make the hydrological processes more complex (van Lierop et al. 2015). This increased complexity may result in a lower accuracy of erosion models compared to undisturbed agro-forest areas (Rompaey and Govers 2002). For instance, the prediction methods to estimate rill erodibility from hydraulic parameters give the same values for treated and untreated soils, since no information is given to models about the changes in soil properties under the two conditions. This inevitably leads to unrealistic estimations of D_c in hydrological modeling in sites treated with soil conservation techniques. Therefore, the reliability of the erosive models must be possibly verified under the largest variety of soil conditions (with or without conservation techniques). Once this reliability is verified in selected case studies, hydrological models can be applied for reliable predictions of erosion in forest soils by hydrologists and forest managers (Merritt et al. 2003).

Among hydrological models, machine learning (such as Random Forest, RF, algorithms) and multiple-regression (MR) methods have been used to predict erosion in several environments. RF algorithms are based on sophisticate mathematical equations, which make these models suitable for accurate hydrological predictions in different conditions (Mohammed et al. 2020; Ghosh and Maiti 2021; Wilder et al. 2021; Tarek et al. 2023). MR methods, thanks to the use of many numerical and categorical variables of different type (soil, water, plants), may accurately predict erosion in different environments (Zema et al. 2022). However, in spite of this potential feasibility due to those intrinsic characteristics, no previous uses of RF or MR models to predict rill erosion are to the authors' best knowledge. Compared to the other erosion models, these tools may better catch the aforementioned complexity and variability of the rill detachment process, and offer a broad applicability in sites with different environmental characteristics. Surprisingly, the literature does not show any previous experiences about D_c modeling by RF or MR methods.

To fill this gap, this study aims to evaluate whether the changes in rill detachment capacity between forest sites with natural tree species or subjected to reforestation and soil conservation treatments, and deforested sites can be predicted using a Random Forest (RF), a Multiple Linear Regression (MLR) and a Partial Least Square Regression (PLR-S) model. To this aim, these three models have been applied to a dataset of 250 case studies simulating D_c under different water flow rates and soil slopes by flume experiments on soil samples collected in forestlands of Northern Iran.

2. Materials and methods

2.1. Study areas

For this study, two forest areas (Saravan and Saqalaksar Parks, geographical coordinates 37°08′04″ N, 49°39′44″ E, and 37°09'23.98'' N, 49°31'49.48'' E) were selected in Guilan province (Northern Iran). These parks, mostly covered with dense vegetation, are located south of Rasht city at elevation between 50 and 205 m above the mean sea level (Figure 1). According to the Köppen–Geiger classification (Kottek et al., 2006), the climate of both areas is "Csa" type, typically Mediterranean. The mean annual rainfall and temperature are 1360 mm and 16.3 °C, respectively (records from the Iran Meteorological Organization of 2016). Precipitation is mainly concentrated in winter, while summer is very dry and hot.

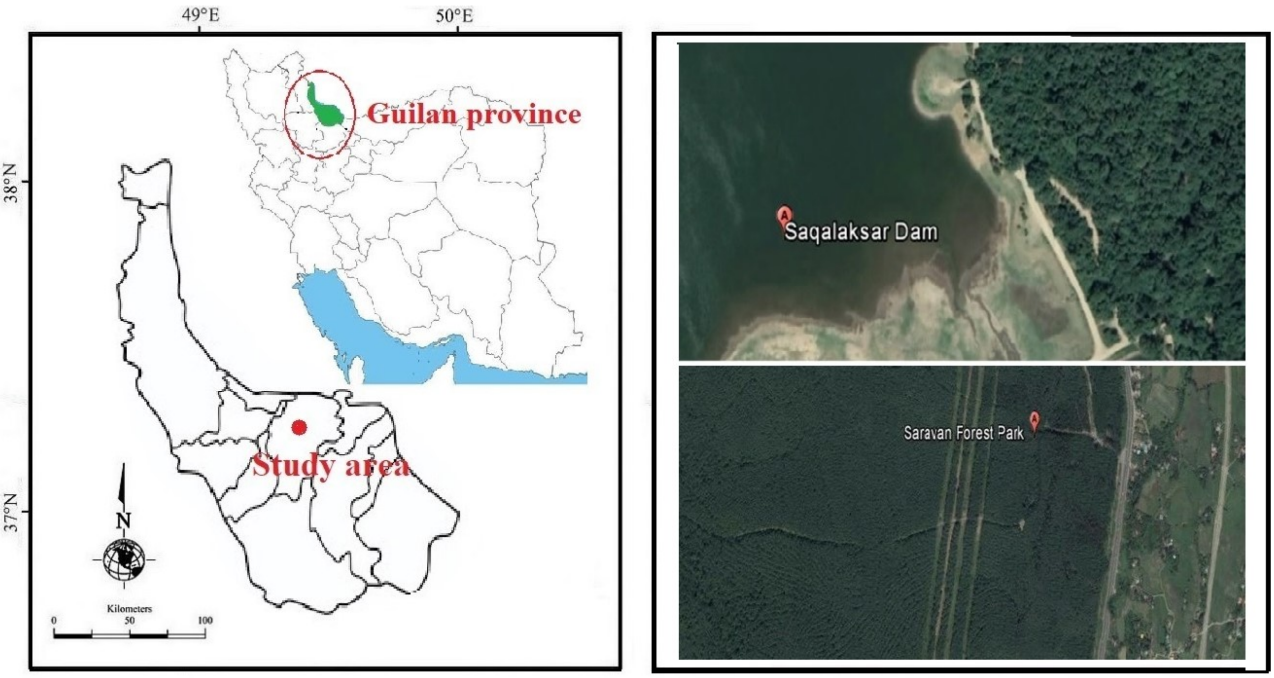

Figure 1 - Geographical location (left) and aerial views (right) of the two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran).

Based on field investigations, both areas show a large variety of tree and plant species. The main tree species are *Zelkova carpinifolia* (hereinafter indicated as "Zc"), *Quercus castaneifolia* (Qc), *Alnus glutinosa* (Ag), *Parrotia persica* (Pp), *Pinus taeda* (Pt), and *Carpinus betulus* (Cb) (Saqalaksar Park), and *Alnus subcordata* (As), *Brachythecium plumose* (Bp), *Gleditsia caspica* (Gc), *Sambucus ebulus* (Se), *Oriental beech* (Ob), *Crataegus ambigue* (Ca), *Rubus persicus* (Rp) and *Primula heterochroma* (Ph) (Saravan Park). In recent years (about ten to twenty years), both parks were intensely deforestation activity, in order to install high-voltage electric power towers. After deforestation, degraded forestland was restored by reforestation activities, using tree species as Zc, Qc and Ag.

Soils in these areas are quite homogenous and have a prevalent silty clay loamy texture (20% of sand, 47% of silt and 33% of clay in Saqalaksar Park, and 13% of sand, 50% of silt and 37% of clay in Saravan Park).

2.2. Experimental design

Four soil conditions were adopted to evaluate the D_c prediction capacity of the three models:

1. a deforested and untreated soil (assumed as reference condition and hereafter indicated as "D")

2. natural forests (“NF”) with one of the following species: *P. persica*, *P. taeda*, *C. betulus*, *Q. castaneifolia*, *C. ambigue*, *R. persicus*, *P. heterochroma*, *F. orientalis*, *A. subcordata*, *B. plumose*, *G. caspica*, and *S. ebulus*
3. forests planted (“PF”) with *A. glutinosa* or *Z. carpinifolia*
4. soils deforested and then subjected to one of the following soil conservation treatments (“D + T”) (see section 2.3).

2.3. Soil treatments

The soil samples collected in the deforested sites “D” of the two parks were placed in five small plots of about 1.5 m x 0.5 m (soil depth of 0.2 m) in laboratory. On these plots, one of the following soil conservation techniques was applied:

a. inoculation and planting of seeds of *Zoysia* grass with *Bacillus polymyxa strain BcP26* (hereafter “D-Thbp”)
b. inoculation of soil with the *Bacillus subtilis OSU 142* (“D-TBs”)
c. application of biochar produced from rice husk (“D-Trhb”)
d. hydromulching using a mixture of water, *Zoysia* grass seed, organic binder, starter fertilizer, cellulose fiber, bio-humus, super absorbent, and green dye (“D-Thzg”)
d. hydromulching using the same mixture but added with silica nanoparticles (“D-Thsn”).

In more detail, *Bacillus polymyxa strain BcP26* (considered as one of plant growth promoting strains (Egamberdieva et al. 2019) and thus used as inoculator in “D-Thbp” plots) was grown in glycerol peptone medium, and added in suspension to seeds of *Zoysia* grass for half an hour. For the “D-TBs” technique, a pure culture from *Bacillus subtilis* OSU 142 strain was grown in liquid nutrient broth media at 28 °C at a density (10^8 CFU/mL) after dilution (Çakmakçı et al. 2001). Biochar used in "D-Trhb" treatment was produced from rice husk by a pyrolysis process in an electrical muffle furnace at a peak temperature of 500 °C and duration of 30-45 min (Ghorbani et al. 2019). The native materials of the hydromulch material in "D-Thzg" plots were blended in the mixture according to the hydromulching international protocol (Sheldon and Bradshaw 1977; Parsakhoo et al. 2018), and used at a dose of 410 kg/ha. Silica nanoparticles for "D-Thsn" treatment were synthesized from rice husk and prepared as white colored nano silica powder with concentration of 100 mg/l, after drying at a temperature of 100 °C for 24 h in a conventional electric oven, and pyrolysis in an electrical muffle furnace at a peak temperature of 700 °C and a duration of 2 h (Sharma et al. 2019). All these additives were applied to the plot through spraying technique.

2.4. Soil sampling

Two paired soil samples were randomly collected at the same location in each deforested sites of the two study areas under the soil conditions “1” to “3”, and in the laboratory plots under the soil condition “4.a” to “4.e” (after a period between three and six months from plot preparation). Soil sampling was carried out following the procedures setup by Zhang et al. (2003; 2008) and Parhizkar et al. (2020). To summarise, rocks, weeds and litter were removed from the soil surface, and then the samples were extracted using a steel ring (0.1-m in diameter and 0.05-m high). Finally, the ring was removed and the samples were transported to laboratory for soil analysis.

2.5. Soil analysis

Of the two paired samples collected in field or in the experimental plots, the first core was subjected to physico-chemical analysis to measure some key properties of plant roots and surface soil: (i) organic carbon content (OC); (ii) root weight density (RWD); (iii) aggregate stability in water of soil (WSA); and (iv) bulk density (BD). OC was determined by the potassium dichromate colorimetric method (Walkley and Black 1934), while RWD, WSA and BD of soils were measured using the wet-sieving (1-mm sieve) and oven-drying (65 °C) methods (Kirkham et al. 1959).

2.6. Flume experiments to measure rill detachment capacity

The second soil sample was used for D_c measurements using an experimental flume. This flume, which had a rectangular cross section with length of 0.5 m and width of 0.2 m, allowed the simulation of variable water flow rates and soil slopes. More details about the experimental procedure and flume characteristics are reported in Parhizkar et al. (2020) and summarised below. The soil core was inserted in a hole excavated in the flume bed, close to its downstream outlet, caring that the upper surface of the sample was placed at the same level as the bed surface. Then, the water flow rate and bed slope were adjusted to the desired values. Using clean water poured upstream of the flume, the experiment started and a steady water flow rate was expected. Once the flow rate stabilised, the mean water depth was measured using a level probe (accuracy of 1 mm) as the average of measurements made at three points, two in the sides, and one in the middle of each of two cross sections (0.4 m and 1 m from the flume outlet). The water volume, collected into a graduated plastic cylinder, was averaged among no less than five replications per experiment. The experimental test ended when the eroded soil depth was 0.015 m or, in the case of lower erosion depth, after 5 minutes. In the first case, the experiment duration was also measured (Δt, [s]). After each test, the wet soil sample was extracted from the flume bed and then oven dried at 105 °C for 24 h to measure its dry weight (ΔM, [kg]). D_c was calculated as the average value of four replicates using equation (1):

$$D_c = \frac{\Delta M}{A \cdot \Delta t} \tag{1}$$

where A ([m^2]) is the area of soil sample.

For each soil sample collected in field, five water flow rates per unit width of flume (WFR, 0.27 ± 0.06, 0.37 ± 0.07, 0.48 ± 0.06, 0.58 ± 0.05, and 0.69 ± 0.05 L m^{-1} s^{-1}) and five slope gradients (SS, 5.9 ± 2.52%, 11.1 ± 2.92%, 17.6 ± 2.11%, 24.5 ± 3.12%, and 31.7 ± 3.04%) were simulated in the flume. Overall, 2000 soil samples (20 soil conditions × 5 water flow rates × 5 slope gradients × 4 replications) were subjected to the experiments. The 20 soil conditions were “D”, “NF” with each of the 12 species, “PF” with two species, and “D-Thbp”, “D-TBs”, “D-Trhb”, “D-Thzg” and “D-Thsn”.

2.7. Data processing and statistical analysis

The site in the D soil condition was assumed to be the “reference” value for each of the following variables: OC, RWD, WSA and BD (soil/plant properties, which were adopted as model’s input parameters), and D_c (output variable). For each flume experiment, the so-called “effect size” (e.g., Vieira et al. 2015; Girona-García et al. 2021) for the change between a given soil condition (deforested soil, natural or planted forest soils, or deforested and treated soils) was calculated. This effect size was the decimal logarithm of the “response ratio” (LRR, Curtis and Wang 1998; Hedges et al. 1999), according to the following equation:

$$LRR = \log \frac{x_{SC}}{x_D} \tag{2}$$

where “x_{SC}” is the mean value of the variable measured in the site under a given soil condition and “x_D” is the value of the same variable measured in the D condition. LRR, which is non-dimensional, estimates the change in a variable on a given soil compared to the reference condition using a logarithmic scale (e.g., Kalies et al. 2010). For instance, a LRR > 0 indicates that the variable in the given soil condition is higher than the D soil. The five calculated LRRs are hereafter indicated as "LRR(D_c)", "LRR(OC)", "LRR(RWD)", "LRR(WSA)" and "LRR(BD)" (plant/soil parameters). Furthermore, a one-way ANOVA followed by pairwise comparisons using Tukey's test (at $p < 0.05$) was carried out, in order to identify significant differences among the numerical variables ("LRR(D_c)", "LRR(OC)", "LRR(RWD)", "LRR(WAS)" and "LRR(BD)"), using the soil condition as factor. The samples were assumed to be independent, and their distribution was checked by QQ-plots. To satisfy the assumptions of the statistical tests, the data were square root transformed whenever necessary.

2.8. Short description and implementation of the prediction models

For the three prediction methods (RF, MLR and PLS-R), the response variable was LRR(D_c), while the input or independent parameters were "LRR(WFR)", "LRR(SS)", "LRR(OC)", "LRR(RWD)", "LRR(WAS)" and "LRR(BD)" (numerical variables), and the "soil condition", "WFR class" and "SS class" (categorical variables). For the categorical variables, the following classes were adopted:

- soil condition: natural forest soil ("NF"); planted forest soil ("PF"); deforested and treated soil ("D + T")
- WFR classes (L m^{-1} s^{-1}): < 0.3; 0.3-0.4; 0.4-0.5; 0.5-0.6; > 0.6
- SS classes (%): < 10; 10-15; 15-20; 20-30; > 30.

2.8.1. Random forest algorithm

"Random Forest" belongs to the set of machine learning methods that are used for classification and/or regression of variables of different types. RF estimates a quantitative response based on independent quantitative and/or qualitative variables, and continuous or discrete variables. This method produces several "decision trees", each being a structure with an internal node that is a test on an attribute. A "branch" of the tree is the test result, while each "leaf" is a class label (i.e., a decision after computing all attributes). RF combines the decision trees, which embed multiple bootstrap samples from the observed data. The input variables are randomly taken to build a decision tree. The bootstrap method introduces many samples from the initial observations, and then the tree is expanded based on bootstrap sampling. Class predictions are produced by each tree, and the class that gets more votes is considered as the prediction. After building the whole tree, the model uses several trees as inputs for the estimation of the final response variable, which is the average value of these estimates (Avand et al. 2019). This response variable is a rank measured by the mean increase error as a prediction error. The importance of the related variable is the highest for the model prediction when this error is the largest (Mohammed et al. 2020).

In this study, RF was applied using the “random input without replacement” method. The “Mtry” parameter (the number of input variables a decision tree has available to consider at any given point in time) was set to 10 over the total 475 observations of D_c, and the “bagging” method was chosen as sample bootstrap. The required number of trees built by the algorithm in the forest was set to 100.

2.8.2. Multiple Linear Regression model

A “Multiple Linear Regression” model builds a linear equation regressing more than one independent variable on one response variable. The coefficients of the model are calculated by a regression method. The prediction MLR equation has the following form:

$$LRR(D_c) = a + \sum_{i=1}^{N} b_i \cdot x_i \tag{3}$$

where a is the intercept and b_i is the coefficient of the independent variable x_i.

In this study, the best independent variables in Eq. (3) to estimate LRR(D_c) were selected when the maximum coefficient of determination (r^2) was obtained among the possible combination of all input parameters. The Least Mean Square method was chosen to estimate a and b_i of Eq. (3).

2.8.3. Partial Least Square Regression model

A Partial Least Square Regression model is used as regression method when the independent variables are many and these variables may be affected by multi-collinearity. The PLS-R equation has the same form as Eq. (3), but the method selects a smaller set of input variables (“components”) based on the covariance among the independent variables used for regression.

In this study, PLS-R was applied to estimate LRR(D_c), adopting the “Jack-and-Knife” cross-validation method. The cumulated values of r^2_y and r^2_x, which measure the correlations between the independent (x) and response (y) variables with the components, were calculated.

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

2.9. Evaluation of the model's accuracy

The "goodness-of-fit" between the LRR(D_c) predictions given by the three models and the corresponding observations (based on D_c measurements by the flume experiments) was evaluated using the following quantitative indicators, commonly adopted in the literature (e.g., Willmott 1982; Loague and Green 1991; Legates and McCabe Jr 1999):

- the main statistics (maximum, minimum, mean and standard deviation of observed and simulated values)
- coefficient of determination (r^2)
- coefficient of efficiency of Nash and Sutcliffe (NSE, Nash and Sutcliffe 1970))
- percentage bias (PBIAS)
- Root Mean Square Error (RMSE).

The equations to calculate these quantitative indicators are reported by Van Liew and Garbrecht (2003), Krause et al. (2005) and Moriasi et al. (2007), and the acceptance or optimal values are shown in Table 1.

Table 1 - Indexes, variability range of and acceptance/optimal values to evaluate the prediction capacity of the three prediction models.

Index	Variability	Acceptance or optimal values
r^2	0 to 1	$r^2 > 0.50$ (Santhi et al. 2001; Van Liew et al. 2003; Vieira et al. 2018)
NSE	-∞ to 1	Model accuracy: good, if NSE ≥ 0.75; satisfactory, if 0.36 ≤ 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	-∞ to ∞	Model accuracy: fair, if PBIAS is < 0.55 (Moriasi et al. 2007) PBIAS > 0 or < 0 indicates model's under- or over-estimation, respectively (Gupta et al. 1999)

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

3. Results

3.1. Characterisation of changes in input and predicted variables

ANOVA and Tukey's tests revealed that the soil condition resulted in significant differences in all LRRs of the input and response variables ($F = 12.519$, $p < 0.001$).

With regard to the models' input variables, the LRR(BD) was on average significantly lower for all soil conditions compared to the deforested and untreated soils, with a significant gradient NF (-0.123 ± 0.031) < D + T (-0.112 ± 0.054) < PF (-0.089 ± 0.008). The PF soils showed the lowest LRR(OC) (-0.329 ± 0.055), which significantly increased in NF (-0.063 ± 0.109) and became positive in D + T soils (0.066 ± 0.058). The lowest LRR(WSA) was found in NF soils (-0.163 ± 0.509), and this LRR significantly increased and became positive in PF soils (0.156 ± 0.191). This ratio was the highest in D + T sites (0.350 ± 0.169). Finally, the minimum and maximum LRR(RWD) ratios were measured in PF (-0.080 ± 0.105) and D + T (-0.138 ± 0.120) soils, the NF sites showing intermediate values (-0.024 ± 0.155) (Figure 2).

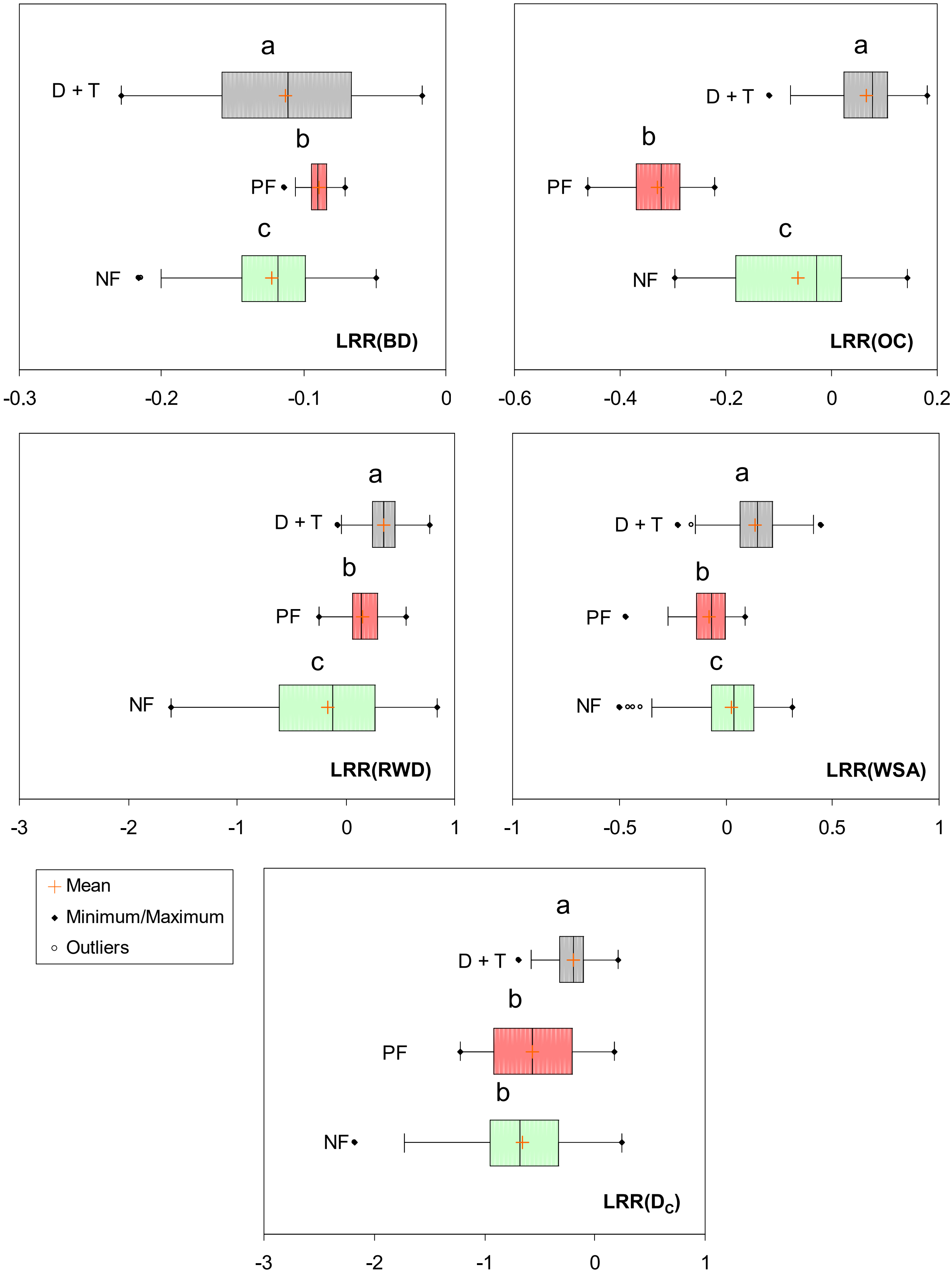

Figure 2 – Box plots of Log Response Ratios (LRR) of organic carbon (OC), bulk density (BD), water stable aggregates (WSA) of soil, root weight density (RWD) of plants and rill detachment capacity (D_c) measured in flume experiments on soil samples collected at the two study areas

(Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran). *Different letters indicate significant differences after Tukey's tests ($p < 0.05$). NF = natural forest; PF = planted forest; D + T = deforested and treated soils.*

In comparison to the deforested sites, LRR(D_c) was negative under all soil conditions. This ratio was the lowest in NF soils (-0.655 ± 0.429) and the highest in D + T sites (-0.195 ± 0.169), while the PF sites showed intermediate values (-0.563 ± 0.393). Only the difference between D + T soils, and NF and PF sites was significant, while no significant difference was found between PF and NF soils (Figure 2).

3.2. Model running

Twenty-five trees were sufficient for RF to minimise the estimation error (MAE of 0.078) of the response variable (Figure 3a). The most sensitive inputs of the model were the three categorical variables (soil condition, and WFR and SS classes), which gave the highest mean increase error., The numerical variables (LRR of BD, OC, WSA and RWD) showed a lower importance on the output (Figure 3b).

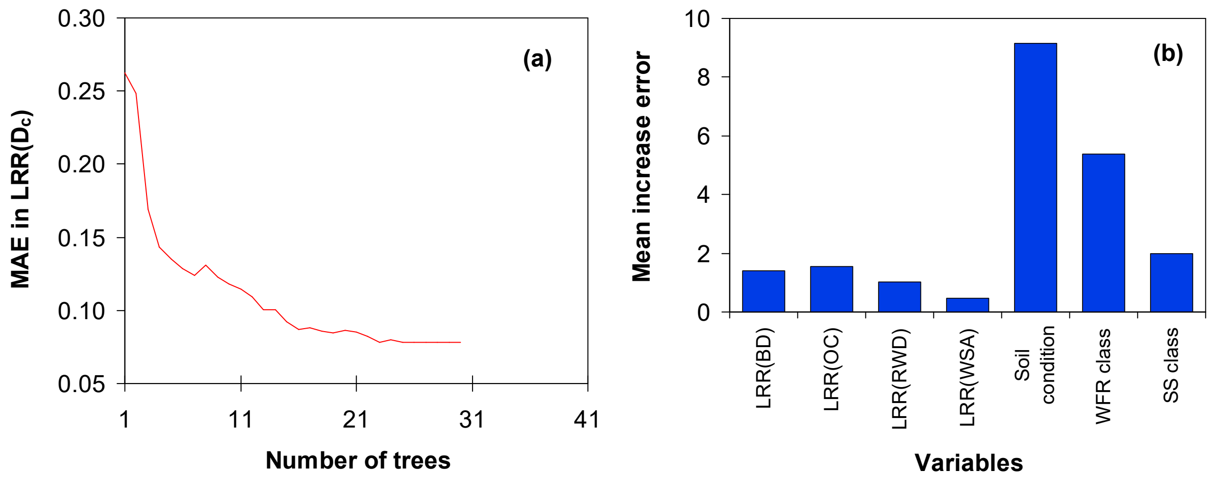

Figure 3 - Variability of the Mean Absolute Error (MAE) with the number of trees (a) and mean increase error (b), expressing the importance of each input variable, in the Random Forest model to the estimate the Log Response Ratio (LRR) of rill detachment capacity (D_c) of soil in two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran). *Legend: LRR = Log Response Ratio; OC = soil organic carbon; BD = soil bulk density; WSA = water stable aggregates; RWD = plant root weight density; D_c = rill detachment capacity.*

The number of input variables needed as best predictors of LRR(D_c) of the MLR model was high, since the highest r^2 (0.818) was achieved using 28 variables, LRR(BD), LRR(RWD), soil condition, and WFR and SS classes. However, the use of only 22 variables allowed the increase of r^2 from 0.422 (18 variables) to 0.788 (Table 2).

The PLS-R model selected only one meaningful component from the original dataset of input variables. The cumulated r^2_y and r^2_x between the input and response variables with this component were 0.770 and 0.044, respectively.

Both models (MLR and PLS-R) used quantitative and categorical variables as input parameters. The intercepts and coefficients of the two multiple regression (MLR and PLS-R) models with Eq. 3 are reported in Tables 1.SI and 2.SI, while Table 3 shows the variable importance in PLS-R model predictions.

Table 2 - Variability of the coefficient of determination (r^2) with input variables in Equation (3) of the Multiple Linear Regression model to predict Log Response Ratio (LRR) of rill detachment capacity (D_c) of soil in the two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran).

Number of variables	**Variables**	**r^2**
18	Soil condition	0.422
22	Soil condition / WFR class	0.788
26	Soil condition / WFR class / SS class	0.814
27	LRR(RWD) / Soil condition / WFR class / SS class	0.817
28	**LRR(BD) / LRR(RWD) / Soil condition / WFR class / SS class**	**0.818**

Notes: 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; LRR = Log Response Ratio; OC = soil organic carbon; BD = soil bulk density; WSA = water stable aggregates; RWD = plant root weight density; D_c = rill detachment capacity; WFR = water flow rate; SS = soil slope.

Table 3 **-** Variable importance in predictions of the Log Response Ratio (LRR) of rill detachment capacity (D_c) of soils in the two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran) using the Partial Least Square Regression model.

Variable	**Variable importance in the prediction**
WFR class (>0.6)	**2.405**
WFR class (<0.3)	**2.359**
Soil condition (D-Thzg)	**1.811**
Soil condition (NF-Pp)	**1.697**
LRR(OC)	**1.688**
WFR class (0.5-0.6)	**1.269**
WFR class (0.3-0.4)	**1.239**
Soil condition (NF-Pt)	**1.193**
Soil condition (D-Trhb)	**1.114**
Soil condition (D-TBs)	**1.062**
Soil condition (NF-As)	**1.038**
Soil condition (NF-Fo)	**0.894**
Soil condition (NF-Cb)	**0.832**
Soil condition (D-Thbp)	0.628
LRR(WSA)	0.570
SS class (10-15)	0.530
SS class (>30)	0.521
SS class (20-30)	0.510
Soil condition (D-Thsn)	0.503
Soil condition (NF-Rp)	0.503
Soil condition (PF-Ag)	0.476
SS class (<10)	0.474
LRR(RWD)	0.442
Soil condition (NF-Ph)	0.420
Soil condition (NF-Bp)	0.355
Soil condition (NF-Gc)	0.281
Soil condition (PF-Qc)	0.172

LRR(BD)	0.127
Soil condition (PF-Zc)	0.107
Soil condition (NF-Ca)	0.095
WFR class (0.4-0.5)	0.076
SS class (15-20)	0.028
Soil condition (NF-Se)	0.002

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

3.3. Prediction accuracy of the models

Figure 5 reports the predictions of LRR(D_c) using the three models in comparison to the corresponding observations under the three groups of soil conditions (natural forest, planted forest, and deforested and treated soils).

The predictions given by the RF model were in general satisfactory for natural forests and treated soils, but poor for planted forests. In more detail, the model tends to underestimate (for NF and PF soils) and overestimate (D + T sites) the LRR(D_c), as shown by the positive (NF and PF) and negative (D + T) values of PBIAS. For NF soil condition, the values of both the coefficient of determination and NSE were acceptable (r^2 = 0.54 and NSE = 0.46). NSE was poor (-0.51) and r^2 good for NF sites, while, for D + T soils, the model evaluation gave an acceptable NSE (0.49) and a poor r^2 (0.18). RMSE was always higher than half observed standard deviation, and thus unsatisfactory. The differences in the observed and predicted LRR(D_c) were low for the mean values (< 23.7%), but high for the maximum (> 99.3%) (Table 4).

The use of linear regression equations to predict LRR(D_c) gave satisfactory to good performances only for NF and PF soil conditions. For the latter, the pairs "predictions vs. observations" were very close to the line of perfect agreement (Figure 5), and also the evaluation indexes confirmed this visual assessment. In more detail, r^2 and NSE were very high (> 0.89), and the values of RMSE were satisfactory. In contrast, the MLR model performances were poor for D + T sites, being the values of r^2 (0.24), NSE (-1.47) and RMSE (0.265, equal to 3-fold half the observed standard deviation) under the acceptance limits of Table 1. The MLR does not underestimate or overestimate the observations (PBIAS close to zero), and the mean values of the predictions were practically equal to the corresponding observations. However, the errors in the maximum predictions of LRR(D_c) were high (over 60% for NF soils with a peak of +137% for D + T sites) (Table 4).

As for the estimations by MLR, the PLS-R model performed well in predicting LRR(D_c) for both NF and PF sites. More specifically, the model slightly underestimated (PBIAS = -0.02, NF soils) or overestimated (PBIAS = 0.17, PF soils) the response variable, but r^2 and NSE were always high (r^2 = 0.84 and NSE = 0.82 for NF soils, and r^2 = 0.95 and NSE = 0.80 for PF sites). RMSE was satisfactory for both soil conditions. Also for this model the predictions of the mean values of LRR(D_c) were close to the corresponding statistics of observations (differences lower than 16.8% with a minimum of 1.9% for NF sites), while the maximum predictions showed an error over 50%. In contrast, the model performance for D + T soils was poor, since the PLS-R overestimated the response variable (PBIAS = -0.13), and r^2 (0.18) and NSE (-1.25) were far below the acceptance limits. Only the mean LRR(D_c) was fairly predicted (+13.2% compared to the observations), while the maximum value was noticeably overestimated (+71.3%). The RMSE was about 200% higher compared to half the observed standard deviation (Table 4).

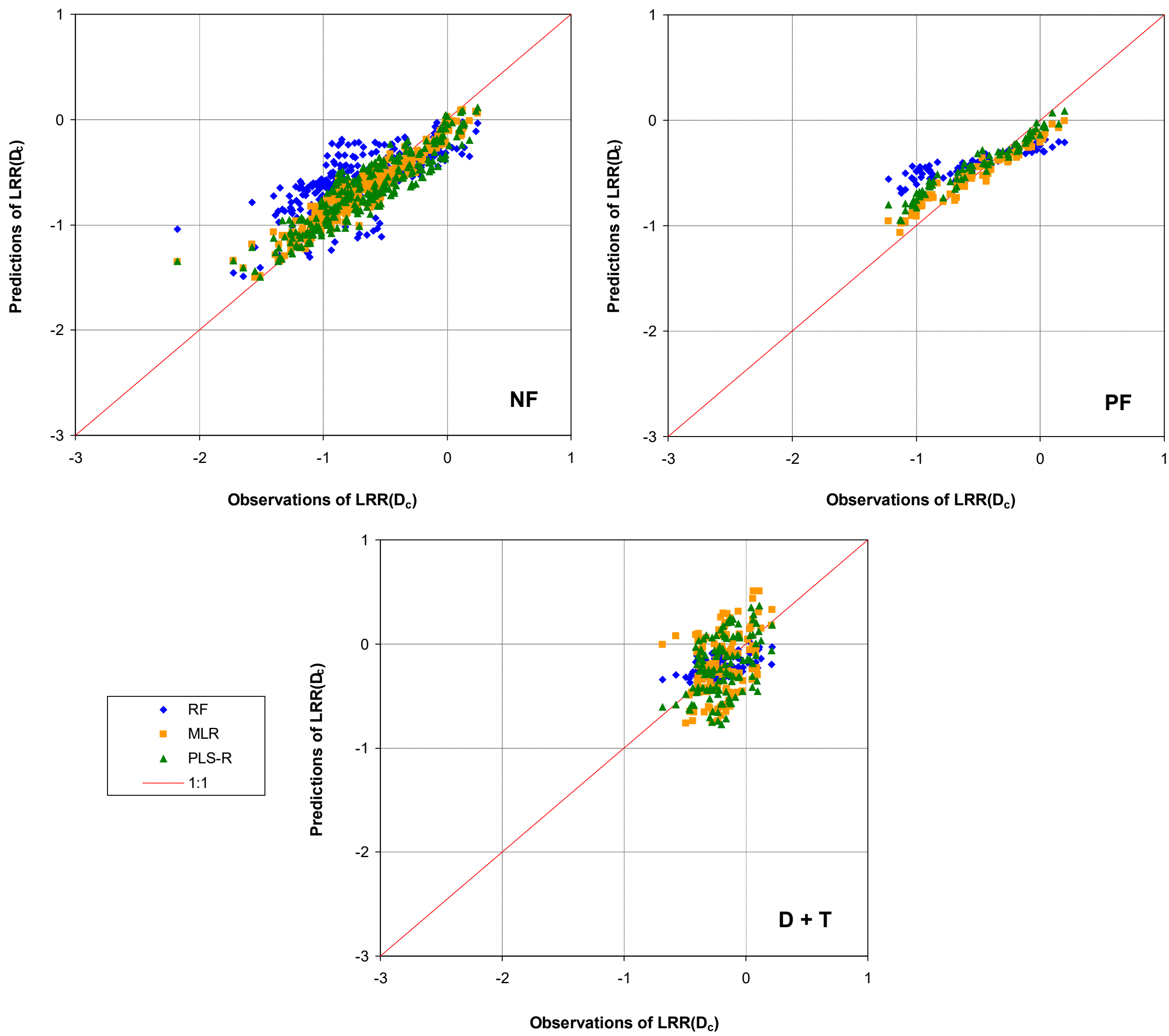

Figure 5 - Scatterplots of observations of the Log Response Ratio (LRR) of rill detachment capacity (D_c) of soils in the two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province,

Northern Iran) vs. the corresponding predictions using three models (RF = Random Forest; MLR = Multiple Linear Regression; PLS-R = Partial Least Square Regression). *Legend: NF = natural forest; PF = planted forest; D + T = deforested and treated soils.*

Table 4 - Indexes used to evaluate the predictions of Log Response Ratio (LRR) of rill detachment capacity (D_c) of soil in the two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran) using three models (RF = Random Forest; MLR = Multiple Linear Regression; PLS-R = Partial Least Square Regression).

LRR(D_c)	**Mean**	**Std. Dev.**	**Min**	**Max**	**r^2**	**NSE**	**PBIAS**	**RMSE**
	RF							
	Natural forest soils							
Observed	-0.664	0.428	-2.176	0.245	0.54	0.46	0.18	0.315
Predicted	-0.543	0.283	-1.489	-0.024				
	Planted forest soils							
Observed	-0.527	0.387	-1.222	0.195	0.82	-0.51	0.24	1.065
Predicted	-0.402	0.126	-0.692	-0.183				
	Deforested and treated soils							
Observed	-0.195	0.169	-0.685	0.215	0.18	0.49	-0.06	0.418
Predicted	-0.207	0.087	-0.402	0.001				
	MLR							
	Natural forest soils							
Observed	-0.664	0.428	-2.176	0.245	0.92	0.90	0.00	0.138
Predicted	-0.664	0.345	-1.500	0.094				
	Planted forest soils							
Observed	-0.527	0.387	-1.222	0.195	0.96	0.89	0.00	0.129
Predicted	-0.527	0.274	-1.064	-0.008				
	Deforested and treated soils							
Observed	-0.195	0.169	-0.685	0.215	0.24	-1.47	0.00	0.265
Predicted	-0.195	0.303	-0.761	0.509				
	PLS-R							
	Natural forest soils							

Observed	-0.664	0.428	-2.176	0.245	0.84	0.82	-0.02	0.180
Predicted	-0.677	0.341	-1.496	0.113				
	Planted forest soils							
Observed	-0.527	0.387	-1.222	0.195	0.95	0.80	0.17	0.171
Predicted	-0.438	0.260	-0.952	0.089				
	Deforested and treated soils							
Observed	-0.195	0.169	-0.685	0.215	0.18	-1.25	-0.13	0.253
Predicted	-0.221	0.273	-0.775	0.368				

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

4. Discussions

The mean values of changes in soil properties and rill detachment capacity were significantly different among the analysed soil conditions. Moreover, all these variables showed a large variability, which demonstrates that generally soil and erosion dynamics is strongly site-specific (Harden 2001; Zhang et al. 2009). This variability may noticeably affect the performances of hydrological models (Owoputi and Stolte 1995; de Vente and Poesen 2005), which could barely simulate the complex dynamics of the soil detachment process as well as the unsteady character of the soil's erosive response over time (Girona-García et al. 2021; Zema et al. 2022). This difficulty explains the contrasting prediction accuracy shown by the three models, with the RF algorithm showing a lower prediction accuracy, and regression models (both MLR and PLS-R) performing much better.

Two of the three models (MLR and PLS-R) gave very good estimations of the variations in the rill detachments capacity in natural forest soils compared to the deforested areas, and also the predictions for planted forests were satisfactory. In contrast, the predictions of LRR(D_c) were very poor for all models in the case of applications in deforested and treated sites.

The poor performances given by the RF model are quite surprising compared to other previous applications. Zema et al. (2023), applying RF to predict the changes in surface runoff and soil erosion between burned and unburned soils, ascribed the limited reproducibility of these variables by this model to the use of too many categorical variables as well as the limited number of observations in the training dataset. In accordance to those results, previous applications of RF algorithms to estimate soil erosion showed higher prediction accuracy in sub-tropical watersheds, compared to a logistic regression model (Ghosh and Maiti 2021), in Mediterranean semi-arid hillslopes, compared to general linear models (Mohammed et al. 2020), in tropical plots, compared to other machine learning techniques (Tarek et al. 2023), and in arid and semi-arid catchments, compared to k-Nearest Neighbor Classifiers (Avand et al. 2019). In our study, the number of categorical variables was limited (only three), and the dataset of observations was instead of several hundred (about 500 records), which should have smoothed the model prediction inaccuracy claimed by those authors. It is worth mentioning that the LRR(D_c) capacity given by RF did not increase with models runs up to 100 decision trees, since the estimation error (MAE of 0.086 with 100 trees against 0.078 with 25 trees) was stable or even increased after 30 trees. Presumably, the integration of other numerical input variables (such as the stream power, which is known as an accurate predictor of D_c, Hairsine and Rose 1992; Foster et al. 1995; Parhizkar et al. 2020) could improve the model reliability in simulating the rill detachment capacity.

The slightly worse performance of the PLS-R model compared to the MLR equation could be explained by the loss of variance due to adoption of a derivative component (explaining about 75% of the total variance of the original input variables), which may have propagated measurement errors in the model. In this regard, it is well known that the adoption of independent derivative variables replacing the original parameters (as for Principal Component Analysis and Factor Analysis) leads to a lost of variance, and therefore of information, Schreiber 2021). It is also worth noting that the prediction capacity of the MLR model is mainly driven by the categorical variables, while the addition of numerical variables does not noticeably improve its accuracy. The introduction of a variable related to the water flow condition (the WFR class) is able to significantly improve the model predictions, while a minor role is played by the other categorical variables associated with the morphological conditions (i.e., the soil slope). This means that the number of input variables is sufficient for reliable estimations of LRR(D_c). In the PLS-R model, the rank of variable importance reveals that the model predictions are again more sensitive to the water flow conditions (especially to the extreme classes, < 0.3 and > 0.6 L m^{-1} s^{-1}).

The satisfactory (PLS-R model) to good (MLR) accuracy in predicting the mean changes in D_c compared to the deforested areas shown by this study in the experimental conditions is in line with previous experiences focusing the reproducibility of the erosion process. For instance, Zema et al. (2022) found that MLR model showed a good prediction capacity of erosion, using both ”dummy“ categorical and numerical variables, such as runoff coefficients and sediment concentrations (from which soil loss can be estimated), and input parameters related to ground cover (e.g., litter, shrub vegetation, ash, bare soil percentage).

The simulations of the changes in rill detachment capacity in sites subjected to soil conservation techniques were always unsatisfactory. In contrast to what found for the LRR(D_c) prediction capacity of the two regression models (good for NF and PF conditions), the RF algorithm showed an acceptable coefficient of efficiency in predicting rill detachment. This better performance may be due to the reproducibility and high transparency of feature importance, which is one of the main advantages of RF algorithms (Wilder et al. 2021). In other words, it can not be excluded that artificial intelligence models, such as the RF algorithms, are more able to capture the complex effects that the addition of additives to soil (such as bacteria or nanoparticles) compared to linear models, given the high non-linearity of soil hydrological processes (Abrahart and See 2007; Medici et al. 2008). Other research activities should explore how RF performs in predicting rill detachment capacity under each of the modeled soil conservation techniques.

5. Conclusions

Among the three models (Random Forest, Multiple Linear Regression and Partial Least Square Regression algorithms) applied to forestlands of Northern Iran, multiple regression models gave reliable predictions of changes in rill detachment capacity in natural and planted forests compared to deforested areas. The accuracy of Random Forest algorithms was noticeably lower in natural forests and poor in reforested sites.

The simulations of changes in rill detachment capacity in sites that were deforested and then treated by five soil conservation techniques were poor when the linear regression models were used. The Random Forest algorithm was more accurate, but its predictions were not as good as for natural and planted forests simulated by the other two models.

The good performance of both multiple regression models in predicting changes in rill erosion for reforested and undisturbed sites may support the tasks of hydrologists and, more in general, landscape managers. The estimations of the increase in rill erodibility due to deforestation compared to undisturbed areas with natural species on one hand, and to predict the decrease in the same erosive variable in the case of reforestation works with a given tree species on the other hand can be supported by the accuracy of the erosion models. In this regard, the parameters of the linear regression equations may be used for modelling purposes in areas with similar climatic and geomorphological characteristics as the experimental sites. These parameters may be adopted as input for physically-based models simulating soil erosion on long and steep hillslopes.

The applicability of these models out of the environmental context of this study must be further validated through targeted modelling exercises. More research is also needed to improve the prediction accuracy of the rill detachment capacity in deforested sites subjected to soil conservation actions. This may be done adopting more sophisticate artificial intelligence algorithms (e.g., Artificial Neural Networks), increasing the number of the input variables (to increase the possibility to capture the intrinsic variability of rill erodibility drivers) and/or of the observations used for model training or adopting a different mathematical structure for multiple regression algorithms (e.g., exponential or power equations).

Statement of conflict of interest

The authors declare no conflict of interest.

Data availability

Data will be made available upon request to the authors.

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SUPPLEMENTARY INFORMATION

Table 1.SI - Values of the coefficients *a* and *b* in equation 3 of the Multiple Linear Regression model used to predict the Log Response Ratio (LRR) of rill detachment capacity (D_c) on soils samples collected at the two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran).

Variables (x_i in equation 3)	**Model coefficients**
Intercept **(*a* in equation 3)**	-0.369
LRR(BD)	-0.515
LRR(RWD)	0.190
Soil condition (D-Thbp)	-0.177
Soil condition (D-Thsn)	-0.203
Soil condition (D-Thzg)	0.251
Soil condition (D-Trhb)	0.043
Soil condition (NF-As)	-0.687
Soil condition (NF-Bp)	-0.442
Soil condition (NF-Ca)	-0.274
Soil condition (NF-Cb)	-0.588
Soil condition (NF-Fo)	-0.608
Soil condition (NF-Gc)	-0.252
Soil condition (NF-Ph)	-0.162
Soil condition (NF-Pp)	-0.892
Soil condition (NF-Pt)	-0.717
Soil condition (NF-Rp)	-0.119
Soil condition (NF-Se)	-0.326
Soil condition (PF-Ag)	-0.454
Soil condition (PF-Qc)	-0.224
Soil condition (PF-Zc)	-0.315
WFR class (0.4-0.5)	0.166
WFR class (0.5-0.6)	0.367
WFR class (<0.3)	-0.178
WFR class (>0.6)	0.543

SS class (15-20)	-0.067
SS class (20-30	-0.152
SS class (<10)	-0.001
SS class (>30)	-0.143

Table 2.SI - Values of the coefficients *a*, *b* and *c* in equation 3 of the Partial Least Square Regression model used to predict the Log Response Ratio (LRR) of rill detachment capacity (D_c) on soils samples collected at the two study areas (Saravan and Saqalaksar Forestland Parks, Guilan Province, Northern Iran).

Variables (x_i in equation 3)	**Model coefficients**
Intercept **(*a* in equation 3)**	-0.448
LRR(BD)	0.183
LRR(OC)	0.606
LRR(RWD)	-0.156
LRR(WSA)	-0.068
Soil condition (D-TBs)	0.263
Soil condition (D-Thbp)	0.155
Soil condition (D-Thsn)	0.124
Soil condition (D-Thzg)	0.448
Soil condition (D-Trhb)	0.276
Soil condition (NF-As)	-0.257
Soil condition (NF-Bp)	-0.088
Soil condition (NF-Ca)	0.024
Soil condition (NF-Cb)	-0.206
Soil condition (NF-Fo)	-0.221
Soil condition (NF-Gc)	0.069
Soil condition (NF-Ph)	0.104
Soil condition (NF-Pp)	-0.420
Soil condition (NF-Pt)	-0.295
Soil condition (NF-Rp)	0.124
Soil condition (NF-Se)	0.000
Soil condition (PF-Ag)	-0.118

Soil condition (PF-Qc)	0.043
Soil condition (PF-Zc)	-0.027
WFR class (0.3-0.4)	-0.171
WFR class (0.4-0.5)	-0.011
WFR class (0.5-0.6)	0.175
WFR class (<0.3)	-0.326
WFR class (>0.6)	0.332
SS class (10-15)	0.073
SS class (15-20)	0.004
SS class (20-30)	-0.070
SS class (<10)	0.065
SS class (>30)	-0.072