Full title: ASSESSING SOIL PROPERTIES CONTROLLING INTERRILL EROSION: AN EMPIRICAL APPROACH UNDER MEDITERRANEAN CONDITIONS

Short title: SOIL PROPERTIES CONTROLLING INTERRILL EROSION

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ABSTRACT

Soil erodibility is a complex phenomenon that comprises a number of different soil properties. However, most current (empirical) erodibility indices are based on only a few soil properties. A feasible soil characterization of interrill erosion (IE) prediction at large scale should be based on simple, quick, and inexpensive tests to perform. The objective of this work was to identify and assess those soil properties that best reflect soil vulnerability to IE. Twenty-three agricultural soil samples located in Spain and Italy were studied. Forty-nine different physical and chemical soil properties that presumably underpin IE were defined. Experiments were carried out in the field (in microplots using simulated rainfall) and in the lab. The most relevant variables were detected using multivariate analysis. Six key variables were finally identified: RUSLE K factor, a granulometric/organic matter content index, exchange sodium percentage, shear strength, penetration resistance, and permeability of soil seal. The latter is proposed as a useful technique to evaluate soil susceptibility to crusting even when the crust is not present at the time of the field survey. The selected variables represented a wide range of soil properties, and they could also be successfully applied to different soils with different characteristics than those evaluated in our experiments.

KEY WORDS: interrill erosion, soil erodibility, soil properties, rainfall simulator, multivariate statistical analysis.

INTRODUCTION

Interrill erosion (IE) (Boardman & Poesen, 2006) is a widely recognized form of water soil erosion which recorded rates as high as 49 t ha^{-1} year^{-1} (Foster, 1986). The IE involves a relatively uniform removal of soil from the land surface between the rills. The primary force for this erosion is raindrop impact, whose erosive potential depends on raindrop size, distribution, fall velocity, and total mass of impact (Lo, 1992). In addition, IE commonly occurs in areas close to the point of impact of raindrops (within around 1 m) where the detached material could be delivered to nearby rills (if these appear on the landscape) (Bryan, 2000). They can also be deposited downslope by the action of the runoff (Laflen, 2003). During IE, detachment and transport of the soil is principally produced by the impact of raindrops (Lassu *et al*., 2015; Marzen *et al*., 2015; Prosdocimi *et al*., 2016a) and, to a lesser extent, surface runoff. Thus, the IE process implies interaction of diverse factors such as rain, topography, vegetation, stone cover and land management and especially soil erodibility (Gessesse *et al*., 2015; Gumiere *et al*., 2009; Keesstra *et al*., 2014; Ola *et al*., 2015; Wang *et al*., 2015). Using a subjective criteria the numerous soil properties related to soil erodibility may be grouped as follows: (1) texture and stoniness of the topsoil (e.g. Dai *et al.*, 2015; Poesen *et al.*, 1994; Poesen and Lavee, 1994; Cerdà, 2001); (2) aggregate stability (e.g. Barthès & Roose, 2002; Le Bissonnais, 1996; Ma *et al.*, 2014); (3) susceptibility to sealing and crusting (e.g. Arjmand Sajjadi & Mahmoodabadi, 2015; Assouline & Mualem, 2006; Le Bissonnaiss *et al.*, 2005); (4) resistance to shear stress (e.g. Luk & Hamilton, 1986; Léonard & Richard, 2004); and (5) physical-chemical properties (e.g. Ben-Hur & Agassi, 1997; Biswas *et al.*, 2015; Singer *et al.*, 1982).

Several indices and parameters have thus been proposed to quantify soil erodibility (Bryan, 2000; Le Bissonnais *et al.*, 2005; Romero *et al.*, 2007; Römkens, 1985; Wischmeier & Smith, 1978); however there is not yet a complete understanding of this complex phenomenon. This is why most of the current models to estimate soil erodibility are still empirical based on statistical relationships between inputs (soil properties) and outputs (erosion rate). Despite the large number of variables intervening in the erosion process, most of the current empirical indices are only based on a limited number of variables –sometimes only one or two– that are assumed *a priori* to be dominant in the erosion process under the study conditions. On the other hand, evaluation of large-scale soil erodibility, e.g. catchment scale, should consider variables that are obtained from simple and economical procedures and techniques (Le Bissonnais *et al.*, 2005).

Commonly, the relationships between erodibility and soil properties have been explored using classic statistical procedures like correlation matrix, simple linear regressions and multivariate techniques (e.g. Arnaez *et al.*, 2007; Cerdan *et al.*, 2010; García-Ruíz *et al.*, 2015; Maetens *et al.*, 2012; Prosdocimi *et al.*, 2016b; Sheridan *et al.*, 2000; Verhaegen, 1984).

The aim of this research was to identify and assess soil properties that are easily and quickly determined and that best reflect the soil vulnerability to interrill erosion.

The experimentation was conducted on agricultural soils of Navarre, León (Spain) and Sicily (Italy). Experiments were carried out in microplots with simulated rainfall and in the laboratory. Forty nine soil variables and parameters were obtained via techniques and methodologies proposed in the literature. Data were analyzed using multivariate statistics tools.

MATERIALS AND METHODS

Study areas

Twenty-three agricultural soils located in three studied areas: (1) León (Spain); (2) Navarre (Spain); and (3) Sicily (Italy) were assessed (Figure 1 and Data S1, Google Earth file). These studied areas are commonly affected by water erosion (e.g. Casalí *et al*., 1999; Casalí *et al*., 2008; Capra *et al*., 2012). The main crop in all studied areas was winter wheat with the exception of one situation (LEO 1; Table I), where the crop was rye. In León study area (NW Spain), with an annual rainfall average of 449 mm and a Mediterranean climate, 2 soils were located: LEO 1, and LEO 2 (Table I). Under a Mediterranean climate and with a mean precipitation range between 547 and 1310 mm, 11 soils were located in the study area of Navarre (N Spain): PIT 1 to PIT 3, AOI 1 to AOI 6, LUM 1 to LUM 3, ABA 1, and ABA 2 (Table I). Finally, 7 soils were located in the Sicilia (S Italy) study area: RAD 1 to RAD 7 (Table I). This last area is characterized by a Mediterranean climate type with an average annual rainfall of 500 mm

The experimentation period was from October to March in the years 2012, 2013 and 2014. In this period the soil moisture is high and almost constant, due to the accumulation of ca. 80% of the annual precipitation.

Experimentation protocol

Rainfall simulation experiments with a drip portable rainfall simulator (Eijkelkamp Agrisearch Equipment, model 09.06, the Netherlands) designed by Kamphorst (1987) were performed at each of the 23 soils studied. This type of rainfall simulator has been widely used to assess soil erodibility (e.g. Bagarello & Ferro, 2004; Iserloh *et al.*, 2013; Martínez-Zavala & Jordán, 2008; Romero *et al.*, 2007). It consists in two main parts: (1) a capillary sprinkler for control the rain shower produced by 49 tubes located at a height of 0.4 m from the soil surface; and (2) a partly buried square metal frame which delimited the test plot (0.0625 m^2) and also prevented the lateral movement of water (Figure 2). In all studied areas the experimental microplot was located in points of the landscape which had a similar terrain slope and where the IE phenomenon were evident.

Three replicate rainfall simulations were conducted at each selected site. The mean intensity of the rain was 131.5 mm h^{-1} and the kinetic energy of drops was 4 J m^{-2} mm^{-1}. The estimated mean annual 30 min maximum rainfall intensity for 10 years is 71.24 mm h^{-1} for the studied areas. This high intensity was adopted to correct the lower kinetic energy of the rain shower generated by the rainfall simulator due to its low fall height (Iserloh *et al.*, 2013).

Rainfall simulations were continued as long as necessary to reach a roughly constant runoff rate, i.e. soil moisture around saturation. This steady flow was achieved in the different experiments after around 20-30 minutes. From this moment, water and sediment samples were collected every 2 minutes during approximately 20 minutes. These were dried in a stove (105 ºC, 24 h) to obtain the weight of eroded soil. Then, the erosion rate (t ha^{-1} h^{-1}) (SL_1, Table II) was calculated (e.g. Cerda et al., 2016; Prodoscimi et al., 2016a; Rodrigo Comino et al., 2016a). The basic infiltration rate (HY_1: mm h^{-1}, Table II) was calculated as the difference between the volume of rain and that of stabilized runoff.

Various soil variables highlighted in the literature as soil erodibility potential drivers (a total of 49 described in Table S1) were determined in each study situation. Briefly, the different methodologies carried out are described below (see Table S1 for more information). A composed soil sample from the first 15 cm of soil depth were collected from various points adjacent to the microplot on each of the 23 studied soils. After oven-drying and sieving (< 2mm), different determinations were performed in the laboratory in order to determinate a large set of different soil parameters: (1) aggregate stability to the 3 disaggregation methods proposed by Le Bissonnaiss (1996): slaking (SI_4), clay swelling (SI_5), and mechanical breakdown by shaking (SI_6); (2) crusting susceptibility index C_{5-10} (CR_1) (De Ploey & Mücher, 1981); (3) relative sealing index (CR_2) (Pla, 1982); (4) seal hydraulic conductivity (HY_2) (Pla, 1982); (5) 4 crusting indices obtained from soil texture and organic matter (CR_3, CR_4, CR_5, and CR_6) (Comerma et al., 1992; FAO, 1980; Florentino, 1998); (6) various physical (i.e. texture, GT_{1-5} and GF_{1-5}; stoniness, GC_{1-6}), chemical (i.e. organic matter percentage, CH_1; electrical conductivity, CH_2; exchangeable sodium percentage, CH_3; pH of soil saturated paste, CH_4; cation exchange capacity, CH_5; and calcium carbonate, CH_6) and physical-chemical soil variables (i.e. 3 structure stability indices, SI_1, SI_2, SI_3; K factor of RUSLE, E_2); and (7) critical shearing (SS_5) and soil erodibility coefficient (E_1) determined by a jet test apparatus by using undisturbed soil samples (Hanson & Cook, 2004) (more details in Table S1, L). Additionally, several soil properties were directly determined on the field.

This was done both on the microplot itself (Table S1, F_{IN}) and at sites near to it (Table S1, F_{OUT}). The following parameters were measured within the microplot: (1) hydraulic conductivity of the crust formed after the drying of the soil seal produced by the rain simulation (HY_3) (Boiffin & Monnier, 1985); and (2) 3 variables of crust resistance to penetration after the rain shower (PR_1, PR_2, and PR_3) (Bradford et al., 1992; Truman & Bradford, 1990). And out of the microplot the following ones: (1) bulk density (PH_1) and (2) 4 different soil shear strength measurements (SS_1, SS_2, SS_3, and SS_4) (Léonard & Richard, 2004).

Statistical analyses

The mean value of the variables was further considered for statistical analysis (see Table S1). The relationships between the IE rate and the rest of the variables were investigated using 3 different multivariable statistical tools: Cluster Analysis (CA), Principal Components Analysis (PCA) and Multiple Regression Analysis (MRA). The results obtained which each statistical tool were analyzed independently from each other. The suitability of the dataset for applying those statistical techniques was assessed via Bartlett`s sphericity test (Bartlett, 1954). All analyses were performed employing version 3.1.1 of the R statistics software (R Core Team, 2015).

The CA is a non-supervised classification technique for the recognition of similar behavior patterns between observations (Vega *et al.*, 1998). This technique uses all the information supplied by the original data set without making any previous assumptions. In this study, a hierarchical agglomerative CA was proposed on the data via Ward´s method (Ward, 1963) and using the Euclidean distance as a similarity measurement. This method was selected for its greater potential as a tool for the creation of groups (Willet, 1987). Thus, each identified group or cluster is characterized by mean values of the variables defining that cluster (mean in cluster), which are significantly different from the respective mean value of the entire population (overall mean) (e.g. Anderberg, 1973; Kabacoff, 2015).

The PCA reduces the dimensions of large-size datasets to restrict the number of explanatory variables without losing important information in the process (Shrestha & Kazama, 2007). On some occasions, it is necessary to orientate the PCA towards those variables of special interest (supplementary variables) and therefore to refer the analytical process to them (Giménez *et al*., 2012). In this study, the supplementary variable selected was SL_1 (Table S1). Thus, PCA transforms the original variables into new non-correlated synthetic variables called Principal Components (PCs). These PCs are useful instruments to study possible relationships and to identify trends between those variables with higher correlation to PCs. When the correlation values between the PCs and the variables are too high (or low) it may be difficult to interpret the results, but rotating the PCs can solve this problem (Westra *et al*., 2010). In this study, the Varimax rotation criterion (Kaiser, 1958) was selected and applied to the PCA.

The MRA allow obtaining the best linear relation between the variables analyzed relating a selected dependent variable (SL_1) as a function of a set of independent variables. In this study, all the possible linear models from one to four of the soil variables were obtained and analyzed to seek the best explanatory model (i.e. principle of parsimony, Vandekerckhove *et al*., 2015). In each of the resulting models, the following evaluation criteria were applied to diagnose the best regression model: (1) calculation of the variance inflation factor (VIF, equation 1) to discard the independent variables presenting multicollinearity (i.e. VIF > 2) (Lin, 2008); (2) outliers were discarded when the standardized error in the regression residues was larger or smaller than 2 (Kabacoff, 2015); (3) Akaike information criterion (AIC, equation 2) values as a scale to select the model's predictors (Akaike, 1974); (4) verifying the goodness of fit obtained by the model employing the Nash-Sutcliffe efficiency coefficient (NSE, equation 3) (Nash & Sutcliffe, 1970), the mean squared error (MSE, equation 4) and the root mean squared error (RMSE, equation 5) (Moriasi *et al.*, 2007); and (5) regression diagnosing based on the significance level ($p < 0.05$, t-test) for the regression coefficients of each independent variable conforming the model (Walpole *et al.*, 2011).

$$VIF = \frac{1}{1-R^2} \quad (1)$$

$$AIC = 2k - 2\ln(L) \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(0_i - S_i)^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(0_i - S_i)^2} \quad (5)$$

where k is the number of parameters included by the model; L is the maximized value of the model`s verisimilitude function; S_i is the simulated value for the i case; O_i is the value observed for the i case; $\bar{O}$ is the mean value for the observed cases; n is the number of observations; and R^2 is the multiple determination coefficient of the fitted model.

RESULTS

The Bartlett test showed a probability $p < 0.05$ (significance at 95% level), which – together with a value of the correlation matrix determinant equal to 0 and with the existence of correlation coefficients between variables of above 0.30 in the same matrix (not shown)– suggests that the variables have a sufficient level of correlation to use the 3 multivariate statistics tools proposed here.

Cluster analysis (CA)

The CA defined the existence of 2 clusters (Cluster 1 and Cluster 2). Each of the clusters was constituted by approximately half of the soils: 11 in Cluster 1 and 12 in Cluster 2. The soils grouped in Cluster 1 presented a 3-fold higher mean erosion rate (SL_1) than that corresponding to the soils in Cluster 2 (median of 6.6 t ha^{-1} h^{-1} and 2.4 t ha^{-1} h^{-1}, respectively). This result suggests that the variables in their respective value ranges discriminated by the CA would be related to some extent to the erodibility of the soil. Of the 19 variables identified (Table II), only those with the highest statistical weight were selected; i.e. those showing a significance level of $p < 0.005$ in the Student t-test (evaluating that the mean of the variables in each cluster differed statistically from the mean value of the whole population): CH_5, CR_5, SI_2, SI_3, E_2, CR_4, CR_3, and PR_3. These variables were then grouped according to its typology in the following groups: (i) cation exchange capacity (CH_5), (ii) soil mechanical resistance to penetration in the first 6 cm (PR_3) and (iii) variables obtained basically via a balance between the soil texture (particle size < 2 mm) and the organic matter present in the soil (CR_5, SI_2, SI_3, E_2, CR_4, and CR_3). As these last variables were similar with regard to their nature and statistical weight, E_2 was selected as being representative of this last group due to its wide support as a soil erodibility parameter in the literature (e.g. Meyer & Harmon, 1984, Romero *et al.*, 2007, Wischmeier & Smith, 1978).

However, variable CH_5 provided ambiguous information on soil erodibility as mentioned later in the discussion section and was rejected. Then, the variables resulting from the CA were E_2 and PR_3.

Principal Components Analysis (PCA)

After fixing SL_1 as the supplementary or reference variable those PCs presenting a lower eigenvalue than unity after their rotation were discarded (Andrews *et al.*, 2002). This resulted in 11 PCs (Table III). The first 2 PCs (PC_1 and PC_2) were capable of explaining 38.4% of the total variance of the data (21.7% and 16.8%, respectively), but PC_2 was discarded due to its lower correlation with variable SL_1 (0.19); PC_1 had a correlation of 0.35. In addition, only those variables from PC_1 with a factor correlation $\geq$ 0.5 were further considered for analysis (Table III).

Thus, 13 variables were selected and divided according to their type into 5 groups: (i) composition of the soil texture and organic matter content (SI_1, SI_2, SI_3, CR_5, CR_6, and E_2); (ii) soil resistance to penetration in the first centimeters of depth (PR_2, PR_3, and PH_1); (iii) soil shear strength (SS_1); (iv) soil chemical composition (CH_2 and CH_3); and (v) permeability of the soil crust measured in the laboratory (HY_2). Of the groups showing more than 1 variable (i, ii and iv), the following were selected: (1) E_2 due to its higher correlation value within PC_1 and therefore with SL_1 (0.86 in absolute value, Table III); (2) PR_3 with a higher statistical weight although similar to that of PR_2 (0.51 in absolute value, Table III) and also for having been prominent in the CA (see above); and (3) CH_3 assuming that the high electrical conductivity values (CH_2) were precisely a result of the high exchangeable sodium percentage (CH_3). From the PCA, the outstanding variables were E_2, PR_3, SS_1, CH_3, and HY_2.

Multiple regression analysis (MRA)

Similarly, the MRA weighted those variables of the total population in the study (Table S1) that would best fit an explanatory linear regression model of SL_1. All possible models with one variable (48), two variables (1128), three variables (17296) and four variables (194580) were obtained.

The best model with one variable (Model 1) had CH_3 as an independent variable. This model showed the highest value of NSE (0.92), the lowest MSE (0.04), RMSE (0.21) and AIC (3.18) from all models with one variable. With respect to the best model with two variables (Model 2), this kept CH_3 as the first variable and introduced CR_6 as the second independent variable. Model 2 showed a lower value for AIC than Model 1 (-9.3 and 3.18, respectively, Table IV). It should be remembered that high values for AIC indicate a loss of quality in the goodness of the model caused by the complexity of the model itself and its goodness of fit (Akaike, 1974). Models with more than 2 explanatory variables were discarded due to their low accuracy (i.e., higher AIC values). Therefore, Model 2 (equation 6) was selected as having the best relationship between soil properties (CH_3 and CR_6) and the IE rate (SL_1).

$$SL_1 = 0.813 + 0.151 \cdot CH_3 + 0.575 \cdot CR_6 \qquad (6)$$

Both variables CH_3 and CR_6 already stood out in the PCA (Table III); only E_2 was selected instead of CR_6 for the reasons given above.

Guide values of the variables selected

The overall evaluation of the 3 statistical analyses identified 6 key soil variables in the establishment of soil erodibility under the experimental conditions of the study: E_2 (K factor of RUSLE), CH_3 (exchangeable sodium percentage), PR_3 (penetration resistance in the first 6 centimeters of the soil depth), SS_1 (shear strength), CR_6 (modified crusting index), and HY_2 (hydraulic conductivity of seal) (see Table S1). Moreover, a guide value is determined from the mean value of each of the aforementioned six variables reaches in the least susceptible cluster (Cluster 2, Table V). Thus, the transition between erosion-resistant and vulnerable soils (Cluster 1, Table V) can be roughly defined.

Figure 3 shows the distribution of the mean values and the standard deviations for these 6 key variables in the 2 clusters. In this way, a new soil (with a similar texture and structure to those presented here) could be roughly classified as most resistant to erosion if it shows values of approximately 0.02 t ha h ha^{-1} MJ^{-1} mm^{-1} for E_2, 0.75 for CR_6, 4.19% for CH_3, 500 kPa for PR_3, 16.00 kPa for SS_1 and 2.60 mm h^{-1} for HY_2 (see Figure 3 and Table V). These guide values must be interpreted independently from one another because we do not evaluate the possible interaction among the proposed key variables.

DISCUSSION

First of all, it is important to highlight that the individual relations between the IE rate and a group of soil properties were established through statistical analysis but without examining interdependency among those variables.

The susceptibility to erosion in the soils analyzed was due to the action of diverse factors. The first factor is the low content in clay and organic particles, both well-known cementing agents of soil aggregates (Boix-Fayos *et al.*, 2001). For example, Wilcox & Wood (1989) applied a rain simulation on 88 microplots of loam and clay soils in New México (USA) and showed that IE rates (between 0.03 and 8 t ha^{-1}) correlated negatively with the increase in clay content, although the authors did not define any threshold value for this relationship. Similar results were obtained by Meyer & Harmon (1984) who recorded the greatest resistance to IE in 18 agricultural soils with contrasting textures. This was determined by rain simulation in 7 soils in which the clay content exceeded 27%. These results are comparable to those obtained in our study in which those soils least vulnerable to erosion (Cluster 2) showed a clay content of approximately 37% (not shown). On the other hand, the effect of organic matter on the improvement of the structure stability of the soil –and thus resistance to erosion– is extensively documented (e.g. Barthès & Roose, 2002; Bryan, 2000; Cerdan *et al.*,2010; Dimoyiannis *et al.*, 1996; Sheridan *et al.*, 2000; Prosdocimi *et al.*,2016b). Le Bissonnais & Arrouays (1997) studied loam soils in France and established that 2.5 to 3.0% of organic matter improved and maintained the stability of their aggregates against the action of simulated rain. This reduced the susceptibility to crusting and erosion. In our experiments, the soils most resistant to erosion presented organic matter values very close to the threshold cited above (Table II). In this line, Rodrigo Comino et al. (2016c), comparing the variability of soil erosion in Mediterranean vineyards in Spain, registered the highest values of soil loss (generated by rainfall experiments) in soils with both the lowest organic matter content and the highest concentration of silt particles.

In fact, E_2 and CR_6 are important explanatory variables for soil erodibility because both are ultimately defined as a balance between the soil texture and organic matter (Table S1). Meyer & Harmon (1984) and Panagos et al. (2014) –the latter from an analysis of approximately 20.000 soil samples obtained from 25 European countries– defined a critical value of E_2 of 0.030-0.035 ta h MJ^{-1} ha^{-1} mm^{-1} to classify soils as being most susceptible to erosion. This threshold is very close to that obtained in our studies (Table V). FAO studies (1980) showed that soils with a CR_6 value over 2 are highly susceptible to crusting, although Pulido-Moncada et al. (2009) reduced this value to 0.70 in a study of 5 agricultural soils in Venezuela. The latter agrees fairly well with the mean value determined in this study (CR_6 = 0.74) for the most erodible soils (Cluster 1). However, the most resistant soils (Cluster 2) gave a mean CR_6 value of only slightly over 1. It should be noted that E_2, unlike CR_6, also includes a permeability and soil structure class quantification (Table S1). While both of these behaved similarly as explanatory variables for soil erodibility, in more contrasting soils –especially with regard to texture and structure to those of our experiments– E_2 would probably stand above CR_6.

Second, the structure stability of some soils –and consequently their vulnerability to erosion– was affected by a high content of Na^+ cations in the soil exchange complex. It is known that high sodicity can lead to an important physical degradation of the soils (Ben-Hur & Agassi, 1997; Shainberg & Letey, 1984). This increases susceptibility to sealing and eventually to erosion. For example, Mamedov et al. (2002) evaluated the effect of different exchangeable sodium percentages (ESP) (2, 5, 10 and 20%) and clay contents (between 22 and 62%) on soil losses triggered by simulated rain in 6 arable Israeli soils. These authors determined that the erosion rate increased as the ESP augmented and the clay content in the soils diminished. Other laboratory studies with simulated rain by Singer et al. (1982) showed that 7 loam, silty loam and silty clay loam soils had an increase of over 20% in the IE rate when the ESP value increased from 4 to 54% as a result of the negative effect of the Na^+ on the resistance of soil aggregates to erosion. Kemper & Koch (1966) confirmed this in a study of 519 soils in the USA and Canada. The lowest values of aggregate stability were observed when the ESP value was over 20% and the clay content was below 22%. The latter trends were similar to those 4 sodic soils identified in Cluster 1 (PIT 1, PIT 2, RAD 5, and RAD 7). These 4 soils exhibited on average a higher ESP value (49.25%, not shown) and a lower clay content (25.38%, not shown) with respect to the rest of the soils analyzed (4.36% and 31.25%, respectively, and not shown). While the cation exchange capacity was another notable soil property in our analysis (variable CH_5, see above), it did not have any effect *per se* on the erosion but would be conditioned by the type of cations dominating in the soil exchange complex. Thus, if bivalent cations dominate, then the soil aggregation would benefit. But if the dominant cation is sodium (see above), then there is an opposite effect (peptization) (Bronick & Lal, 2005). Hence, we decided to exclude the variable CH_5 from the key explanatory variables selected as discussed in the previous section.

Third, soil susceptibility to sealing is also important and it was quantified via permeability values of the seal formed in the laboratory after rain simulation (variable HY_2). Thus, lower values of HY_2 would lead to higher runoff and erosion rates in the field (Ben-Hur & Agassi, 1997). Ramos et al. (2003) proposed a minimum threshold value of 5 mm h^{-1} for the variable HY_2 under which the risk of sealing and erosion in soils cultivated with cereal and vineyards in Catalonia (Spain) was increased. Those authors related the increase in the value of HY_2 to a reduction in the percentage of medium-sized particles (fine sands and silts) and to a higher content of organic matter in the soil. In our experiments, both Clusters 1 and 2 soil groups showed a lower value of HY_2 than that proposed by Ramos et al. (2003): 1.84 and 2.73 mm h^{-1}, respectively. Even so, we can claim that the crusting problem plays a key role in the soil erodibility of the soils assessed based on field observations. This statement has been also supported by numerous research carried out on cultivated soils of Spain and Italy (e.g. Cerdà, 1997; Cerdà *et al.*, 2016; Marzen *et al.*, 2015; Prosdocimi *et al.*, 2016b; Ramos & Martínez-Casasnovas, 2007; Rodrigo Comino *et al.*, 2016b,c). On the other hand, while variable HY_2 was originally proposed to detect soil sealing susceptibility (Pla, 1982), it also supplies information on aggregate stability because the seal is formed with the soil particles disaggregated due to action of rainfall (Assouline & Mualem, 2006). As a matter of fact, none of the 3 variables (SI_4, SI_5, and SI_6) proposed by Le Bissonnais (1996) to evaluate structure stability stood out in our assessment. This was unexpected because several works have shown a clear relationship between one or other of these variables with crusting and subsequent erosion of the soil under simulated rain (e.g. Amézketa *et al*., 1996; Barthès & Roose, 2002; Le Bissonnais, 1996; Leguédois & Le Bissonnais, 2004; Ma *et al*., 2014; Ramos *et al*., 2003; Wang *et al*., 2015). Thus, the disaggregation and subsequent sealing of our soils was a direct result of the impact of the raindrops (variable HY_2, see above); this erosive agent was not properly reflected in the variable SI_6 (Le Bissonnais, 1996) in which the action of the rain try to be simulated by agitating the soil aggregates. Thus, HY_2 would reflect both the susceptibility of the soil to sealing and its aggregate stability. It is important to use a technique that evaluates the soil potential to crusting without the crust being present in the field at the moment of determination.

Finally, erosion susceptibility was somewhat reflected in the soil resistance to shear strength and/or to penetration (variables SS_1 and PR_3, respectively). Concretely, increases in the value of SS_1 would be related to a greater soil resistance to detachment caused by raindrop impact and surface runoff (Léonard & Richard, 2004). Meanwhile, high values of PR_3 would be associated with soil physical degradation from rain. This led to soil compaction and, consequently, a diminution in its permeability (Herrick & Jones, 2002). That is why our mean values of PR_3 and SS_1 were 50% lower and 15% higher, respectively, in the soils most resistant to erosion (Cluster 2) than in the more vulnerable ones (Cluster 1). Luk & Hamilton (1986) studied 2 non-agricultural soils (loam and silty loam) and proposed a shear strength threshold value (measured with a vane shear apparatus) between 13 and 15 kPa. Below this, the IE rate –determined by in-field rain simulation– increased. In our experiments, the least erodible soils (Cluster 2) gave a higher SS_1 value (16.00 kPa, Table V) than the threshold cited. However, the soils most susceptible to erosion (Cluster 1), had a value of this variable that was lower (14.11 kPa, Table V). However, this was within the previous range and these data should be interpreted with caution because Luk & Hamilton (1986) studied non-agricultural soils and our study used agricultural ones. It is worth noting that the variable SS_1 was obtained with a disk of our own design with a high depth/diameter ratio (Table S1), in order to increase the volume of the soil submitted to shearing and thus obtained more representative measurements of this parameter (Léonard & Richard, 2004). For the variable PR_3, mean values almost twice larger were obtained in Cluster 1 (916.15 kPa) than in Cluster 2 (462.46 kPa). Although several works report general trends on the compaction effect on the soil after a rain event and the subsequent variation on the IE rate (e.g. Laufer *et al.*, 2016; Neave & Rayburg, 2007; Truman & Bradford, 1990), no clear threshold value for this parameter in relation to the potential erosion rate were reported

In short, soil response to IE was mainly controlled by the soil aggregates stability against the rainfall erosivity and for the soil tendency to sealing and crusting. These finding has been commonly reported in several studies conducted in similar agricultural areas such as those analyzed here (e.g. Capra *et al.*, 2012; Cerdà 1997, 2002; Ramos *et al.*, 2000; Rodrigo Comino *et al.*, 2016b,c). Therefore, the 6 most important soil variables here presented (i.e. E_2, CR_6, CH_3, HY_2, SS_1, and PR_3) would allow identified soil behavior against the IE processes. Moreover, these variables were determined through a quick and easy methodologies (Table S1), which allows a rapid and economic characterization of soil erodibility to IE on large study areas. Nevertheless, due to the high variability in the soil properties that characterize agricultural soils (Ruiz Sinoga & Martinez Murillo, 2009) the guide values of these variables can only applied in similar soils to those evaluated herein. Further investigation is needed to evaluate the 6 keys variables and their interaction on other types of soils. This would allow to define soil erodibility indices that can eventually be applied to improve current empirical models about IE.

CONCLUSIONS

The soils response to interrill erosion was mainly reflected in 6 variables identified from multivariate statistical procedures: the K factor of the RUSLE model (E_2); an erodibility index obtained from a granulometric balance and the organic matter content in the soil (CR_6); the soil exchangeable sodium percentage (CH_3); the soil seal permeability (HY_2); the soil shear strength (SS_1); and the soil resistance to penetration (PR_3). For each variables, guide values roughly indicating the transition between vulnerable and resistance soils are given. These can be at least successfully applied in some typical Mediterranean soils.

All these variables resulted from field and laboratory techniques, which are economic and easily implemented, allowing then a relatively rapid characterization of large areas, e.g., catchment scale.

The varied nature –physical, chemical and physical-chemical– of the soil properties comprising those variables permits one to assume that they could be also successfully applied even in soils of different natures and characteristics from those studied in this work. However, in this latter case, the guide values proposed –given their empirical character– would probably have to be reformulated. It is advisable to count on techniques permitting the evaluation of soil susceptibility to forming crusts (e.g. many European loess soils) without it being necessarily present at the moment of its determination, since in agricultural soils frequent tilling could be hidding this important problem. A variable for evaluating that soil propensity is proposed (HY_2). Further research is needed to study the interaction among the 6 key variables prosed herein. And after that, to define new empirical models about interrill erosion or to improve current ones.

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SUPPORTING INFORMATION

Supporting Data

Data S1. Google Earth file with the location of the 23 studied area.

Supporting Tables

Table S1. Characterization of the soil variables. L = laboratory determination, F_{IN} = field determination on the microplot, F_{OUT} = field determination at points surrounding the microplot, SD = standard deviation. Each determination was repeated 3-5 times at each studied soil, and the average values were considered.

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Tables

Table I. Main physical-chemical properties of the soils (epipedon) in the study. EC = electrical conductivity, ESP = exchange sodium percentage, CEC = cation exchange capacity.

Soil name	Soil type [a] (FAO-WRB)	Sand (%)	Silt (%)	Clay (%)	Organic matter (%)	Stoniness (%)	Bulk density (g cm^{-3})	EC (dS m^{-1})	ESP (%)	pH	CEC (cmol (+) kg^{-1})	$CaCO_3$ (%)
PIT 1	Pellic cambisol	26.2	48.5	25.3	1.1	0.6	1.6	7.9	66.5	8.9	16.0	41.2
PIT 2	Pellic cambisol	10.7	62.4	26.9	1.7	7.0	1.5	21.9	72.0	8.1	12.0	38.9
PIT 3	Pellic cambisol	30.7	44.8	24.4	1.0	2.2	1.4	0.7	8.4	8.5	10.0	40.9
AOI 1	Rendzic cambisol	5.5	61.9	32.6	3.3	12.1	1.2	0.6	1.8	8.1	16.8	39.4
AOI 2	Rendzic cambisol	10.4	63.1	26.5	2.3	25.5	1.2	0.5	3.0	8.1	13.0	46.8
AOI 3	Rendzic cambisol	13.8	48.8	37.4	2.3	19.5	1.2	0.3	1.6	8.3	16.3	25.2
AOI 4	Rendzic cambisol	17.3	49.2	33.5	1.9	26.9	1.3	0.6	2.1	8.3	14.3	25.4
AOI 5	Rendzic cambisol	20.3	44.6	35.1	2.2	17.6	1.4	0.8	3.4	8.5	14.8	24.9
AOI 6	Rendzic cambisol	66.4	21.8	11.8	1.1	0.6	1.5	0.3	2.0	7.8	6.4	0.6
LUM 1	Pellic kastanozen	13.1	55.4	31.5	2.3	12.6	1.2	0.3	3.8	7.3	14.6	40.1
LUM 2	Pellic kastanozen	9.4	52.8	37.8	1.8	2.7	1.4	0.3	3.2	8.3	15.5	39.3
LUM 3	Pellic kastanozen	8.2	65.7	26.1	2.3	1.9	1.4	0.4	4.1	8.3	13.0	46.2
ABA 1	Rendzic leptosol	17.3	55.1	27.5	4.3	30.2	1.1	0.6	1.5	7.2	17.0	1.0
ABA 2	Rendzic leptosol	24.2	47.3	28.6	3.7	5.1	1.2	0.7	0.9	7.0	15.5	1.1
LEO 1	Haplic leptosol	28.8	45.1	26.1	1.4	0.8	1.5	0.4	1.2	7.9	11.2	1.3
LEO 2	Haplic leptosol	52.0	32.9	15.2	2.3	44.5	1.1	0.8	1.3	7.6	10.8	3.5
RAD 1	Eutric cambisol	6.9	55.1	38.0	1.1	1.1	1.1	3.2	7.1	7.7	14.3	7.8
RAD 2	Eutric cambisol	12.5	60.8	26.8	1.2	25.9	1.2	3.6	12.6	7.8	11.1	12.5
RAD 3	Eutric cambisol	6.6	42.0	51.4	1.6	6.9	1.0	1.7	12.0	8.2	19.1	8.5
RAD 4	Eutric cambisol	8.4	52.6	38.9	2.0	17.9	1.1	1.0	8.2	8.3	16.1	10.7
RAD 5	Eutric cambisol	36.5	42.9	20.6	1.1	41.7	1.1	4.3	27.4	7.8	9.0	1.3
RAD 6	Eutric cambisol	28.2	24.7	47.1	1.6	20.9	1.1	1.2	4.6	7.7	17.8	0.8
RAD 7	Eutric cambisol	21.3	50.0	28.7	1.5	64.7	1.2	9.8	31.1	7.8	12.3	32.5

a: soil type classification according IUSS (2014).

Table II. Inset of the 2 clusters obtained from the cluster analysis (CA).

CLUSTER 1

Variables [a]	t-test [b]	Significance level	p value	Mean in cluster	% Variation	Overall mean	SD [c] in cluster	Overall SD [c]
CH_5	-3.97	****	0.0001	10.79	-20.15	13.52	1.84	3.08
CR_5	3.82	****	0.0001	1.20	24.29	0.97	0.16	0.28
SI_2	3.79	****	0.0002	2.23	23.83	1.80	0.24	0.51
SI_3	3.59	****	0.0003	2.39	23.59	1.94	0.31	0.57
E_2	3.27	****	0.001	0.04	28.71	0.03	0.01	0.01
CR_4	2.98	****	0.003	4.10	31.32	3.12	1.41	1.48
CR_3	2.96	****	0.003	3.22	35.22	2.38	1.37	1.28
PR_3	2.87	****	0.004	900.59	35.77	663.30	413.58	370.85
GT_1	2.70	***	0.007	0.001	35.27	0.0004	0.0003	0.0002
PR_2	2.56	**	0.013	787.18	31.87	596.94	394.69	334.30
CR_1	2.47	**	0.014	0.59	23.80	0.47	0.22	0.21
HY_2	-2.39	**	0.017	1.74	-20.77	2.19	0.47	0.85
CR_6	2.37	**	0.018	1.01	16.21	0.87	0.27	0.27
GF_1	2.31	*	0.021	0.00	56.57	0.00	0.00	0.00
CH_1	-2.24	*	0.025	1.53	-21.68	1.96	0.51	0.85
PH_1	2.13	*	0.033	1.32	5.91	1.25	0.16	0.16
GT_4	2.05	*	0.041	0.04	62.69	0.02	0.04	0.03
CH_3	2.03	*	0.042	20.87	71.56	12.17	24.85	19.24
HY_2	-2.00	*	0.046	1.84	-20.03	2.30	0.85	1.04
CLUSTER 2								
CH_5	3.97	****	0.0001	16.02	18.47	13.52	1.43	3.08
CR_5	-3.82	****	0.0001	0.75	-22.26	0.97	0.16	0.28
SI_2	-3.79	****	0.0002	1.41	-21.84	1.80	0.35	0.51
SI_3	-3.59	****	0.0003	1.52	-21.62	1.94	0.42	0.57
E_2	-3.27	****	0.001	0.02	-24.74	0.03	0.01	0.01
CR_4	-2.98	****	0.003	2.23	-28.71	3.12	0.81	1.48
CR_3	-2.96	****	0.003	1.61	-32.29	2.38	0.39	1.28
PR_3	-2.87	****	0.004	445.79	-32.79	663.30	88.80	370.85
GT_1	-2.70	***	0.007	0.0002	-32.33	0.0004	0.0001	0.0002
PR_2	-2.56	**	0.013	422.54	-29.22	596.94	88.37	334.30
CR_1	-2.47	**	0.014	0.37	-21.81	0.47	0.11	0.21
HY_2	2.39	**	0.017	2.61	19.03	2.19	0.91	0.85
CR_6	-2.37	**	0.018	0.74	-14.86	0.87	0.19	0.27
GF_1	-2.31	*	0.021	0.00	-51.85	0.00	0.00	0.00
CH_1	2.24	*	0.025	2.35	19.87	1.96	0.91	0.85
PH_1	-2.13	*	0.033	1.18	-5.42	1.25	0.11	0.16
GT_4	-2.05	*	0.041	0.01	-57.47	0.02	0.00	0.03
CH_3	-2.03	*	0.042	4.19	-65.59	12.17	3.19	19.24
HY_2	2.00	*	0.046	2.73	18.36	2.30	1.02	1.04

* $p < 0.05$; ** $p < 0.02$; *** $p < 0.01$; **** $p < 0.005$.

a: the names and the measure units of the soil parameters are displayed in Table S1.

b: value of Student´s t-test.

c: standard deviation.

Table III. Principal components (PCs) with an eigenvalue value of above 1 and correlation coefficients of the experimental variables over the first two PCs for the 23 soils.

Number of PCs	*Eigenvalue*	*Percentage*	*Cumulated Percentage*
1	10.39	21.65	21.65
2	8.05	16.77	38.42
3	6.12	12.75	51.17
4	4.99	10.39	61.56
5	3.63	7.55	69.11
6	2.95	6.14	75.24
7	2.57	5.36	80.60
8	1.79	3.72	84.32
9	1.54	3.20	87.53
10	1.26	2.63	90.15
11	1.07	2.22	92.38

Active variables – Factors correlations [a]

Variable [b]	*Axis 1*	*Axis 2*
CH_2	**0.55**	-0.08
CH_3	**0.58**	-0.06
CH_5	-0.38	**-0.73**
CH_6	-0.34	**0.75**
CR_3	0.13	**0.97**
CR_5	**0.77**	0.35
CR_6	**0.81**	-0.22
E_2	**0.86**	0.15
GF_1	0.08	**0.95**
GF_2	-0.15	**0.92**
GF_3	-0.13	**0.95**
GF_4	-0.14	**0.97**
GF_5	-0.20	**0.82**
GT_1	0.01	**0.63**
HY_2	**-0.62**	0.03
PH_1	**0.62**	0.30
PR_2	**0.51**	0.14
PR_3	**0.51**	0.14
SI_1	**0.69**	-0.39
SI_2	**0.63**	0.69
SI_3	**0.57**	0.71
SS_1	**-0.53**	-0.10

Supplementary variables (SL_1) – Factors correlations

Variable	*Axis 1*	*Axis 2*
SL_1	**0.35**	**-0.19**

a: bold factors present a correlation loading greater than 0.50.

b: the names and the measure units of the soil parameters are displayed in Table S1.

Table IV. The best linear regression models obtained for one and two independent variables in terms of the criteria established for regression diagnosing.

Indicators of the regression diagnosis		**Model 1**	**Model 2**
Number of variables		1	2
Variables [a]		CH_3	CH_3, CR_6
NSE [b]		0.915	0.996
MSE [c]		0.04	0.01
RMSE [d]		0.21	0.10
AIC [e]		3.18	-9.30
Regression coefficients	Intercept	0.903	0.813
	1^{*}	1.166	0.151
	2^{**}	-	0.575
p (t-test) [f]	Intercept	$4.16\ e^{-05}$	$2.010\ e^{-06}$
	1^{*}	$1.45\ e^{-05}$	$4.96\ e^{-09}$
	2^{**}	-	$2.08\ e^{-06}$
VIF [g]	1^{*}	-	1.05
	2^{**}	-	1.05

*: values for the first variable introduced by the model; **: Values for the second variable introduced by the model.

a: the names and the measure units of the soil parameters are displayed in Table S1.

b: Nash-Sutcliffe efficiency coefficient.

c: mean square error.

d: root mean square error.

e: Akaike information criterion.

f: significance level of Student´s t-test.

g: variance inflation factor.

Table V. Range of the values in the 2 clusters for the 6 variables identified as conditioners of the interrill erosion after carrying out the 3 multivariate statistics analyses (see caption in Table S1).

Cluster 1	**E_2 (t ha h ha^{-1} MJ^{-1}mm^{-1})**	**CR_6 (dimensionless)**	**CH_3 (%)**	**PR_3 (kPa)**	**SS_1 (kPa)**	**HY_2 (mm h^{-1})**
Min [a]	0.023	0.455	1.16	194.500	8.728	0.967
Mean [b]	0.040	1.011	20.87	916.153	14.118	1.737
Max [c]	0.053	1.285	71.95	1797.500	20.947	2.506
SD [d]	0.009	0.284	26.06	427.681	2.993	0.495
Cluster 2						
Min [a]	0.015	0.273	0.88	316.000	11.346	1.854
Mean [b]	0.023	0.741	4.19	462.458	16.001	2.610
Max [c]	0.033	0.982	11.98	834.000	27.493	5.399
SD [d]	0.006	0.195	3.33	137.041	4.731	0.952

a: minimum value of the variable in the cluster.

b: mean value of the variable in the cluster.

c: maximum value of the variable in the cluster.

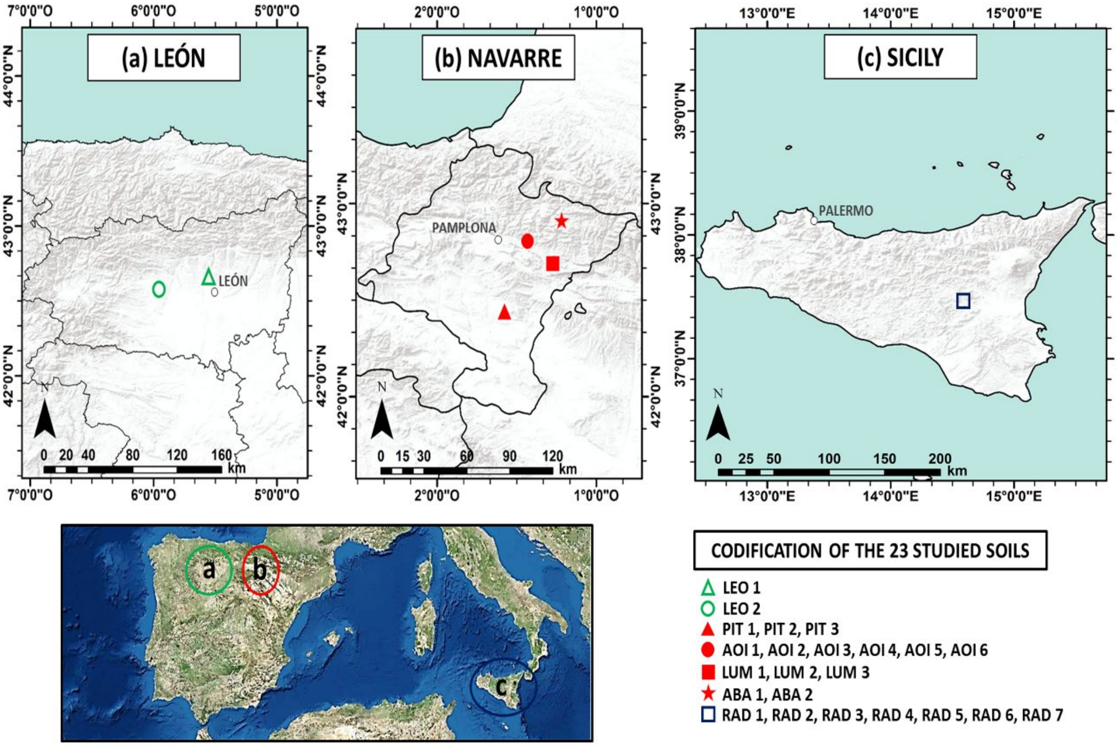
d: standard deviation of the variable in the cluster.

List of figures and titles

Figure 1. Location map of the studied areas: (a) 2 soils in León (northwest of Spain) (green symbols), (b) 14 soils in Navarre (north of Spain) (red symbols), and (c) 7 soils in Sicily (south of Italy) (blue symbol).

Figure 2. Rainfall simulator setup: (a) typical experimental site in the field (red arrows), and (b) rainfall simulator.

Figure 3. Distribution of the mean values and standard deviations for the interrill erosion rate (SL_1) and the 6 soil variables statistically identified in Cluster 1 (red circles and black error bars) and in Cluster 2 (blue squares and green error bars). The gray dashed line demarcates the transition area between the 2 clusters. Variables E_2 (K factor of RUSLE), CH_3 (exchangeable sodium percentage), PR_3 (penetration resistance in the first 6 centimeters of the soil depth) and CR_6 (modified crusting index) are positively related to the erosion rate, whereas variables SS_1 (shear strength) and HY_2 (hydraulic conductivity of seal) are negatively related to the aforementioned (e.g. a value higher than 8% for CH_3 would imply a higher vulnerability degree of the soil against erosion).The horizontal axis shows the name of the variables. The left-hand vertical axis shows, first, PR_3 (kPa) and SS_1 (kPa); and, second, CH_3 (%). The right-hand vertical axes show first SL_1 (t ha^{-1} h^{-1}), HY_2 (mm h^{-1}) and CR_6 (dimensionless x 10^{-1}); and, second, E_2 (t ha h ha^{-1} MJ^{-1} mm^{-1}).



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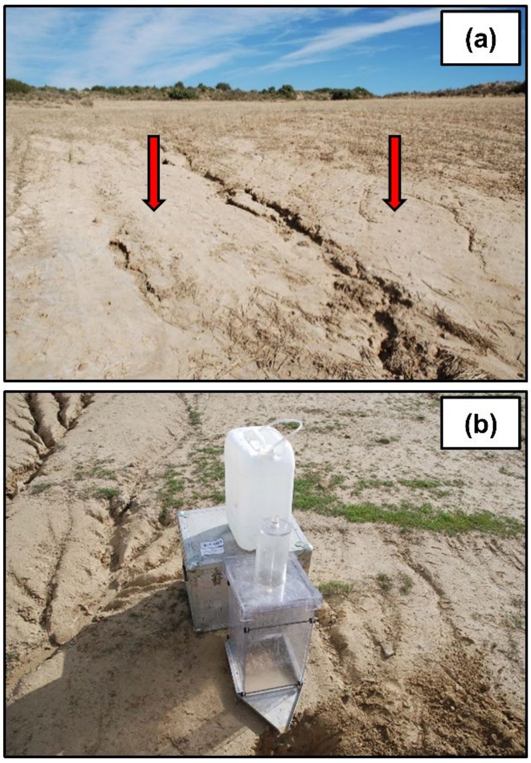

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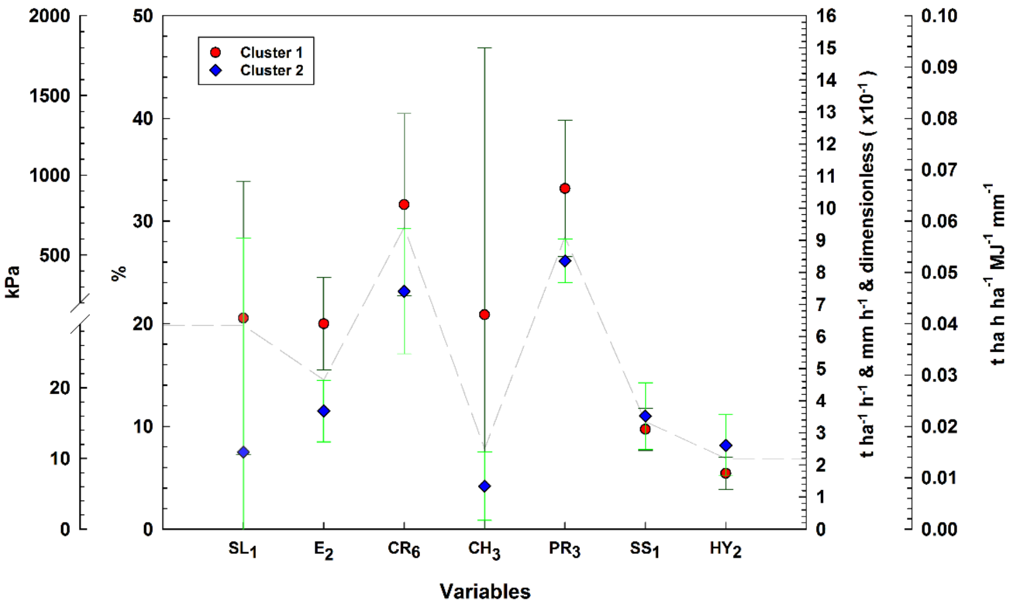

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