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Modelling the event-based hydrological response of olive groves on steep slopes and clayey soils under mulching and tillage management using the SCS-CN, Horton and USLE-family models

Giuseppe Bombino[1] | **Pietro Denisi**[1] | **José Alfonso Gómez**[2] | **Demetrio Antonio Zema**[1] | **Santo Marcello Zimbone**[1]

[1]Department "Agraria", Mediterranea University of Reggio Calabria, Reggio Calabria, Italy

[2]Agronomy Department, Institute for Sustainable Agriculture (IAS-CSIC), Córdoba, Spain

Correspondence
Pietro Denisi, Department "Agraria", Mediterranea University of Reggio Calabria, Località Feo di Vito, I-89122 Reggio Calabria, Italy.
Email: pietro.denisi@unirc.it

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Abstract

The SCS-CN, Horton and USLE-family models are used worldwide, but few examples are available for olive groves on steep and clayey soils under mulching of pruning residues. We evaluate the accuracy in predicting runoff and soil loss of a steep (20%) and clayey olive grove subject to three soil conservation practices: mechanical tillage (MT), mulching with pruning residues (NTR) and standard protection (SP), measured at plot scale in Southern Italy during 30 months under natural rainfall. The models were calibrated by adjusting the Curve Numbers (for the SCS-CN model) and the C-factors (MUSLE and USLE-M); the Horton model was not calibrated. The model performance was assessed by qualitative and quantitative procedures. In all practices, the SCS-CN was more accurate for runoff predictions (mean difference of 7% compared with corresponding observations) compared with the Horton (mean difference of 30%). For soil erosion, the MUSLE showed better performance in soils subject to MT or total protection (differences lower than 10%), while the USLE-M was more reliable to simulate soil loss in mulched plots (differences of 8%). A set of Curve Numbers (95 for MT, 70 for SP and 85 for NTR) and C-factors (0.4 for MT, 0.2 for SP and 0.1 for NTR) are proposed for applications in steep slope and clayey soil olive orchards using the SCS-CN and USLE proposed models, respectively. Validation exercises in other environmental experimental conditions would enhance the export these models for runoff and erosion control in agricultural soils treated with mulching.

KEYWORDS

pruning residue, SCS-CN model, soil conservation, soil loss, surface runoff, USLE

1 | INTRODUCTION

In Europe, sheet and rill erosion causes soil loss at a rate of almost 2.5 tons ha^{-1} year^{-1}, which is 1.6 times the soil formation rate (Panagos et al., 2015). The assessment report on land degradation and restoration (IPBES, Fisher et al., 2018) recommends 'to increase efforts to reduce soil erosion and increase soil organic matter and reduce agricultural areas with severe soil erosion rates (>10 tons ha^{-1} year^{-1}) by 2030' (Montanarella & Panagos, 2021). Soil erosion rates in olive groves (*Olea europaea* L.) in Southern Europe are estimated to have average soil losses of 95 tons ha^{-1} year^{-1} over a period of 50–100 years (Vanwalleghem et al., 2010).

In Italy, olives are often cultivated on steep slopes (sometime terraced), and these erosion rates can be higher (Costantini & Dazzi, 2013), which is exacerbated by specific climatic conditions (heavy and infrequent storms with intense and often destructive floods, Fortugno et al., 2017; Zema et al., 2018). Moreover, Italian olive groves in the past decades have been frequently abandoned, and this has determined additional soil erosion, uneven landscape transformations and ecosystem degradation (Ferrara et al., 2014; Pardini & Gispert, 2013).

Reports (e.g. Gómez et al., 2014; Polykretis et al., 2020) have shown that mechanical tillage (Gómez et al., 2014, Gomez, 2017, Gómez et al., 2018; Beaufoy, 2002; Xiloyannis et al., 2008) is often employed at olive groves in order to improve nutrient levels (by incorporating fertilizer and organic matter into the soil) and soil water balance (by reducing the soil evaporation), as well as to facilitate harvesting. However, this practice, when intensive, may result in rapid oxidation of organic matter (Kassam et al., 2009), worsening of the soil structure and thus increasing runoff and erosion rates, particularly during wetter periods (Sastre et al., 2018). Because of frequent mechanical tillage coupled with the absence of vegetative cover among trees, the current management of olive groves is highly unsustainable and results in an average soil erosion rate of 23.2 tons ha^{-1} year^{-1} (Vanwalleghem et al., 2011). It is, therefore, important to control the hydrological response of olive groves, especially when located on steep slopes or growing on clayey impervious soils.

Several hydrological models have been developed and used to predict water discharge and runoff, sediment transport and soil loss. These models are able to simulate the hydrological processes at the watershed and hillslope scale in a cost-effective and time-efficient way, helping land planners to identify the best practices for farmland management (Zema et al., 2020).

More than 20 models to predict runoff and erosion are available and relevant applications have been globally carried out (Borrelli et al., 2021). Specifically, regarding erosion modelling, the USLE-family models are by far the most widely applied at the global scale with over 1200 applications. Other common erosion models are WEPP, LISEM, EROSION-3D, PESERA and EUROSEM, although applications of some of these models are decreasing (Bezak et al., 2021). Other models of common use are the Soil and Water Assessment Tool (SWAT, Arnold et al., 1998), AnnAGNPS (Bingner & Theurer, 2001), SEDD (Ferro & Porto, 2000), Water and Tillage Erosion Model, the Sediment Delivery Model (WaTEM/SEDEM, Van Oost et al., 2000) and the Morgan-Morgan–Finney ((R)MMF, Morgan et al., 1984). The SWAT, SEDD and AnnAGNPS models have been also used to predict erosion in olive groves (e.g. Zema et al., 2016 for AnnGNPS application in a large Spanish watershed covered by olive groves, Massetti et al., 2020, who simulated soil loss in olive groves using SWAT in central Italy, and Burguet et al., 2017, who used the SEDD model in olive micro catchments of Spain).

Among the methods used to predict surface runoff, the Soil Conservation Service (SCS)-Curve Number (CN) (hereinafter 'SCS-CN model') is the most common for estimating runoff (Mishra & Singh, 1999, 2013). The popularity of these methods is owing to their simplicity, ease of use, widespread acceptance and large availability of input data (Soulis, 2021; Suresh Babu & Mishra, 2012); thus, the SCS-CN and USLE models are the hydrological and erosion components used in many catchments scale hydrological models. The prediction accuracy of the SCS-CN and USLE-family models has been verified in a large range of climatic and geomorphological conditions, with generally satisfying results. Reliable estimations of runoff and erosion can be gained if model calibration is carried out (Jackson et al., 1986; Michalec et al., 2017; Williams, 1977). However, examples of SCS-CN and USLE models calibrated for olive groves are few (Di Stefano et al., 2016; Nekhay et al., 2009; Romero et al., 2007; Taguas et al., 2012; Taguas, Gómez, et al., 2015).

In olive growing, soil conservation practices (hereinafter indicated as 'SCPs') are needed with the combined purposes of increasing crop productivity and protecting soil quality. Mulching and cover crops with seeded or spontaneous species have been suggested and experimented for several years as SCPs. These innovative practices, if properly carried out, are beneficial for erosion reduction, water conservation and fertility maintenance. With regard to the hydrological impacts, several studies have demonstrated that mulching with pruning residues and cover crops are able to reduce the runoff and erosion rates under a wide range of climatic and morphological conditions (e.g. Bombino et al., 2019, 2021; Gomez, 2017; Gómez et al., 2011, 2014).

To consolidate the large use of conservative SCPs as anti-erosive practices, there is the need for more research to quantify of their hydrological impact. For this, the use of the hydrological models is reliable, easy and time-saving. Thanks to the hydrological models, the effectiveness of alternative SCPs can be predicted for a given environmental condition and this helps the task of land managers and olive farmers. Unfortunately, the studies that have applied the SCS-CN and USLE-family models to simulate the hydrological response of olive groves under different SCPs are limited in number, and therefore, the literature shows several research gaps. To the best authors' knowledge, the prior applications of SCS-CN at plot scale have been carried out by Romero et al. (2007) and Mollenhauer et al. (2002), but none considered the SCP based on mulching of pruning residues in the lanes and their effects on steep slopes. Moreover, very few studies were carried out in similar environmental contexts as southern Italy with applications of different methods under variable spatial and temporal scales (Covelli et al., 2020; Rosskopf et al., 2020).

For these purposes, this study evaluates the accuracy of the SCS-CN and Horton methods as well as two USLE-family models (MUSLE and USLE-M) to predict runoff and soil loss in a steep olive orchard in Calabria (Southern Italy) and subjected to different SCPs. More specifically, we hypothesize that some of these models are able to simulate surface runoff and soil erosion with more accuracy compared with the other models. The research questions to which this study aims to reply are the following: (i) which is the dominant runoff generation mechanism (by saturation or infiltration excess) of the experimental soils? (ii) to which process (rainsplash erosion or particle detachment and transport owing to overland flow) is erosion due in the experimental conditions? (iii) are all the tested models accurate for hydrological predictions under all the modelled SCPs? (iv) what are the optimal CNs and C-factors values in the steep and clayey soils of olive groves in Southern Italy, to be integrated into the application guidelines of the studied models? The results of this study, to be further validated in other olive cultivation environments, could be a useful contribution for a broader and more reliable applicability of the studied models, helping land managers to predict the impact of best management practices based on mulching to runoff and erosion control in olive growing areas.

2 | MATERIALS AND METHODS

2.1 | Study area

The experimental site is an olive grove (38.2671° N, 16.1872° E, Locri, Southern Calabria, Italy) at a mean altitude of 114 m a.s.l. (Figure 1a). The olive grove was 10–12 years old at the start of the experiment (2016) and planted with trees of *Olea europea* (cultivar Geracese) at 6 m × 6 m spacing (Figure 1b).

The climate of the area is typically semi-arid Hot-summer Mediterranean (Csa class, according to Koppen classification, Kottek et al., 2006), with mild and rainy winters, and dry and warm summers. The annual average rainfall and minimum/maximum temperatures are 1350 mm and 11 and 28°C, respectively (historical observations of 1923–2017).

The olive grove has a uniform slope of 20%. The soil is a Eutric cambisol (FAO, 2006) with prevalent clayey texture (28% of sand, 28% of silt and 44% of clay, w w^{-1}). In the olive grove, the grass cover spontaneously growing over the soil is usually mowed twice a year, in April and August, while the olive trees are pruned each year (in March) and residues are chopped by a shredder (size between 5 and 8 cm). Grass (40%) and pruning residues (60%) are left on the ground surface (around 3 tons ha^{-1} year^{-1} of dry matter) under the tree canopy and in the inter-row areas as mulching cover.

The experimental site in the olive grove consisted of a series of three plots (42-m long and 6-m wide, area of 252 m^2) that were hydraulically isolated by metallic sheets, in order to avoid the inflow/outflow of runoff (Figure 1b). The noticeable plot length (which is higher compared with the value suggested by Wischmeier & Smith, 1978, close to 20 m) allows the collection of a fair quantity of runoff also for mid-intensity events as well as the activation of erosion forms (e.g. rill erosion) that in short-length plots (especially with clayey soil texture) rarely or only partly develop. Each plot simulated one of the following soil management practices (SCPs): (i) standard protection of soil (hereinafter indicated as SP); (ii) mechanical tillage (MT) and (iii) no tillage and retention of pruning residues at dry matter doses of 350 g m^{-2} (NTR).

Standard protection, assumed as the control practice, represents the ideal cover layer for soil protection; to simulate this condition, the plot was covered by a horizontal plastic net (mesh of 1 mm^2), placed 10 cm over the ground, allowing the growth of living vegetation. The net reduces the splash erosion and intercepts a share of the precipitation, protecting the soil from the direct raindrop impact, but does not cause concentrate flow on the ground surface during heavy storms. The MT, carried out in autumn and spring by a rotary tiller, is the most common SCP in farmers of Southern Italy, who, however, complain about high soil losses in their olive groves. Under the NTR, the soil was covered with pruning and grass residues distributed at a dose of 3.5×10^3 kg ha^{-1} (in spring) every year as mulching. In a previous study (Bombino et al., 2021), this dose was able to modify the hydrological response of soil with significantly lower runoff and erosion rates (Figure 2).

2.2 | Hydrological measurements

A campaign of hydrological measurements was carried out between January 2016 and June 2018, one year after the implementation of the SCPs (January 2015). Sub-hourly

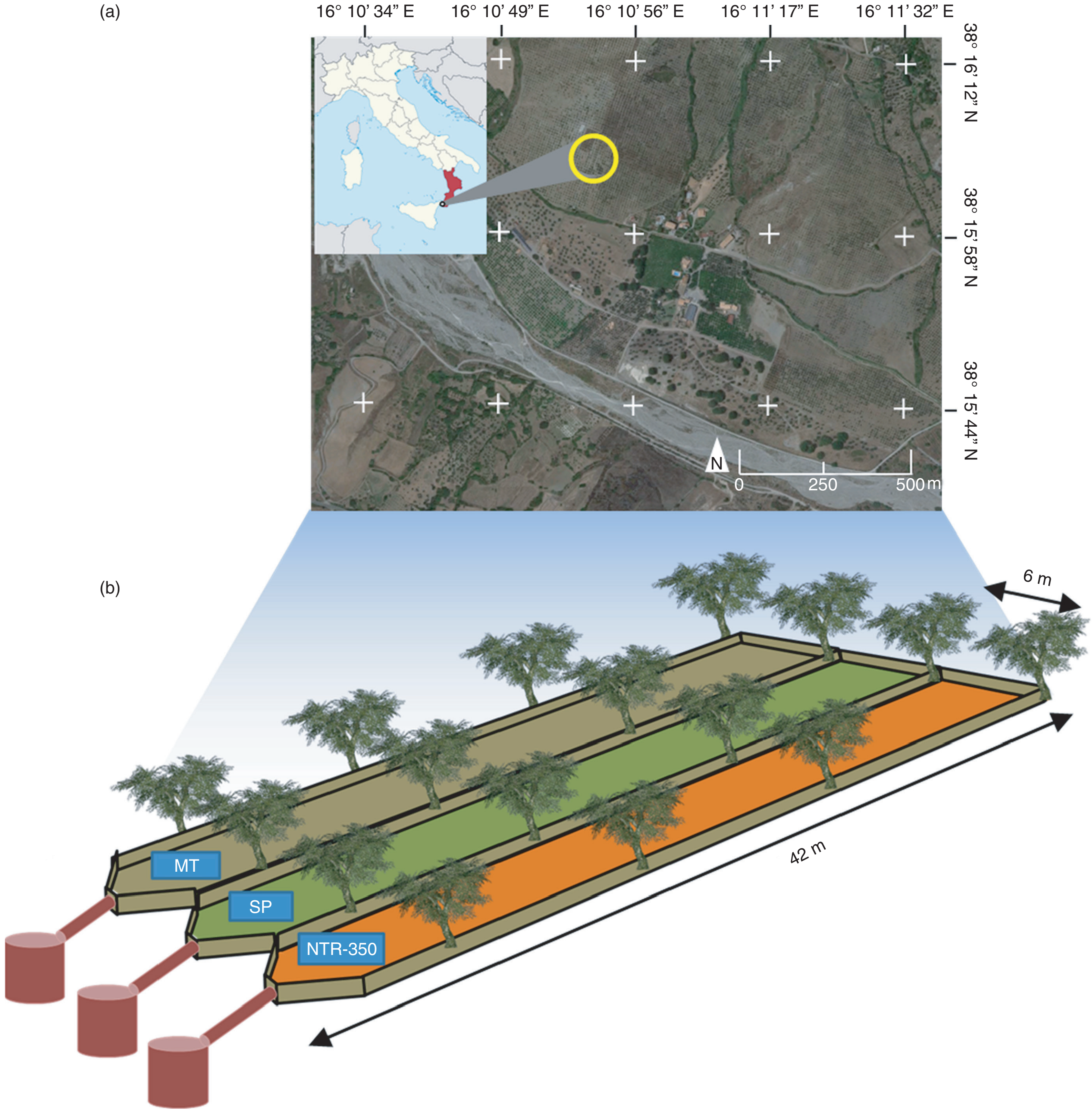

FIGURE 1 Location and aerial map (a), and illustrative layout of the experimental equipment (b) to measure the hydrological variables in the experimental site (Locri, Calabria, Italy)

(5-min interval) data of rainfall depth and intensity were measured at the gauging station of Antonimina (327 m a.s.l.), 1-km far from the experimental site and used to calculate rainfall intensity for each event.

Surface runoff after the 26 monitored rainfalls was measured by an ultrasonic flow logger (Stingray 2.0 - Greyline Inc.). For each event, the runoff volume was stored (using a by-pass) into a 1000-L tank, connected by a v-shaped collector and a pipe at the bottom side of the plots. To avoid manipulating too large volumes of runoff water and sediments (over the capacity of the tanks) when abundant rainfall occurred, we used an automatic hydraulic device, which discarded 90% of the runoff water generated in the plot and collected the remaining 10% of runoff and sediment flows. This was simply made by a by-pass device with a 't-shaped' pipeline. Measured runoff volumes were upscaled to the original amount generated in the plot as a simple product by 10.

For erosion modelling, fifteen events with intensity higher than 50 mm h^{-1} calculated on 30-min duration were

FIGURE 2 Plots with the three different SCPs monitored in Locri (Calabria, Italy). Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR = no tillage and retention of vegetal residues

selected. This rainfall intensity is typical of erosive events occurring in this area every 30–50 years (Bombino et al., 2019). For sediment yield measurements, the runoff volume inside the tanks was manually shaken and three samples, totalling 0.5 L, were collected. Each composite sample was dried in oven at 105 °C for 24 h, and the dried sediment was weighted and referred as the sample volume, in order to measure the sediment concentration (Hudson, 1993). The latter was multiplied by the runoff volume to estimate the soil loss and thus the erosion after each precipitation event.

2.3 | Model implementation in the experimental plots

A short description of the four models tested in this study is reported in Appendix S1. The model implementation procedures in the experimental plots are explained in the following sub-sections.

2.3.1 | SCS-CN model

The sub-hourly (5-min interval) rainfall data measured at the gauging station of the experimental site were aggregated at the daily scale and needed as input to the SCS-CN model. The AMC was derived for each event analysing the antecedent 5-day rainfall depths. The soil hydrological group was assumed according to the Soil Map of Calabria (ARSSA—Regional Agency for Agricultural Services, 2003) and with reference to Bombino et al. (2021), who reported values of the saturated hydraulic conductivity for the same soils and conditions. Because of very small number of measurements available in the experimental design, the calibration of the CN values for olive orchards was not possible. Consequently, the CN values ('default' CN) used as input in the SCS-CN model were derived from the original tables of the USDA Soil Conservation Service (USDA-SCS, 1972) (Table 1).

2.3.2 | Horton equation

The infiltration rate (Appendix S1 Eq. 10) was calculated by interpolating the infiltration curves measured using a double-cylinder infiltrometer for each SCPs. The infiltrometer consisted of two coaxial cylinders having inner and outer diameters of 0.32 and 0.57 m, respectively, and height of 0.30 m, and driven into the soil to a depth of 150 mm. For each measurement, updated in a 6-monthly step, the test measured the time needed for the infiltration of 20 mm of water in the cylinders filled with 50–70 mm of clean water. The infiltration test was repeated until three equal time measurements had been recorded between filling operations (Bombino et al., 2021; Zema et al., 2019).

TABLE 1 Values of input parameters adopted to simulate surface runoff volumes and soil loss using the SCS, Horton MUSLE and USLE-M models applied in the three SCPs monitored in Locri (Calabria, Italy)

			Soil management practice					
			MT		SP		NTR	
Model	**Input parameter**	**Measuring unit**	**Default model**	**Calibrated model**	**Default model**	**Calibrated model**	**Default model**	**Calibrated model**
SCS-CN	CN	–	88	85	79	70	90	75
	λ	–	0.2					
Horton	f_o	mm h^{-1}	22.6		10.2		20.6	
	f_c	mm h^{-1}	3.6		6.5		4.8	
	k	h^{-1}	0.05					
MUSLE	a	–	0.87					
	b	–	0.56					
	K-factor	tons h MJ^{-1} mm^{-1}	0.16					
	C-factor	–	0.78	0.4	0.4	0.09	0.09	0.045
	P-factor	–	1					
USLE-M	a	–	0.87					
	b	–	0.56					
	Average R_e-factor	MJ mm ha^{-1} h^{-1}	67.5					
	K_{UM}-factor	tons h MJ^{-1} mm^{-1}	0.02					
	C_{UM}-factor	–	0.08	0.06	0.04	0.02	0.02	0.01
	P-factor		1					

Notes. Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR 350 = No Tillage and Retention of vegetal residues of 350 g m^{-2}. CN = Curve number; λ = initial abstraction ratio; f_o = maximum infiltration rate; f_c = minimum infiltration rate; k = decay rate of infiltration in time; a and b = site-specific factors; R_e = RUSLE rainfall R-factor; K, C and P = factors of the MUSLE model; K_{UM} and C_{UM} = factors of the USLE-M model.

TABLE 2 Indexes used to evaluate the prediction capacity of the SCS-CN and Horton models applied to plots subjected to the three SCPs (Locri, Southern Italy)

Index	Equation	Acceptance limits or optimal values
r^2	$r^2 = \left[\frac{\sum_{i=1}^{n}(O_i-\bar{O})(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i-\bar{P})^2}} \right]^2$	$r^2 > .50$ (Santhi et al., 2001; Van Liew & Garbrecht, 2003; Vieira et al., 2018)
E	$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(O_i-P_i)^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2}$	Model accuracy (Van Liew et al., 2003): • good if NSE ≥ 0.75 • satisfactory if 0.36 ≤ NSE < 0.75 • unsatisfactory if NSE < 0.36
PBIAS	$\mathrm{CRM} = \frac{\sum_{i=1}^{n} O_i - \sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} O_i}$	<0.25 (Moriasi et al., 2007) • PBIAS < 0 indicates model underestimation • PBIAS > 0 indicates model overestimation (Gupta et al., 1999)

Notes. n = number of observations; O_i, P_i = observed and predicted values at the time step i; $\overline{O}$ = mean of observed values; P^{-} = mean of predicted values; SD = standard deviation.

For the 26 events, the hyetograph *i(t)* was derived and the difference between *i(t)* and *f(t)* gave the runoff rate *q(t)* at a time step of 5 min. Given the very short time of concentration (lower than 1 min) of the plot, the surface runoff stop was considered the same as the rainfall end.

2.3.3 | MUSLE equation

The MUSLE model is usually applied at the catchment scale, but there are examples of its use at plot scale (e.g. McConkey et al., 1997; Pongsai et al., 2010). In the expression of the MUSLE equation (Appendix S1 Eq. 11), Q is the observed runoff after each event, while q_p was the peak flow predicted by Horton method. For the site-specific factors a and b, the values were 0.87 and 0.56, respectively, taken from the experiences of Williams (1982). The K-factor was calculated using the nomograph of Wischmeier and Smith (1978). The C-factor, which depends on the management practice applied to the soil, was related to the tree density canopy diameter and ground cover of the plots. In this study, this USLE C-factor was calculated following the study by Bombino et al. (2002), who proposed an empirical equation based on canopy cover and aboveground biomass. Finally, the values of the P-factor were always set to one for all SCPs (Table 1).

2.3.4 | USLE-M equation

The runoff coefficient Q_R was calculated as:

$$Q_R = Q / P_e$$

where Q is the measured runoff volume (mm) and P_e is the observed rainfall depth (mm). The R_e -factor was calculated following the common method proposed by Renard et al. (1991) for the USLE model.

$$R_e = EI_{30} / 1735$$

where R_e is the rainfall R-factor (MJ mm ha^{-1} h^{-1}), E is the rainfall kinetic energy for each event (tons m ha^{-1}), and I_{30} is the maximum rainfall intensity for a duration of 30 min (mm h^{-1}). Different values for C and K were proposed for use with USLE-M by Kinnell & Risse (1998), hereafter indicated as K_{UM} and C_{UM}, while the P-factor is the same as the MUSLE model.

2.3.5 | Model calibration

The SCS-CN, MUSLE and USLE-M models were initially run with default parameters. However, owing to the unsatisfactory predictions (see section 3), the models were calibrated taking into account the most sensitive input parameters (CN for the SCS-CN model, and the C-factor for the MUSLE and USLE-M equations). The C-factor is the most used calibration parameter for USLE-family erosion models (Biddoccu et al., 2020; Hammad et al., 2004; Khemiri & Jebari, 2021). For this reason, the hydrological effects of mulching practice were taken into account by tuning this factor.

The objective of the calibration process was the minimization of both the coefficient of efficiency (Nash & Sutcliffe, 1970) and the error between the mean values of the observations and simulations of runoff or soil loss manually by the trial-and-error procedure. No calibration was carried out for the Horton equation, because the calibration was made through the infiltration tests during the hydrological measurements. For the used models, the default and calibrated parameters and their sources are listed in Table 1.

2.4 | Model performance evaluation

Two separate approaches were adopted for model performance evaluation. A qualitative procedure consisted of visually comparing observed and simulated values in scatterplots. A quantitative evaluation was also adopted using statistics (i.e. maximum, minimum, mean and standard deviation of both observed and simulated values) and a set of indexes, commonly used in hydrological modelling (Table 2).

3 | RESULTS AND DISCUSSION

3.1 | Hydrological characterization

Throughout the 2.5-year observation period, the annual rainfall recorded at the Antonimina meteorological station was between 815 and 1275 mm year^{-1}, and the maximum daily precipitation was 183 mm. Twenty-six rainfalls were recorded with depths between 16.6 mm (25 March 2018) and 183 mm (25 November 2016) (Figure 3). All these rainfalls were classified as erosive events (i.e. with depth over 13 mm), according to Wischmeier and Smith (1978).

These 26 rainfall events generated runoff volumes from 7.4 to 146 mm, and these extreme values were recorded under the MT treatment. In the plots subject to the other treatments, the runoff measured was in the range 9.3–137.3 mm (SP) and 9.1–109.8 mm (NTR) (Figure 3). The runoff produced in the NTR treatment was not significantly different from the corresponding values of the control SP, but significantly lower than MT plots (Figure 3). During a rainfall event, we noticed that the net installed in the SP plots fragmented the raindrops, which passed through the net, reducing the kinetic energy of rainfall on soil and thus the splash erosion.

The event runoff coefficients were in the range 30%–82% for MT, 25.9%–79.6% for SP and 25.8%–69.8% for NTR. The runoff coefficient in the latter SCPs was significantly different from MT and SP. The sediment yield generated by the sample of 15 events ranged from 0.001 to 0.19 tons ha^{-1} (MT), 0.01–0.12 (SP) and 0.01–0.05 (NTR) tons ha^{-1} (Figure 4). On average, the sediment yielded in the NTR treatment was not significantly different from the corresponding values of the control SP, but significantly lower than MT.

3.2 | Runoff modelling

Both the evaluated models (SCS-CN and Horton) showed acceptable coefficients of determination ($r^2 > 0.53$), which show strong correlations between observations and predictions of runoff volumes (Figure 5a–c and Table 3). The prediction accuracy of the Horton model in simulating runoff volume was generally low. Moreover, although the model efficiency was satisfactory for three of the three simulated SCPs (NSE > 0.54), the value of NSE was poor for the NTR practice and the differences between the mean observed and predicted runoff volumes were always over 30%.

Model inaccuracy is attributed to the noticeable overestimation of the modelled runoff volumes, shown by the negative values of PBIAS (i.e. over 0.30) (Table 3), since the model was not calibrated and the infiltration rate curves, although updated every six months, were not able to reproduce the variability of infiltration rates over time. Also, the variability of the infiltration rate between the

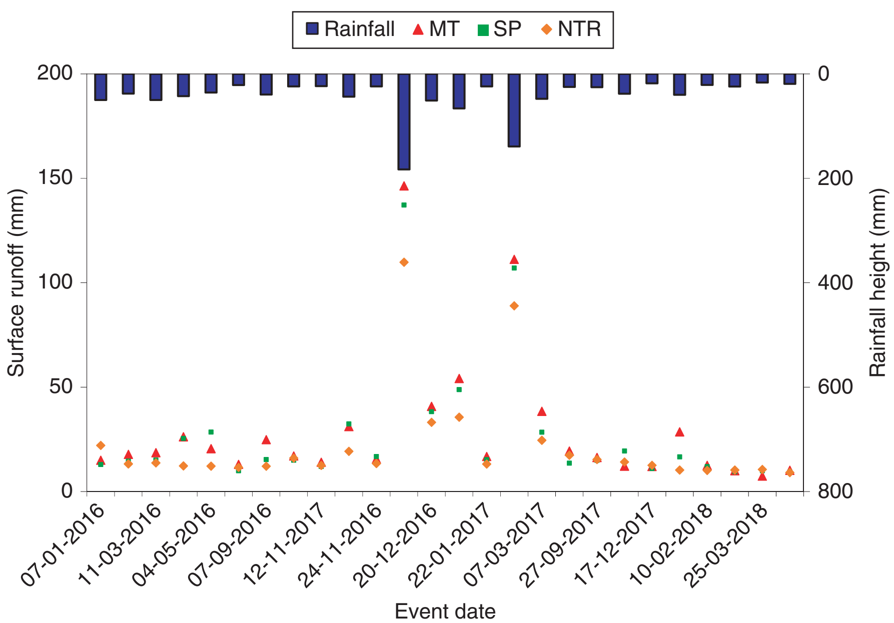

FIGURE 3 Surface runoff volume measured after natural rainfalls in the experimental plots subjected to three soil management practices (Locri, Southern Italy). Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR = no tillage and retention of vegetal residues

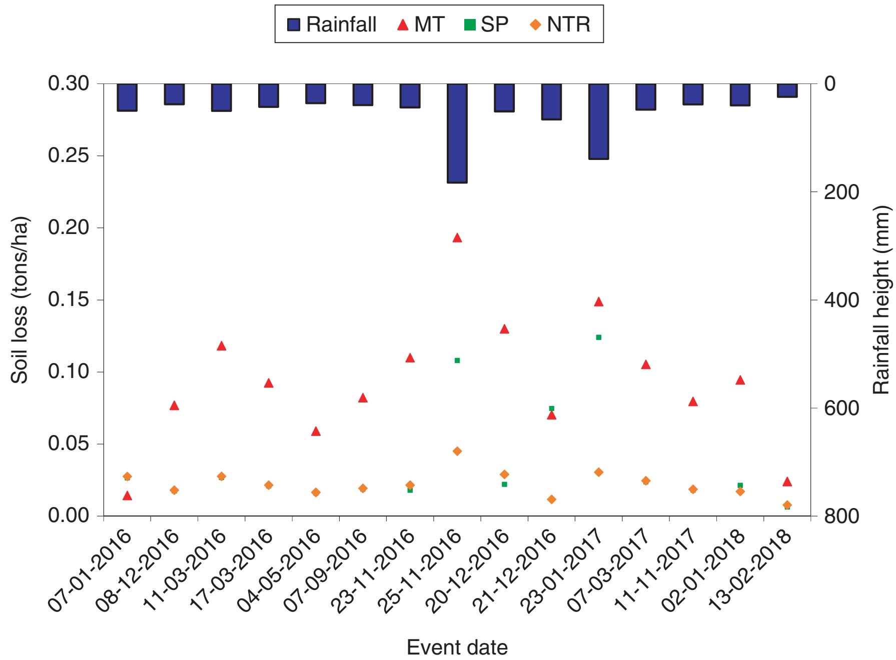

FIGURE 4 Soil loss measured after natural rainfalls in the experimental plots subjected to three soil management practices (Locri, Southern Italy). Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR = no tillage and retention of vegetal residues

areas beneath the tree canopies and the lanes, which is typical of an orchard, may explain the outlined model inaccuracy to simulate runoff. In this study, infiltration was measured in the lanes to reduce interferences with trees, and this could have affected the model reliability.

Runoff predictions using the SCS-CN model running with default parameters were not satisfactory. The runoff volumes were slightly over-predicted by the SCS-CN model (PBIAS <0) for NTR and under-predicted for MT and SP plots (PBIAS equal to 0.09 and 0.34, respectively). The model prediction accuracy was poor for SP ($E = 0.49$) and satisfactory for MT, and NTR plots (E equal to 0.71 and 0.65, respectively), but not optimal (in this case E would be over 0.75).

To improve the model reliability, the CNs were decreased in all plots during the calibration, which noticeably improved the runoff prediction capability of the SCS-CN model. The model's tendency to over- or under-prediction decreased, particularly for the SP plot (PBIAS from 0.34, before calibration, to 0.13, with calibrated CN). Calibration generally gave runoff prediction close to the corresponding observations for all the investigated SCPs. The differences between the observed and simulated mean runoff were lower than 7% with a minimum of 3.4% recorded for MT plot (Figure 5a and Table 3). The optimal values of model efficiency were good (NSE > 0.85). Further model simulations using higher CNs in winter and lower values in summer did not improve the runoff prediction accuracy (data not shown). The use of mulching leads to further decrease the hydrological response of soils.

The calibrated CNs, although being lower compared with the default values, were higher compared with the values suggested for olive groves with clay soils (between 64 and 88) by Romero et al. (2007). However, these authors carried out their modelling experience in olive groves with a slope of 5%, which is much lower compared with our experimental plots (Table 1). Only the CN values calibrated for mulching were close to the experimental values by Romero et al. (2007), who, however, did not evaluate the hydrological effects of mulching.

In other modelling experiences using the SCS-CN model, Taguas, Yuan, et al. (2015) successfully used a CN close to 66 to model runoff in the CN-based DWBR (Daily Water Balance and Runoff) model in a large olive grove of Southern Spain. The same authors achieved optimal CNs between 83 and 87 in a small catchment in the same environment (Taguas, Yuan, et al., 2015). In clayey olive groves of Southern Italy, the AnnAGNPS model was able to predict with accuracy runoff volumes, after calibration of the CN-based rainfall–runoff sub-component (Bisantino et al., 2015). Good model performances were also shown by Uwizeyimana et al. (2019) and Jain et al. (2006) in applications of the SCS-CN model in clayey soils of Rwanda and USA, respectively.

This study suggests the feasibility of using the SCS-CN method in similar conditions as the experimental soils and slopes of Southern Italy. However, the model should be further validated in the same climate using further experimental data on rainfall–runoff relationships in olive groves with different soils and slopes. Moreover, we feel the need to (i) investigate the performance of the suggested CN values at the catchment scale, (ii) implement the effect of various soil moisture accounting systems and (iii) extend the suggested CNs to a broader range of regions, in accordance with Soulis (2021).

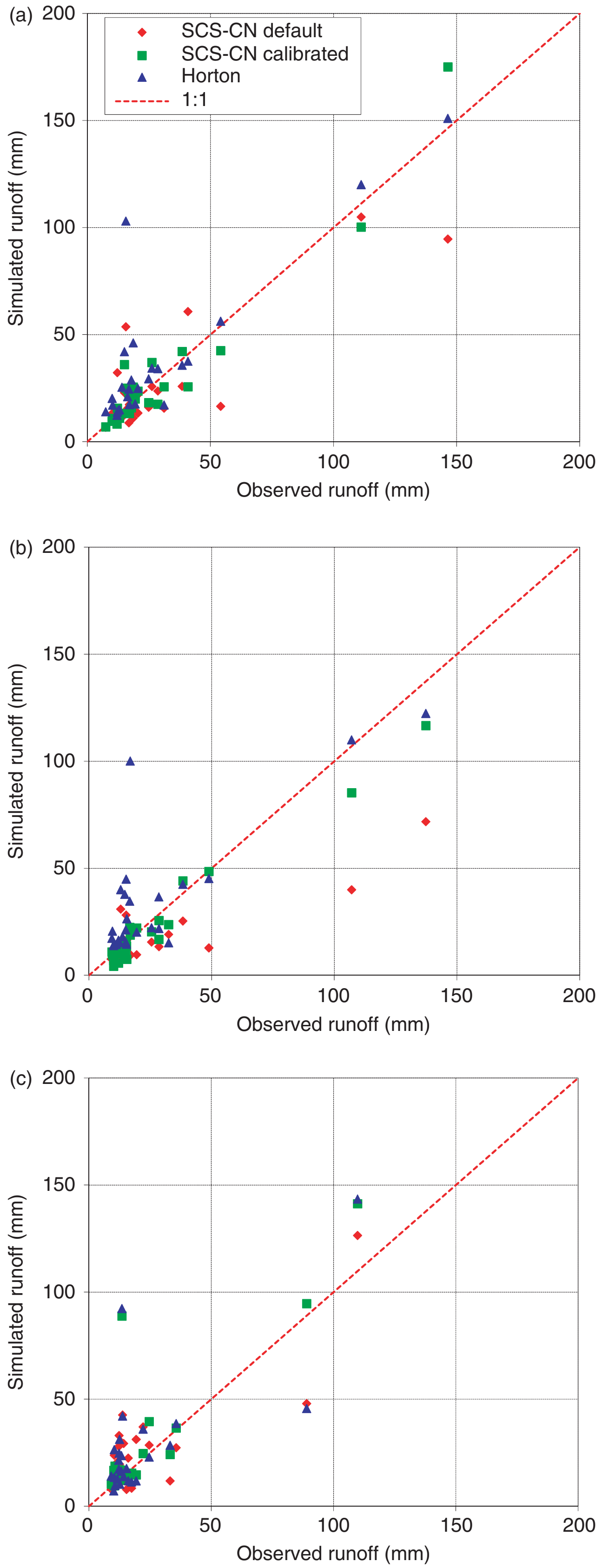

FIGURE 5 Scatterplots of observed vs. simulated runoff volumes using the SCS-CN (with default or calibrated CNs) and Horton models in the plots simulating three SCPs (a, MT; b, SP, and c, NTR) (Locri, Southern Italy). Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR = No tillage and retention of vegetal residues

Improvements in the available conversion equations for AMCs, which were prepared in non-arid environments (Farran & Elfeki, 2020), may be beneficial to refine runoff estimations using the SCS-CN method. Finally, since the SCS-CN method does not reproduce the changes in soil properties owing to management or other factors, more studies may improve the model simulation of temporal evolution of soil properties (Romero et al., 2007). Until then, our results indicate that the suggested values of CN should be used instead of the standard SCS values for runoff predictions in olive groves of the Mediterranean region with similar soils, climate and management conditions.

3.3 | Erosion modelling

Erosion models with default C-factors showed a poor prediction capacity for soil losses measured under all the three SCPs. The coefficient of determination was over the acceptance limit of 0.50 only for the MT plot (Figure 6a); both the coefficients of efficiency and the differences between the mean observed and simulated soil losses were poor (NSE <0 and errors over 17% with a peak of +70%). This inaccuracy is mainly attributed to the overestimation (in all the modelled SCPs for the MUSLE and USLE-M models) tendency of the observed soil losses, as clearly shown by the large values of the PBIAS index (always under 0.16 with a peak of −2.42 recorded for the MUSLE model) (Table 4 and Figure 6).

The over-prediction of the MUSLE model was reported in some other studies carried out for different environments (Chen & Mackay, 2004; Noor et al., 2010; Shen et al., 2009). The low prediction capability was attributed to the fact that the model is applied in an environmental context that is different from those for which the MUSLE model was developed. More generally, Nearing (2000) and Flanagan and Nearing (1995) have highlighted that small soil loss is usually over-predicted by USLE-family models.

The observed overestimation tendencies shown by both erosion models suggest their calibration through the C-factor for each SCP. Therefore, this factor was decreased for all SCPs in order to reduce these tendencies (Table 1). For both the MUSLE and USLE-M models, the calibration process was considered necessary for improving their prediction accuracy. For instance, Di Stefano et al. (2016) and Bagarello et al. (2015), applying the USLE-M in plots of Western Sicily (Italy), highlighted the importance of the calibration process to make possible its adaption to the different climatic and edaphic conditions.

TABLE 3 Values of the indicators evaluating runoff predictions capacity of the SCS-CN and Horton models applied to plots subjected to the three SCPs (Locri, Southern Italy)

Soil condition	Variable	Model	Input CN	Mean [mm]	Standard deviation [mm]	r^2	NSE	PBIAS
MT	Observed			28.85	31.73	–	–	–
	Simulated	Horton		37.41	34.68	.73	0.65	−0.30
		SCS-CN	Default	26.12	25.08	.72	0.71	0.09
			Calibrated	29.87	34.88	.93	0.91	−0.04
SP	Observed			26.52	30.07	–	–	–
	Simulated	Horton		34.68	30.09	.65	0.54	-0.31
		SCS-CN	Default	17.47	13.83	.74	0.49	0.34
			Calibrated	23.02	25.62	.97	0.94	0.13
NTR 350	Observed			22.06	23.89	–	–	–
	Simulated	Horton		28.62	29.22	.53	0.26	−0.30
		SCS-CN	Default	25.70	23.44	.67	0.65	−0.16
			Calibrated	25.27	29.16	.93	0.85	−0.16

Notes: Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR 350 = No Tillage and Retention of vegetal residues at dry matter dose of 350 g m^{-2}; r^2 = coefficient of determination; NSE = Nash & Sutcliffe, coefficient of efficiency; PBIAS = percent bias.

In this study, calibration noticeably increased the prediction accuracy of both models. The coefficients of determination (Figure 6a–c and Table 4) were over 0.75, with a maximum of 0.92 (USLE-M model applied to SP plot). For almost all the SCPs evaluated, the coefficients of efficiency were good (NSE > 0.75) (Table 4). Thanks to the calibration process, the tendency to erosion overestimations was noticeably reduced, both the calibrated models showing values of the PBIAS indexes under 0.09 (noticeably lower compared with the acceptance limit of 0.55, suggested by Moriasi et al., 2007, for erosion modelling).

The calibrated models produced differences between the mean observed and predicted soil losses lower than 10% (MUSLE model applied to SP plots) and 8% (USLE-M model predicting soil loss under NTR management). Even a simple visual comparison of the observed vs. modelled soil losses shows a low scattering of points around the line of perfect agreement (Figure 6).

The satisfactory performance of the MUSLE model was somewhat surprising given that this model has been applied at the pilot scale in only a few previous studies after calibration (McConkey et al., 1997; Pongsai et al., 2010). In order to further improve the MUSLE performance in erosion modelling, Sadeghi et al. (2014) and Michalec et al. (2017) proposed its calibration using a long-lasting series of observations, which allows the reduction of model uncertainty, even if a good correlation has been reported after a few erosive events. Moreover, Gwapedza et al. (2018) suggested testing sensitivity to different physical factors including plot or basin size by adopting a distributed form of the plot in order to improve the model performance.

The under-prediction detected for these USLE-M and MUSLE models in this study is in contrast with the usual behaviour of USLE-family models, which generally over-predict the lower soil loss (Nearing, 2000). Other modelling experiences highlighted that the applications of USLE-family models in different contexts can both over- or under-predict soil loss. More specifically, Biddoccu et al. (2020), applying the RUSLE model to the soils with permanent cover crops, predicted soil losses that were lower or close to soil formation rate in Europe. Bagarello et al. (2017, 2020), using the USLE-M model, reported an underestimation of soil loss for lower-intensity events.

Since five (K, L, S, C and P) of the six USLE-factors are common in the two models under each SCP, it is possible to compare the effects of the R-factor (linked to the rainfall erosivity) on the predicted soil losses. It cannot be excluded that the higher accuracy found for the USLE-M in simulating erosion of soils treated with mulching (NTR) is because of the information provided through the use of observed Q and q_p in the R-factor, missing in the MUSLE model. The applications of Q and q_p simulated in modelling soil loss in the absence of measured input variables could reduce this accuracy. Soil mulching reduces erosion limiting the particle detachment because of the rainsplash process rather than limiting sediment transport due to overland flow (Li et al., 2014; Pan et al., 2010; Singer et al., 1981). Conversely, the best performance of the MUSLE model detected in the MT and SP plots may be linked to the presence of a factor linked to the peak flow rate, which is better able to reproduce the particle detachment owing to the erosivity of the overland (laminar and concentrated) flow. However, the practical applicability of

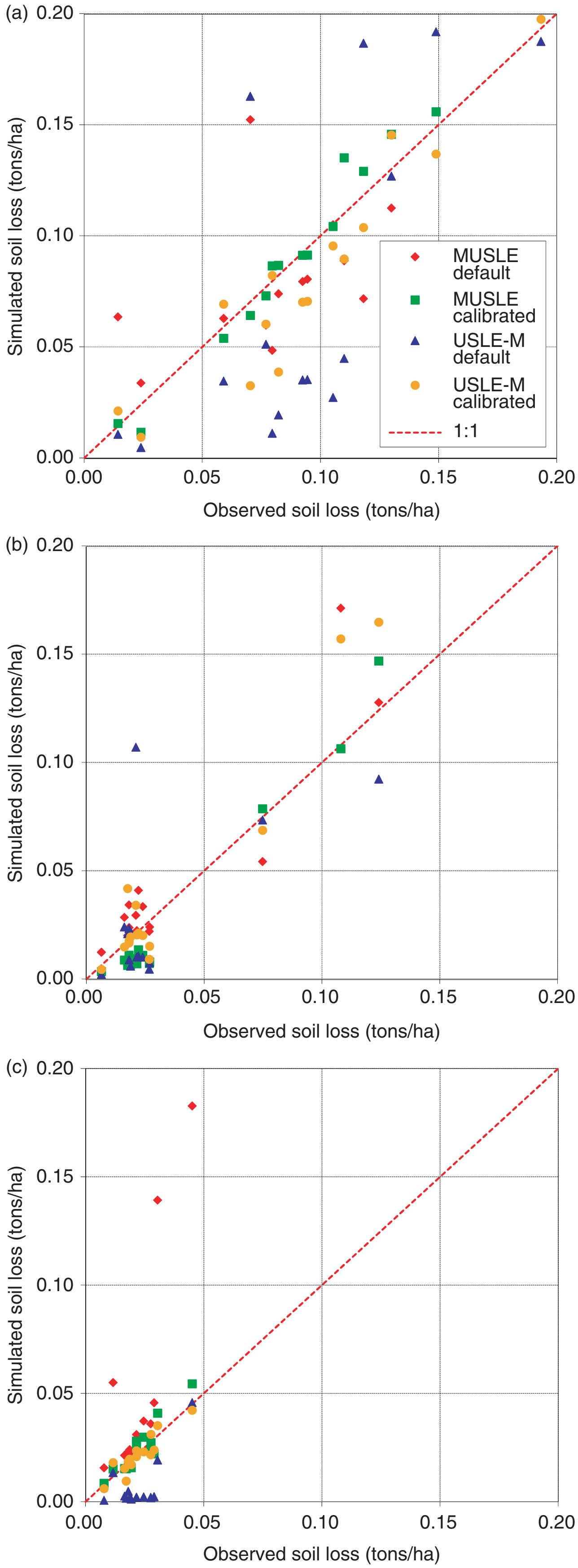

FIGURE 6 Scatterplots of observed vs. simulated soil losses using the MUSLE and USLE-M models (with default or calibrated C-factor) in the plots simulating three SCPs (a, MT; b, SP, and c, NTR) (Locri, Southern Italy). Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR = no tillage and retention of vegetal residues

the MUSLE model is lower, since the determination of the q_p subfactor is generally less easy compared with the coefficient of runoff, only required by the USLE-M equation.

In our study, further attempts to improve the erosion prediction capacity of both models using other calibration strategies were not successful. For instance, neither the use of the C-factors suggested by the European Soil Data Center (ESDC) (Panagos et al., 2015) or the input of seasonally varying values (that is, higher and lower values in winter and summer, respectively, Sadeghi et al., 2014) did not improve the prediction performance of both models (data not shown).

In other studies, model accuracy and reliability under variable C-factors were evaluated in different environmental conditions (Laflen et al., 2004; Risse et al., 1993). At the European scale, Panagos et al. (2015) proposed C-factors between 0.1 and 0.3 (Italy), and 0.22 and 0.24 (Spain) were suggested for croplands of those countries. Several authors proposed C-values for cultivation operations in olive groves (Moreira Madueño, 1991, 0.4; Kok et al., 1995, 0.54; Giraldez et al., 1989, 0.4 for conventional tillage and 0.45 for no tillage; Gomez et al., 2003, 0.41 for conventional and no tillage). Gómez et al. (2021) found a range between 0.12 and 0.50 for the different soil management declared by farmers in Southern Spain, while Brini et al. (2021) and Chafai et al. (2020) proposed for olive groves generic values of 0.2 and 0.5, respectively. Folly et al. (1996) used much higher C-values (0.7) for olive areas, and López-Vicente and Navas (2009) even suggested a mean C-factor of one for olive trees in a catchment of Spanish pre-Pyrenees.

Modellers frequently propose C-factors based on poor understanding of the methodological and geographical origin of these values and often without a description of the specific crop management systems. Therefore, the results may not be compatible with other sites (Rocha & Sparovek, 2021). Therefore, the estimation of the site-specific C-factors using locally measured data, as was the aim of our study, increases the erosion prediction accuracy of USLE-family models (Kebede et al., 2021).

In this investigation, the C-values proposed for the modelled SCPs were calibrated using observations collected at only one site following a standard procedure that is based on approximations and visual comparison. In many cases,

TABLE 4 Values of the indicators evaluating runoff predictions capacity of the MUSLE and USLE-M models applied to plots subjected to the three SCPs (Locri, Southern Italy)

Soil condition	Variable	Model	C-factor	Mean [tons ha^{-1}]	Standard deviation [tons ha^{-1}]	r^2	NSE	PBIAS
MT	Observed			0.09	0.05	–	–	–
	Simulated	MUSLE	Default	0.12	0.12	0.60	−3.50	−0.32
			Calibrated	0.09	0.06	0.87	0.76	−0.02
		USLE-M	Default	0.11	0.07	0.66	−0.23	−0.22
			Calibrated	0.09	0.05	0.89	0.87	0.02
SP	Observed			0.03	0.04	–	–	–
	Simulated	MUSLE	Default	0.12	0.05	0.38	−6.67	−2.42
			Calibrated	0.04	0.03	0.83	0.81	−0.11
		USLE-M	Default	0.05	0.04	0.33	−0.18	−0.49
			Calibrated	0.03	0.04	0.92	0.90	0.05
NTR 350	Observed			0.02	0.01	–	–	–
	Simulated	MUSLE	Default	0.02	0.02	0.49	−2.38	−0.16
			Calibrated	0.02	0.01	0.78	0.76	−0.03
		USLE-M	Default	0.02	0.02	0.14	−2.57	−0.23
			Calibrated	0.02	0.01	0.86	0.83	0.07

Notes: Soil management practices: SP = standard protection of soil; MT = mechanical tillage; NTR 350 = No Tillage and Retention of vegetal residues at dry matter dose of 350 g m^{-2}; r^2 = coefficient of determination; NSE = Nash & Sutcliffe, coefficient of efficiency; PBIAS = percent bias.

this procedure can be misleading and must be validated in other environmental conditions or supported by external parameters. For example, Soil Moisture Tension (SMT) comparison is one suitable method to detect the difference between the measured C-factor and the RUSLE C-factor with SMT (Hammad et al., 2004). Bearing in mind the limitation of our study, the C-value proposed for mulched plots could be reliable at least for steep and clayey soils of Mediterranean conditions and fills the lack of similar values for mulching applications in the literature.

Further improvements of the USLE-family models could consider: (i) the use of a subfactor, which introduces the modification of the erosion risk because of changes in the soil moisture content, according to the suggestions by Biddoccu et al. (2020); and (ii) the evaluation of the effects of management on soil conditions, to improve the understanding of the system and to predict its temporal changes (Gomez et al., 2003).

4 | CONCLUSIONS

This study has modelled runoff and erosion for an olive grove with a steep slope and clayey soil under different SCPs typical of Southern Italy, providing important information regarding four research questions. Firstly, the dominant runoff generation mechanism of the experimental soils may be due to soil saturation (as shown by the higher runoff prediction accuracy of the SCS-CN model compared with the infiltration model proposed by Horton) rather than to infiltration excess, as it would expected in soils of the semi-arid environments. Secondly, soil loss was mainly due to rainsplash erosion in the soils treated with mulching (suggested by the better performance for this management by the USLE-M model, whose rainfall erosivity is based on the R-factor performed better). Soil loss produced under the other modelled SCPs (mechanical tillage and total soil protection) mainly depends on overland flow, which determines particle detachment (suggested by the higher accuracy of the MUSLE equation, which includes parameters related to surface runoff). Thirdly, for all soil conditions, the SCS-CN model provides more accurate predictions of surface runoff as compared to the Horton equation. For soil erosion, the MUSLE model showed better performances in soils subject to mechanical tillage or total protection, while the USLE-M equations provided more accurate soil loss predictions in plots treated with mulching. Fourthly, our study confirms other literature results, stating that the calibration process is a prerequisite for the tested models for accurate predictions of surface runoff and soil loss. For olive orchards with a steep slope and clayey soil of Southern Italy, the following two sets of CNs and C-factors values can be suggested for applications of the SCS-CN and USLE-family models, respectively:

- 95 (MT), 70 (SP) and 85 (NTR) for runoff modelling;
- 0.4 (MT), 0.2 (SP) and 0.1 (NTR) for soil loss predictions.

Overall, this study has confirmed the viability of the SCS-CN and USLE-family models to simulate runoff and water erosion in olive groves of the Mediterranean semi-arid environments under different soil conditions. Although this assumption is limited to the experimental conditions, the results are encouraging for further application of these conceptually simple and widely used models in analogous climatic and geomorphologic conditions. Further modelling studies should also enlarge the spatial scale from plots to watersheds, using more complex hydrological models including the studied equation as rainfall–runoff transformation and erosive components. Once validated in a wider range of environmental contexts, these models may support the land managers to control runoff and erosion in agricultural soils that are prone to hydrogeological risks.

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DATA AVAILABILITY STATEMENT

Data available on request from the authors

ORCID

Pietro Denisi https://orcid.org/0000-0003-4714-4717

REFERENCES

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. (1998). Large area hydrologic modeling and assessment part I: model development 1. *Journal of the American Water Resources Association*, *34*(1), 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x

ARSSA Calabria (Regional Agency for Development and Services in Agriculture) (2003). Pedological map scale 1:250.000. Agenzia Regionale per lo Sviluppo ed i Servizi in Agricoltura della Calabria. Catanzaro (Italy) (in Italian).

Bagarello, V., Ferro, V., & Pampalone, V. (2015). A new version of the USLE-MM for predicting bare plot soil loss at the Sparacia (South Italy) experimental site. *Hydrological Processes*, *29*(19), 4210–4219. https://doi.org/10.1002/hyp.10486

Bagarello, V., Ferro, V., & Pampalone, V. (2017). Comparing two applicative criteria of the soil erosion physical model concept. *Vadose Zone Journal*, *16*(12), 1–10. https://doi.org/10.2136/vzj2017.06.0117

Bagarello, V., Ferro, V., & Pampalone, V. (2020). A comprehensive analysis of Universal Soil Loss Equation-based models at the Sparacia experimental area. *Hydrological Processes*, *34*(7), 1545–1557. https://doi.org/10.1002/hyp.13681

Beaufoy, G. (2002). The environmental impact of the olive oil production in the European Union: Practical options for improving the environmental impact. http://www.ec.europa.eu/environment/agriculture/pdf/oliveoil.pdf.

Bezak, N., Mikoš, M., Borrelli, P., Alewell, C., Alvarez, P., Anache, J. A. A., … Panagos, P. (2021). Soil erosion modelling: A bibliometric analysis. *Environmental Research*, *197*, 111087. https://doi.org/10.1016/j.envres.2021.111087

Biddoccu, M., Guzmán, G., Capello, G., Thielke, T., Strauss, P., Winter, S., … Gómez, J. A. (2020). Evaluation of soil erosion risk and identification of soil cover and management factor (C) for RUSLE in European vineyards with different soil management. *International Soil and Water Conservation Research*, *8*(4), 337–353. https://doi.org/10.1016/j.iswcr.2020.07.003

Bingner, R. L., & Theurer, F. D. (2001). AnnAGNPS: Estimating sediment yield by particle size for sheet and rill erosion. In 7th Federal Interagency Sedimentation Conference: Sedimentation Monitoring, Modeling, and Managing, 1: I–1 to I–7, Washington, DC: Interagency Advisory Committee on Water Data, Subcommittee on Sedimentation.

Bisantino, T., Bingner, R., Chouaib, W., Gentile, F., & Trisorio Liuzzi, G. (2015). Estimation of runoff, peak discharge and sediment load at the event scale in a medium size Mediterranean watershed using the AnnAGNPS model. *Land Degradation & Development*, *26*(4), 340–355. https://doi.org/10.1002/ldr.2213

Bombino, G., Porto, P., & Zimbone, S. M. (2002). Evaluating the crop and management factor C for applying RUSLE at plot scale. In 2002 ASAE Annual Meeting (p. 1). American Society of Agricultural and Biological Engineers.

Bombino, G., Denisi, P., Gómez, J. A., & Zema, D. A. (2019). Water infiltration and surface runoff in steep clayey soils of olive groves under different management practices. *Water*, *11*(2), 240. https://doi.org/10.3390/w11020240

Bombino, G., Denisi, P., Gomez, J. A., & Zema, D. A. (2021). Mulching as best management practice to reduce surface runoff and erosion in steep clayey olive groves. *International Soil and Water Conservation Research*, *9*(1), 26–36. https://doi.org/10.1016/j.iswcr.2020.10.002

Borrelli, P., Alewell, C., Alvarez, P., Anache, J. A. A., Baartman, J., Ballabio, C., … Panagos, P. (2021). Soil erosion modelling: A global review and statistical analysis. *Science of the Total Environment*, *780*, 146494.

Brini, I., Alexakis, D. D., & Kalaitzidis, C. (2021). Linking soil erosion modeling to landscape patterns and geomorphometry: An application in Crete, Greece. *Applied Sciences*, *11*(12), 5684.

Burguet, M., Taguas, E. V., & Gómez, J. A. (2017). Exploring calibration strategies of the SEDD model in two olive orchard catchments. *Geomorphology*, *290*, 17–28.

Chafai, A., Brahim, N., & Shimi, N. S. (2020). Mapping of water erosion by GIS/RUSLE approach: watershed Ayda river—Tunisia study. *Arabian Journal of Geosciences*, *13*(16), 1–14.

Chen, E., & Mackay, D. S. (2004). Effects of distribution-based parameter aggregation on a spatially distributed agricultural nonpoint source pollution model. *Journal of Hydrology*, *295*, 211–224. https://doi.org/10.1016/j.jhydrol.2004.03.029

Costantini, E. A., & Dazzi, C. (Eds.). (2013). *The soils of Italy*. Springer Science & Business Media.

Covelli, C., Cimorelli, L., Pagliuca, D. N., Molino, B., & Pianese, D. (2020). Assessment of erosion in river basins: A distributed model to estimate the sediment production over watersheds by a 3-dimensional LS factor in RUSLE model. *Hydrology*, *7*(1), 13.

Di Stefano, C., Ferro, V., Burguet, M., & Taguas, E. V. (2016). Testing the long term applicability of USLE-M equation at a olive orchard microcatchment in Spain. *Catena*, *147*, 71–79. https://doi.org/10.1016/j.catena.2016.07.001

FAO. (2006). *Guidelines for soil description*. Food and Agriculture Organisation of the United States.

Farran, M. M., & Elfeki, A. M. (2020). Evaluation and validity of the antecedent moisture condition (AMC) of Natural Resources Conservation Service-Curve Number (NRCS-CN) procedure in undeveloped arid basins. *Arabian Journal of Geosciences*, *13*(6), 1–17.

Ferro, V., & Porto, P. (2000). Sediment Delivery Distributed (SEDD) Model. *Journal of Hydrologic Engineering*, *5*, 411–422.

Ferrara, A., Salvati, L., Sabbi, A., & Colantoni, A. (2014). Urbanization, soil quality and rural areas: Towards a spatial mismatch? *Science of Total Environment.*, *478*, 116–122.

Fisher, J., Scholes, R., & Montanarella, L. (2018). Assessment Report on land degradation and restoration of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.

Flanagan, D. C., & Nearing, M. A. (1995). USDA Water Erosion Prediction Project: Hillslope Profile and Watershed Model Documentation. NSERL Report No. 10, USDA-ARS National Soil Erosion Research Laboratory, West Lafayette, IN 47907-1194.

Folly, A., Bronsveld, M. C., & Clavaux, M. (1996). A knowledge-based approach for C-factor mapping in Spain using Landsat TM and GIS. *International Journal of Remote Sensing*, *12*, 2401–2415.

Fortugno, D., Boix-Fayos, C., Bombino, G., Denisi, P., Quiñonero Rubio, J. M., Tamburino, V., & Zema, D. A. (2017). Adjustments in channel morphology due to land-use changes and check dam installation in mountain torrents of Calabria (southern Italy). *Earth Surface Processes and Landforms*, *42*(14), 2469–2483. https://doi.org/10.1002/esp.4197

Giraldez, J. V., Laguna, A., & Gonzalez, P. (1989). Soil conservation under minimum tillage techniques in Mediterranean dry farming. *Soil Technology Series*, *1*, 139–147.

Gomez, J. A., Battany, M., Renschler, C. S., & Fereres, E. (2003). Evaluating the impact of soil management on soil loss in olive orchards. *Soil Use and Management*, *19*, 127–134. https://doi.org/10.1111/j.1475-2743.2003.tb00292.x

Gómez, J. A., Llewellyn, C., Basch, G., Sutton, P. B., Dyson, J. S., & Jones, C. A. (2011). The effects of cover crops and conventional tillage on soil and runoff loss in vineyards and olive groves in several Mediterranean countries. *Soil Use and Management*, *27*(4), 502–514.

Gómez, J. A., Infante-Amate, J., González de Molina, M., Vanwalleghem, T., Taguas, E. V., & Lorite, I. (2014). Olive cultivation, its impact on soil erosion and its progression into yield impacts in Southern Spain in the past as a key to a future of increasing climate uncertainty. *Agriculture*, *4*, 170–198. https://doi.org/10.3390/agriculture4020170

Gomez, J. A. (2017). Sustainability using cover crops in Mediterranean tree crops, olives and vines – Challenges and current knowledge. *Hungarian Geographical Bulletin*, *66*(1), 13–28. https://doi.org/10.15201/hungeobull.66.1.2

Gómez, J. A., Campos, M., Guzmán, G., Castillo-Llanque, F., Vanwalleghem, T., Lora, Á., & Giráldez, J. V. (2018). Soil erosion control, plant diversity, and arthropod communities under heterogeneous cover crops in an olive orchard. *Environmental Science and Pollution Research*, *25*(2), 977–989. https://doi.org/10.1007/s11356-016-8339-9

Gómez, J. A., Montero, A. S., Guzmán, G., & Soriano, M.-A. (2021). In-depth analysis of soil management and farmers' perceptions of related risks in two olive grove areas in southern Spain. *International Soil and Water Conservation Research*, *9*(3), 461–473. https://doi.org/10.1016/j.iswcr.2021.01.003

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering*, *4*(2), 135–143.

Gwapedza, D., Hughes, D. A., & Slaughter, A. R. (2018). Spatial scale dependency issues in the application of the Modified Universal Soil Loss Equation (MUSLE). *Hydrological Sciences Journal*, *63*(13–14), 1890–1900. https://doi.org/10.1080/02626667.2018.1546388

Hammad, A. A., Lundekvam, H., & Børresen, T. (2004). Adaptation of RUSLE in the Eastern Part of the Mediterranean Region. *Environmental Management*, *34*(6), 829–841. https://doi.org/10.1007/s00267-003-0296-7

Hudson, N. W. (1993). Field Measurement of Soil Erosion and Runoff. FAO Soils Bulletin 68. Rome.

Jackson, W. L., Gebhard, K., & van Haveren, B. P. (1986). Use of the modified universal soil loss equation for average annual sediment yield estimates on small rangeland drainage basins. Published in Drainage Basin Sediment Delivery, IAHS Publ. *159*, 413–422

Jain, M. K., Mishra, S. K., & Singh, V. P. (2006). Evaluation of AMC-dependent SCS-CN-based models using watershed characteristics. *Water Resources Management*, *20*(4), 531–552. https://doi.org/10.1007/s11269-006-3086-1

Kassam, A., Friedrich, T., Shaxson, F., & Pretty, J. (2009). The spread of conservation agriculture: justification, sustainability and uptake. *International Journal of Agricultural Sustainability*, *7*(4), 292–320.

Kebede, B., Tsunekawa, A., Haregeweyn, N., Adgo, E., Ebabu, K., Meshesha, D. T., … Fenta, A. A. (2021). Determining C-and P-factors of RUSLE for different land uses and management practices across agro-ecologies: case studies from the Upper Blue Nile basin. *Ethiopia. Physical Geography*, *42*(2), 160–182. https://doi.org/10.1080/02723646.2020.1762831

Khemiri, K., & Jebari, S. (2021). Évaluation de l'érosion hydrique dans des bassins versants de la zone semi-aride tunisienne avec les modèles RUSLE et MUSLE couplés à un Système d'information géographique. *Cahiers Agricultures*, *30*, 7. https://doi.org/10.1051/cagri/2020048

Kinnell, P. I. A., & Risse, L. M. (1998). USLE-M: Empirical modeling rainfall erosion through runoff and sediment concentration. *Soil Science Society of America Journal*, *62*(6), 1667–1672.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, *15*(3), 259–263.

Kok, K., Clavaux, M. W., Heerebout, W. M., & Bronsveld, K. (1995). Land degradation and land cover change detection using low-resolution satellite images and the CORINE database: A case study in Spain. *ITC Journal*, *3*, 217–228.

Laflen, J. M., Flanagan, D. C., & Engel, B. A. (2004). Soil erosion and sediment yield prediction accuracy using WEPP. *Journal of the American Water Resources Association*, *40*(2), 289–297. https://doi.org/10.1111/j.1752-1688.2004.tb01029.x

Li, X., Niu, J., & Xie, B. (2014). The effect of leaf litter cover on surface runoff and soil erosion in Northern China. *PLoS One*, *9*(9), e107789. https://doi.org/10.1371/journal.pone.0107789.t004

López-Vicente, M., & Navas, A. (2009). Predicting soil erosion with RUSLE in Mediterranean agricultural systems at catchment scale. *Soil Science*, *174*(5), 272–282. https://doi.org/10.1097/SS.0b013e3181a4bf50

Massetti, L., Grassi, C., Orlandini, S., & Napoli, M. (2020). Modelling hydrological processes in agricultural areas with complex topography. *Agronomy*, *10*(5), 750.

McConkey, B. G., Nicholaichuk, W., Steppuhn, H., & Reimer, C. D. (1997). Sediment yield and seasonal soil erodibility for semiarid cropland in western Canada. *Canadian Journal of Soil Science*, *77*(1), 33–40. https://doi.org/10.4141/S95-060

Michalec, B., Wałęga, A., Cupak, A., & Strutyński, M. (2017). Verification of the MUSLE to determine the amount of suspended sediment. *Carpathian Journal of Earth and Environmental Sciences*, *12*(1), 235–244.

Mishra, S. K., & Singh, V. P. (1999). Another look at SCS-CN method. *Journal of Hydrologic Engineering*, *4*(3), 257–264. https://doi.org/10.1061/(ASCE)1084-0699(1999)4:3(257)

Mishra, S. K., & Singh, V. P. (2013). *Soil conservation service curve number (SCS-CN) methodology* (Vol. *42*). Springer Science & Business Media.

Mollenhauer, K., Taysun, A., & Frede, H. G. (2002). C-factors of the universal soil loss equation for olive plantations in water Anatolia (central Egean region). *Journal of Plant Nutrition and Soil Science*, *165*, 313–319. https://doi.org/10.1002/1522-2624(200206)165:3<313::AID-JPLN313>3.0.CO;2-Q

Montanarella, L., & Panagos, P. (2021). The relevance of sustainable soil management within the European Green Deal. *Land Use Policy*, *100*, 104950. https://doi.org/10.1016/j.landusepol.2020.104950

Moreira Madueño, M. J. (1991). Capacidad de uso y erosion de suelos: Una aproximacion a la evaluacion de tierras en Andalucia. Agencia de Medio Ambiente Sevilla.

Morgan, R. P. C., Morgan, D. D. V., & Finney, H. J. (1984). A predictive model for the assessment of soil erosion risk. *Journal of Agricultural Engineering Research*, *30*, 245–253.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, *50*(3), 885–900 10.13031/2013.23153

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models. Part I. A discussion of principles. *Journal of Hydrology*, *10*, 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Nearing, M. A. (2000). Evaluating soil erosion models using measured plot data: accounting for variability in the data. *Earth Surface Processes and Landforms: The Journal of the British Geomorphological Research Group*, *25*(9), 1035–1043. https://doi.org/10.1002/1096-9837(200008)25:9<1035::AID-ESP121>3.0.CO;2-B

Nekhay, O., Arriaza, M., & Boerboom, L. (2009). Evaluation of soil erosion risk using Analytic Network Process and GIS: A case study from Spanish mountain olive plantations. *Journal of Environmental Management*, *90*(10), 3091–3104. https://doi.org/10.1016/j.jenvman.2009.04.022

Noor, H., Mirnia, S. K., Fazli, S., Raisi, M. B., & Vafakhah, M. (2010). Application of MUSLE for the prediction of phosphorus losses. *Water Science and Technology*, *62*(4), 809–815. https://doi.org/10.2166/wst.2010.092

Pan, C., Ma, L., & Shangguan, Z. (2010). Effectiveness of grass strips in trapping suspended sediments from runoff. *Earth Surface Processes and Landforms*, *35*(9), 1006–1013.

Panagos, P., Borrelli, P., Meusburger, C., Alewell, C., Lugato, E., & Montanarella, L. (2015). Estimating the soil erosion cover-management factor at European scale. *Land Use Policy*, *48C*, 38–50. https://doi.org/10.1016/j.landusepol.2015.05.021

Pardini, G., & Gispert, M. (2013). Soil quality assessment through a multi-approach analysis in soils of abandoned terraced land in NE Spain, Cuad. *Investigation in Geography.*, *38*, 7–38.

Polykretis, C., Alexakis, D. D., Grillakis, M. G., & Manoudakis, S. (2020). Assessment of intra-annual and inter-annual variabilities of soil erosion in Crete Island (Greece) by incorporating the Dynamic "Nature" of R and C-Factors in RUSLE modeling. *Remote Sensing*, *12*(15), 2439.

Pongsai, S., Schmidt Vogt, D., Shrestha, R. P., Clemente, R. S., & Eiumnoh, A. (2010). Calibration and validation of the Modified Universal Soil Loss Equation for estimating sediment yield on sloping plots: A case study in Khun Satan catchment of northern Thailand. *Canadian Journal of Soil Science*, *90*(4), 585–596. https://doi.org/10.4141/cjss09076

Renard, K. G., Foster, G. R., Weesies, G. A., & Porter, J. P. (1991). RUSLE: Revised universal soil loss equation. *Journal of Soil and Water Conservation*, *46*(1), 30–33 (January–February).

Risse, L. M., Nearing, M. A., Laflen, J. M., & Nicks, A. D. (1993). Error assessment in the universal soil loss equation. *Soil Science Society of America Journal*, *57*, 825. https://doi.org/10.2136/sssaj1993.03615995005700030032x

Rocha, G. C., & Sparovek, G. (2021). Scientific and technical knowledge of sugarcane cover-management USLE/RUSLE factor. *Scientia Agricola*, *78*(suppl 1). https://doi.org/10.1590/1678-992x-2020-0234

Romero, P., Castro, G., Gómez, J. A., & Fereres, E. (2007). Curve number values for olive orchards under different soil management. *Soil Science Society of America Journal*, *71*(6), 1758–1769. https://doi.org/10.2136/sssaj2007.0034

Rosskopf, C. M., Di Iorio, E., Circelli, L., Colombo, C., & Aucelli, P. P. (2020). Assessing spatial variability and erosion susceptibility of soils in hilly agricultural areas in Southern Italy. *International Soil and Water Conservation Research*, *8*(4), 354–362.

Sadeghi, S. H. R., Gholami, L., Khaledi Darvishan, A., & Saeidi, P. (2014). A review of the application of the MUSLE model worldwide. *Hydrological Sciences Journal*, *59*(2), 365–375. https://doi.org/10.1080/02626667.2013.866239

Santhi, C., Arnold, J. G., Williams, J. R., Dugas, W. A., Srinivasan, R., & Hauck, L. M. (2001). Validation of the Swat model on a large River basin with point and nonpoint sources 1. *Journal of the American Water Resources Association*, *37*, 1169–1188.

Sastre, B., Marques, M. J., García-Díaz, A., & Bienes, R. (2018). Three years of management with cover crops protecting sloping olive groves soils, carbon and water effects on gypsiferous soil. *Catena*, *171*, 115–124. https://doi.org/10.1016/j.catena.2018.07.003

Shen, Z. Y., Gong, Y. W., Li, Y. H., Hong, Q., Xu, L., & Liu, R. M. (2009). A comparison of WEPP and SWAT for modeling soil erosion of the Zhangjiachong Watershed in the Three Gorges Reservoir Area. *Agricultural Water Management*, *96*(10), 1435–1442. https://doi.org/10.1016/j.agwat.2009.04.017

Singer, M. J., Matsuda, Y., & Blackard, J. (1981). Effect of mulch rate on soil loss by raindrop splash. *Soil Science Society of America Journal*, *45*(1), 107–110. https://doi.org/10.2136/sssaj1981.03615995004500010023x

Soulis, K. X. (2021). Soil Conservation Service Curve Number (SCS-CN) method: Current applications, remaining challenges, and future perspectives. *Water*, *2021*(13), 192.

Suresh Babu, P., & Mishra, S. K. (2012). Improved SCS-CN–inspired model. *Journal of Hydrologic Engineering*, *17*(11), 1164–1172. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000435

Taguas, E. V., Yuan, Y., Bingner, R. L., & Gomez, J. A. (2012). Modeling the contribution of ephemeral gully erosion under different soil managements: A case study in an olive orchard microcatchment using the AnnAGNPS model. *Catena*, *98*, 1–16. https://doi.org/10.1016/j.catena.2012.06.002

Taguas, E. V., Yuan, Y., Licciardello, F., & Gómez, J. A. (2015). Curve numbers for olive orchard catchments: Case study in Southern Spain. *Journal of Irrigation and Drainage Engineering*, *141*(11), 05015003. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000892

Taguas, E. V., Gómez, J. A., Denisi, P., & Mateos, L. (2015). Modelling the rainfall-runoff relationships in a large olive orchard catchment in southern Spain. *Water Resources Management*, *29*(7), 2361–2375.

USDA, Soil Conservation Service. (1972). *National Engineering Handbook*. Hydrology, Section 4: 548. Washington, DC.

Uwizeyimana, D., Mureithi, S. M., Mvuyekure, S. M., Karuku, G., & Kironchi, G. (2019). Modelling surface runoff using the soil conservation service-curve number method in a drought prone agro-ecological zone in Rwanda. *International Soil and Water Conservation Research*, *7*(1), 9–17. https://doi.org/10.1016/j.iswcr.2018.12.001

Van Liew, M. W., Arnold, J. G., & Garbrecht, J. D. (2003). Hydrologic simulation on agricultural watersheds: Choosing between two models. *Transactions of the ASAE*, *46*, 1539. https://doi.org/10.13031/2013.15643

Van Liew, M. W., & Garbrecht, J. (2003). Hydrologic simulation of the little Washita river experimental watershed using SWAT. *Journal of the American Water Resources Association*, *39*(2), 413–426. https://doi.org/10.1111/j.1752-1688.2003.tb04395.x

Van Oost, K., Govers, G., & Desmet, P. (2000). Evaluating the effects of changes in landscape structure on soil erosion by water and tillage. *Landscape Ecology*, *15*(6), 577–589.

Vanwalleghem, T., Laguna, A., Giráldez, J. V., & Jiménez-Hornero, F. J. (2010). Applying a simple methodology to assess historical soil erosion in olive orchards. *Geomorphology*, *114*(3), 294–302. https://doi.org/10.1016/j.geomorph.2009.07.010

Vanwalleghem, T., Amate, J. I., de Molina, M. G., Fernández, D. S., & Gómez, J. A. (2011). Quantifying the effect of historical soil management on soil erosion rates in Mediterranean olive orchards. *Agriculture, Ecosystems & Environment*, *142*(3-4), 341–351. https://doi.org/10.1016/j.agee.2011.06.003

Vieira, D. C. S., Serpa, D., Nunes, J. P. C., Prats, S. A., Neves, R., & Keizer, J. J. (2018). Predicting the effectiveness of different mulching techniques in reducing post-fire runoff and erosion at plot scale with the RUSLE, MMF and PESERA models. *Environmental Research*, *165*, 365–378. https://doi.org/10.1016/j.envres.2018.04.029

Williams, J. R. (1977). Sediment delivery ratios determined with sediment and runoff models. *IAHS Publ*, *122*, 168–179.

Williams, J. R. (1982). Testing the modified universal soil loss equation. In Proceedings of the Workshop on Estimating Erosion and Sediment Yield on Rangelands, Tucson, Arizona March 7-9, 1981, Agricultural Reviews and Manuals ARM-W-26, June 1982, p 157-165.

Wischmeier, W. H., & Smith, D. D. (1978). *Predicting rainfall erosion losses: A guide to conservation planning* (Vol. *No. 537*). Department of Agriculture, Science and Education Administration.

Xiloyannis, C., Raya, A. M., Kosmas, C., & Favia, M. (2008). Semi-intensive olive orchards on sloping land: Requiring good land husbandry for future development. *Journal of Environmental Management*, *89*(2), 110–119.

Zema, D. A., Denisi, P., Taguas Ruiz, E. V., Gómez, J. A., Bombino, G., & Fortugno, D. (2016). Evaluation of surface runoff prediction by a nn AGNPS model in a large Mediterranean watershed covered by olive groves. *Land Degradation & Development*, *27*(3), 811–822.

Zema, D. A., Lucas-Borja, M. E., Carrà, B. G., Denisi, P., Rodrigues, V. A., Ranzini, M., Soriano, F. C., de Cicco, V., & Zimbone, S. M. (2018). Simulating the hydrological response of a small tropical forest watershed (Mata Atlantica, Brazil) by the AnnAGNPS model. *Science of The Total Environment*, *636*, 737–750. https://doi.org/10.1016/j.scitotenv.2018.04.339

Zema, D. A., Lucas-Borja, M. E., Andiloro, S., Tamburino, V., & Zimbone, S. M. (2019). Short-term effects of olive mill wastewater application on the hydrological and physico-chemical properties of a loamy soil. *Agricultural Water Management*, *221*, 312–321. https://doi.org/10.1016/j.agwat.2019.04.011

Zema, D. A., Nunes, J. P., & Lucas-Borja, M. E. (2020). Improvement of seasonal runoff and soil loss predictions by the MMF (Morgan-Morgan-Finney) model after wildfire and soil treatment in Mediterranean forest ecosystems. *Catena*, *188*, 104415.

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