Environmental Research 165 (2018) 365–378

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Predicting the effectiveness of different mulching techniques in reducing post-fire runoff and erosion at plot scale with the RUSLE, MMF and PESERA models

D.C.S. Vieira[a,b,*], D. Serpa[a], J.P.C. Nunes[c], S.A. Prats[a], R. Neves[b], J.J. Keizer[a]

[a] Centre for Environmental and Marine Studies (CESAM), Dpt. of Environment and Planning, University of Aveiro, Aveiro 3810-193, Portugal
[b] MARETEC, Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais, 1049-001 Lisboa, Portugal
[c] CE3C – Centre for Ecology, Evolution and Environmental Changes, Faculdade de Ciências, Universidade de Lisboa, 1749-016 Lisboa, Portugal

ARTICLE INFO

Keywords:
Modelling
Soil erosion
Post-fire
Land management
Mitigation

ABSTRACT

Wildfires have become a recurrent threat for many Mediterranean forest ecosystems. The characteristics of the Mediterranean climate, with its warm and dry summers and mild and wet winters, make this a region prone to wildfire occurrence as well as to post-fire soil erosion. This threat is expected to be aggravated in the future due to climate change and land management practices and planning.

The wide recognition of wildfires as a driver for runoff and erosion in burnt forest areas has created a strong demand for model-based tools for predicting the post-fire hydrological and erosion response and, in particular, for predicting the effectiveness of post-fire management operations to mitigate these responses.

In this study, the effectiveness of two post-fire treatments (hydromulch and natural pine needle mulch) in reducing post-fire runoff and soil erosion was evaluated against control conditions (i.e. untreated conditions), at different spatial scales.

The main objective of this study was to use field data to evaluate the ability of different erosion models: (i) empirical (RUSLE), (ii) semi-empirical (MMF), and (iii) physically-based (PESERA), to predict the hydrological and erosive response as well as the effectiveness of different mulching techniques in fire-affected areas.

The results of this study showed that all three models were reasonably able to reproduce the hydrological and erosive processes occurring in burned forest areas. In addition, it was demonstrated that the models can be calibrated at a small spatial scale (0.5 m^2) but provide accurate results at greater spatial scales (10 m^2).

From this work, the RUSLE model seems to be ideal for fast and simple applications (i.e. prioritization of areas-at-risk) mainly due to its simplicity and reduced data requirements. On the other hand, the more complex MMF and PESERA models would be valuable as a base of a possible tool for assessing the risk of water contamination in fire-affected water bodies and for testing different land management scenarios.

1. Introduction

Wildfires have become a persistent threat in the Mediterranean, especially in the Iberian Peninsula where, on average, more than 100,000 ha y^{-1} land burned in the past decade (San-Miguel-Ayanz et al., 2017). Fire activity is foreseen to increase in Mediterranean countries throughout the 21st century, as a result of shifts in climate and socio-economic conditions (Nunes et al., 2017; Turco et al., 2014, 2016; Viedma et al., 2015).

From the commonly reported environmental disturbances associated to wildfires, soil erosion by water is probably the one raising most concern (Esteves et al., 2012; Moody et al., 2013; Santín and Doerr, 2016; Shakesby, 2011; Shakesby et al., 2016). By reducing or eliminating the vegetation and ground cover, wildfires make the soil more susceptible to raindrop impact, reducing aggregate stability and promoting sediment detachment (e.g. Certini, 2005; Prats et al., 2014; Shakesby and Doerr, 2006). Fire-induced soil water repellency, often reported following wildfires (Keizer et al., 2008; Shakesby, 2011), can also contribute to an enhancement in runoff and soil erosion in burned forest areas (Fernández et al., 2010; Vieira et al., 2016). Fire-induced changes on forest hydrology and geomorphology are likely to negatively affect forest ecosystem services, including raw material and water provisioning, erosion and flood control, and biodiversity maintenance (Carvalho-Santos et al., 2016; Nunes et al., 2017; Smith et al., 2011;

* Corresponding author at: Centre for Environmental and Marine Studies (CESAM), Dpt. of Environment and Planning, University of Aveiro, Aveiro 3810-193, Portugal.
E-mail address: dianac.s.vieira@ua.pt (D.C.S. Vieira).

https://doi.org/10.1016/j.envres.2018.04.029
Received 15 November 2017; Received in revised form 17 April 2018; Accepted 25 April 2018
Available online 25 May 2018

Verkaik et al., 2013).

Mitigation measures can be applied to help reduce the on-site and off-site negative effects of post-fire water erosion (Robichaud et al., 2010). Mulch treatments (e.g. straw mulch, chopped-bark mulch, pine needle mulch and hydromulch) are considered the most effective in minimizing post-fire soil erosion (Férnandez and Vega, 2016; Neary et al., 2005; Prats et al., 2014, 2016; Robichaud et al., 2013). This is mainly because mulch provides surface cover to soils prior to vegetation regrowth, thereby minimizing rain splash detachment while improving soil stabilization (Robichaud et al., 2007; Wohlgemuth et al., 2009).

As the hydrological and erosive response of burned areas is extremely complex, depending on an interplay of factors such as, vegetation, fire severity, climate, geology, soil type, topography, and land management (Certini, 2005; Shakesby and Doerr, 2006), post-fire treatments must be adapted to local conditions (Shakesby, 2011). Models are valuable tools for guiding management decisions mitigating post-fire soil erosion and for planning the rehabilitation of burned areas (Fernández et al., 2010; Fernández and Vega, 2016; Hyde et al., 2012; Robichaud and Ashmun, 2012), as they have been reported to accurately predict post-fire runoff and sediment yields in a multiplicity of forest catchments. However, in order to be realistic and accurate, models should be parameterized using field data to reduce uncertainties (Férnandez et al., 2010, Fernández and Vega, 2016; Larsen and MacDonald, 2007; Rulli et al., 2013; Shakesby, 2011).

Most of the models that have been used to simulate post-fire conditions were originally developed for unburned conditions. The adaptation of these models to burned conditions was typically achieved by introducing an empirical “fire factor” or by adjusting input parameters such as ground cover, surface roughness, soil hydraulic properties (Chen et al., 2013).

The existing post-fire erosion modelling studies include applications and adaptations of simple empirical models, such as the Universal Soil Loss Equation (USLE, Wischmeier and Smith, 1978) and its revised version, the RUSLE model (Renard et al., 1997), but also semi-empirical models, such as the revised Morgan–Morgan–Finney model (MMF, Morgan, 2001), and physically-based models, the Water Erosion Prediction Project (WEPP,), the Pan-European Soil Erosion Risk Assessment (PESERA, Kirkby et al., 2003) and the Soil and Water Assessment Tool – SWAT model (Arnold et al., 1998).

In the Mediterranean region, post-fire erosion predictions were performed using the RUSLE (Fernández et al., 2010, 2016; Karamesouti et al., 2016; Rulli et al., 2013; Terranova et al., 2009); MMF (Fernández et al., 2010; Vieira et al., 2014), WEPP (Soto and Díaz-Fierros, 1998), PESERA (Esteves et al., 2012; Fernández et al., 2016; Karamesouti et al., 2016) and SWAT models (Nunes et al., 2017). These model applications however, often yield different erosion rates (Fernández et al., 2010, Fernández and Vega, 2016; Karamesouti et al., 2016) and only few from these studies present results validation with field data (Fernández et al., 2010, Fernández and Vega, 2016; Nunes et al., 2017; Soto and Díaz-Fierros, 1998; Vieira et al., 2014).

As regards to post-fire rehabilitation, in general, there is a lack of model applications to simulate post-fire runoff and erosion in mitigated areas (Fernández et al., 2010; Robichaud et al., 2007). In the USA, the ERMiT tool has been widely used as an operational tool for decision support in post-fire land management (Robichaud et al., 2007). In the Mediterranean region, the RUSLE (Fernández et al., 2010; Rulli et al., 2013) and MMF models (Fernández et al., 2010; Vieira et al., 2014) have been applied and both models showed their ability to be used as operational tools to help land managers prioritize treatment areas and therefore, to optimize the limited resources that are typically available for post-fire land management.

The main objective of this study was to compare the ability of an empirical (RUSLE), semi-empirical (MMF) and physically-based (PESERA) model to predict the hydrological and erosive response and the effectiveness of different mulching techniques, namely hydromulching and natural mulching with pine needle, following a moderate severity wildfire in North-Central Portugal (Colmeal, Coimbra district). The ultimate goal of this work is to identify the best model to be used as base for a post-fire management tool, which aims for planning erosion mitigation and rehabilitation measures for this region, so that land managers can prioritize resources and evaluate trade-offs between different management strategies.

2. Materials and methods

2.1. Study area and study sites

On August 27, 2008, a wildfire ravaged and consumed almost 68 ha of forest lands, located near the Colmeal village, in the municipality of Góis, north-central Portugal (40°08′42″ N, 7°59′16″ W; 490 m a.s.l.). Prior to the fire, the Colmeal study area was predominantly dominated by maritime pine (*Pinus pinaster* Ait.) stands but also included some eucalypt (*Eucalyptus globulus* Labill.) stands (Vieira et al., 2016).

The climate of the study area can be characterized as humid mesothermal (Köppen, Csb), with prolonged dry and warm summers. Mean annual temperature and precipitation at the nearest meteorological station (GÓIS (13I/01 G); 10 km) are, respectively12 °C and 1133 mm (SNIRH, 2012).

The study area lies over pre-Ordovician schists and greywackes (Ferreira, 1978; Pimentel, 1994), which have given rise to shallow soils typically mapped as Humic Cambisols (Cardoso et al., 1971, 1973).

Within the burned area, 2 pine-dominated hillslopes were selected for testing two post-fire treatments, i.e. hydromulch and natural pine-needle mulch (Fig. 1). This study site had already been previously selected for several other studies concerning post-fire vegetation recovery (Maia et al., 2012a, 2012b), modelling post-fire hydrological response at catchment scale (van Eck et al., 2016), the effectiveness of hydromulch to reduce runoff and erosion after the wildfire (Prats et al., 2016), and also the effect of pre-fire plowing in the post-fire response (Vieira et al., 2016).

According to simple field indicators (i.e. tree canopy and woody debris consumption, litter combustion, ash colour and mineral soil), the two hillslopes appeared to have experienced a low-to-moderate burn severity since tree canopies and most of the logs were only partially consumed, the litter layer was fully consumed, the ash was black and the mineral soil was unaffected (DeBano et al., 1998; Hungerford, 1996). The ‘Twig Diameter Index’ (TDI), calculated based on the diameter of the 3 thinnest remaining twigs of each measured shrub (10 per site), also confirmed the existence of a moderate severity fire since an intermediate value (0.5) was found for an index that typically varies from 0 (unburned) to 1 (severely burned) (Maia et al., 2012a, 2012b; Vieira et al., 2016).

2.2. Model description and parameterization

The RUSLE, the revised MMF and the PESERA models, were applied to predict the hydrological and erosive response, and the effectiveness of different mulching techniques in reducing post-fire runoff and erosion at the Colmeal study area. A brief description of the three models is given below.

2.2.1. RUSLE

RUSLE (Renard et al., 1997) is an erosion model designed to predict long-term annual average soil losses induced by runoff, at slope scale. According to Wischmeier and Smith (1978), soil losses (A, Mg ha^{-1} y^{-1}) can be calculated as a product of five factors (Eq. (1)): rainfall erosivity (R, MJ mm h^{-1} ha-1 y^{-1}), soil erodibility (K, Mg h MJ^{-1} mm^{-1}), topography (LS, non-dimensional), crop (C, non-dimensional) and soil conservation practices (P, non-dimensional).

$$\boldsymbol{A} = \boldsymbol{R} \times \boldsymbol{K} \times \boldsymbol{LS} \times \boldsymbol{C} \times \boldsymbol{P} \tag{1}$$

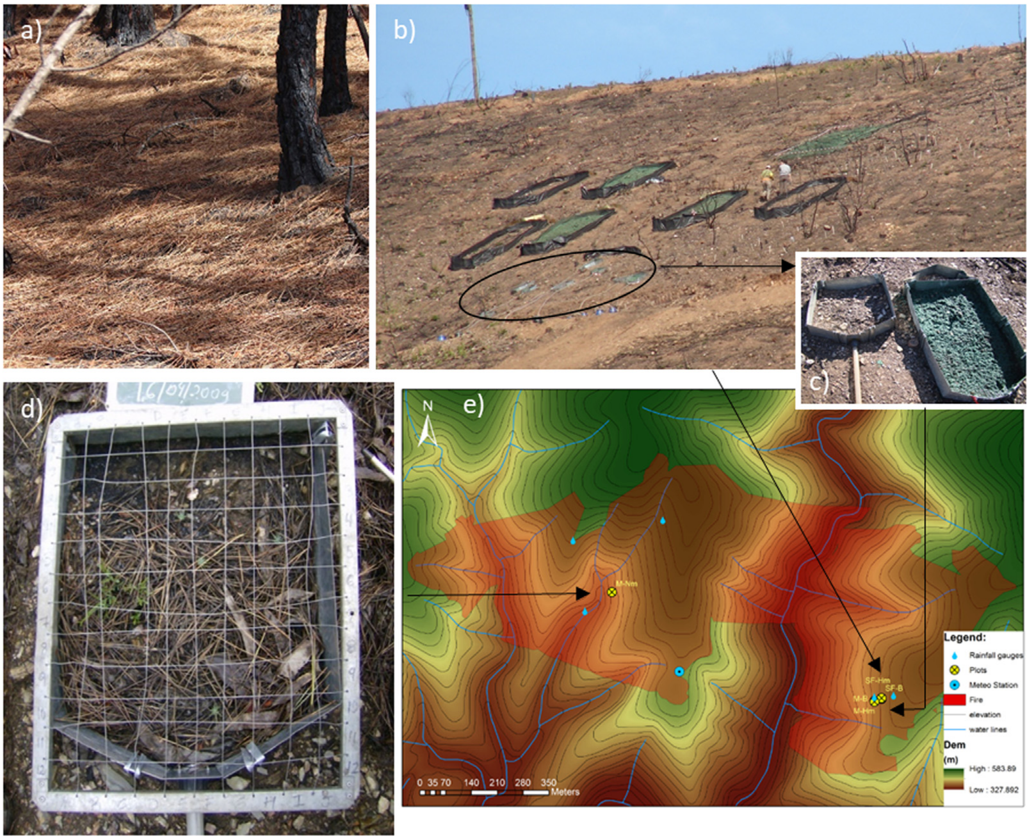

Fig. 1. Experimental design and study sites; a) "natural" needle cast at the pine stand; b) slope view of burned untreated and treated SF plots (SF-B, SF-Hm); c) detail of the burned untreated and treated M plots (M-B, M-Hm); d) detail of M plots with needle cast (M-Nm); e) location of study sites.

In the present work, the R factor was calculated by three different methods:

1. by summing the rainfall erosivity of all the events separated by 6 or more hours with no rainfall and with rainfall amounts greater than 50 mm. For each event, the kinetic energy was calculated according to the formula of Coutinho and Tomás (1995), which is considered the most suitable for the western part of the Mediterranean basin and then multiplied by the maximum rainfall intensity per 30 min of that specific event;
2. by multiplying annual rainfall by a factor of 0.865, as proposed by Roose (1977) and Morgan (1995) for tropical areas and suggested by Fernández et al. (2010) for NW Spain;
3. based on the available rainfall erosivity maps for Europe (Panagos et al., 2015).

In the end, the chosen rainfall erosivity method for the present study was the one from Panagos et al. (2015), as it led to the best model calibration (see Section 3.2.1).

Soil erodibility, K, was calculated according to Wischmeier and Smith (1978) since the percentage of organic matter was higher than 4% (Renard et al., 1997).

The topographic factor was calculated based on the formulation of Renard et al. (1997), taking into account plot characteristics.

The C factor was calculated in two different ways:

1. according to the Renard et al. (1997) formulation (Eq. (2))

$$C = PLU \times CC \times SC \times SR \times SM \tag{2}$$

Where PLU corresponds to the previous land use, CC to the canopy cover, SC to the surface cover, SR to surface roughness and SM to soil moisture content (Renard et al., 1997). For the calculation of the C factor, the authors have taken into account the post-fire changes made by Fernández et al. (2010) and Vieira et al. (2014) for predicting annual soil losses with RUSLE. In this study, however, the mean volumetric water content in soil (m^3/m^3) was used since the SM factor has never been calibrated for burned forest soils (González-Bonorino and Osterkamp, 2004).
2. Based on the reference table from Borrelli et al. (2016), which presents several disturbed C values according to the type of disturbance (wildfire or logging) and time since the disturbance.

In the end, the chosen C factor for the present study with the RUSLE model was the one from Borrelli et al. (2016), as it led to the best model calibration (see Section 3.2.1).

The P factor was calculated according to Eq. (3) following the approach of previous modelling studies in the Iberian Peninsula (Fernández et al., 2010; Vieira et al., 2014):

$$P = 1\text{–}(GC/100) \tag{3}$$

Where GC corresponds to the ground cover measured under field conditions.

The parameter values used for the RUSLE model are listed in Table 2.

2.2.2. MMF

The MMF model (Morgan et al., 1984) and its revised version (Morgan, 2001), were developed to predict annual soil losses at slope scale. While retaining the simplicity of the Universal Soil Loss Equation (Wischmeier and Smith, 1978), this model also incorporates the more recent knowledge on erosion processes. The model differentiates soil erosion into a water and a sediment phase. The sediment phase considers soil erosion to result from the detachment of soil particles by raindrop impact and runoff, whereas the water phase reflects the transport of soil particles by overland flow.

The model was implemented as defined by Morgan (2001) and considering the post-fire adaptations described by Fernández et al. (2010) and Vieira et al. (2014). For consistency reasons (i.e. comparison with the other models), the revised MMF was applied at annual scale only although it has been reported that the model performs better for post-fire conditions at seasonal scale (Vieira et al., 2014).

The revised MMF model (hereafter called MMF) requires 16 input parameters. For the present work, most of these parameters were estimated from field measurements but 3 had to be estimated from literature data (Table 3).

Model parameters can be divided into four categories:

Rainfall – which includes the following parameters: annual rainfall (R, mm yr^{-1}), mean rainfall per raining day (Rn, mm day^{-1}) and rainfall intensity (I, mm h^{-1}). Rainfall data (R and Rn) recorded in the study sites was used to calculate rainfall kinetic energy following the procedure outlined by Coutinho and Tomás (1995), which considers 30 mm h^{-1} as the most suitable rainfall intensity predictor for the Mediterranean climate (Morgan, 2001).

Soil – including the parameters: bulk density (BD, g cm^{-3}), effective hydrological depth of soil (EHD, m), soil detachability index (K, g J^{-1}), and cohesion of the surface soil (COH, kPa). All these parameters were estimated from field data (Prats et al., 2016; Vieira et al., 2016). Effective hydrological depth of soil (EHD, m) was estimated as a linear function of ground cover (GC, %) (Vieira et al., 2014), such that for a ground cover of 0% the effective hydrological depth of soil value corresponded to that of shallow soils on steep slopes (EHD = 0.05 m; Morgan, 2001) and for a ground cover of 100% the effective hydrological depth of soil value corresponded to that of a mature forest (EHD = 0.20 m; Morgan, 2001). Soil detachability index (K, g J^{-1})and cohesion of the surface soil (COH, kPa) were estimated from soil texture analysis of samples collected by Prats et al. (2016) and Vieira et al. (2015).

Landform – includes only one parameter: slope steepness (S, °), which was determined in the field.

Land cover – including the parameters: interception (A), ratio of actual (Et, mm) to potential (E0, mm) evapotranspiration, crop cover management factor (C), which combines C and P factors from the Universal Soil Loss Equation (Eq. (2), Eq. (3)), canopy cover (CC, %), ground cover (GC, %), plant height (PH, m). The parameters interception (A), canopy cover (CC, %) and plant height (PH, m), were all zero considering that the study site was a burned area. Actual evapotranspiration (Et, mm) and potential evapotranspiration (E0, mm) was an output of the Soil and Water Assessment Tool model (Arnold et al., 1998) that was applied to calculate the water balance for Colmeal catchment in the 4 years after fire. In SWAT, the effective evapotranspiration (Et, mm) was calculated as the sum of the evaporation of plant canopy and the maximum soil evaporation and transpiration (Ritchie, 1972). The potential evapotranspiration (E0, mm) was calculated following the Hargreaves and Samani (1985) method. The C and P factors were estimated as described for the RUSLE model (Renard et al., 1997), as it led to the best model calibration (see Section 3.2.1).

Runoff estimations (Q) were scaled according to Morgan and Duzant (2008) equation (Eq. (4)):

$$Q = exp\left(-\frac{R_c}{R_0}\right) \times \left(\frac{L_{prediction}}{L_{calibration}}\right)^{0.1} \tag{4}$$

Where R_0 is the mean rainfall per rainy day (mm), R_c the soil moisture at storage capacity, $L_{prediction}$ the slope length to be predicted and $L_{calibration}$ the slope length of the calibration plots.

The left-hand term of this equation corresponds to the original Morgan (2001) equation, whereas the right-hand term is an empirical adjustment for slope length, considering the scale at which the parameters were calibrated.

2.2.3. PESERA

PESERA is a physically based erosion model constructed around the conceptual separation of precipitation into overland flow generation and infiltration, with runoff depending primarily on soil and vegetation properties. In this model, sediment transport is estimated from runoff totals and their transport capacity in each storm. Therefore, soil erosion reflects mainly sheet and rill erosion processes (Kirkby et al., 2008). The PESERA model was implemented with the Visual Basic one-cell version (Kirkby et al., 2003).

The calibrated model parameters (Table 4) can be grouped into 5 classes:

Soil properties – includes the parameters: erodibility class, crusting class, soil storage, and scale depth. The erodibility class, crusting class, and soil storage were defined according to the texture class (Medium Fine) as described in the Kirkby et al. (2003) manual. Scale depth was set as 10 mm, as described in by Kirkby et al. (2008) for organic soils.

Transport law exponents – includes the parameters: distance and gradient. The distance parameter was calibrated from the hydrological and erosive response of the micro-plots.

Runoff – includes only one parameter: runoff threshold (%). This parameter was estimated for each treatment (M-B, M-Hm, M-Nm) using the runoff data collected at micro plot scale.

Land cover – correspond to the average ground cover (%) measured monthly in each experimental plot.

Climate – includes the monthly rainfall (mm), average rainfall per rainy day (mm) and corresponding standard deviation (mm), average temperature (°C) and average daily amplitude (°C), and monthly potential evapotranspiration (mm) (Table 4). Rainfall and temperature data was measured it the study area. Potential evapotranspiration was determined according to the Hargreaves and Samani (1985) method, as described for the MMF model (see section 2.3.2).

2.3. Data collection and modelling approach

Runoff and erosion data from plots submitted to three different

Table 1
General description of the dataset used for modelling: phase (calibration/validation), treatment (control burned, burned treated with hydromulch, burned treated with natural needle mulch), hillslope number (1 and 2) number of replicates, plot area, and type of data (runoff and/or erosion).

Modelling phase	Treatment	Hillslope nr.	Nr. plots	plot area (m^2)	runoff	erosion
Calibration	**M - B** (burned)	1	4	0.28-0.64	Yes	Yes
	M - Hm (burned + hydromulch)		4		Yes	Yes
	M - Nm (burned + needle mulch)	2	4	0.28-0.64	Yes	Yes
Validation	**SF - B** (burned)	1	3	9-10	No	Yes
	SF - Hm (burned + hydromulch)		3		No	Yes

treatments: burned untreated (B), burned with natural needle cover (Nm), and burned with hydromulch (Hm) (Table 1), were used for modelling. Most of the experimental plots were installed immediately after the wildfire (September 2008), however, only data from the first year following hydromulch application (March 2009 to March 2010) was selected for this study to ensure comparability between plots.

For each treatment (Tables 1), 4 micro-plots were randomly installed at the base of the hillslopes. The outlets of the micro-plots were connected, using garden hose, to 30 or 70 L polyethylene tanks to collect runoff on a weekly to bi-weekly basis. Whenever the runoff in a tank exceeded 250 mL, the runoff volume was measured and a sample was collected in a 1.5 L plastic bottle to determine sediment concentration.

Additionally, in a greater scale (Tables 1), 3 sediment-fence plots for each B and Hm treatments were also installed, at the middle of the hillslope. The geotextile fabric of the sediment fences filtered the runoff and the sediments accumulated at the bottom of the plots were collected at monthly intervals.

Each field trip also involved the measurement of rainfall through the recordings of 5 tipping-bucket rainfall gauges (Pronamic Professional Rain Gauge with 0.2 mm resolution linked to an ONSET Hobo Event Logger Automatic) (Fig. 1).

Once a month, ground cover (GC, %) was described over a square grid of 50 × 50 cm laid out over the micro-plots, and of a 100 × 100 cm grid in the case of the sediment fence plots, by recording the cover category (i.e. stones, bare soil, ash/charred material, litter and vegetation) at each grid intersection.

Volumetric soil moisture content was monitored at a depth of 0–5 cm at eight locations: four within the untreated plots and four within the hydromulch plots, using eight EC-5 sensors linked to two Em5b data loggers (Decagon Devices, Inc.) and recording data at 10 min intervals.

Model calibration was carried out using runoff and erosion data collected at micro plot scale (M; plot area: 0.28–0.64 m^2), whereas model validation was restricted to erosion data from sediment-fence plots (SF; plot area: 9–10 m^2). This calibration was focused on key parameters (Tables 2–4), so that runoff and erosion predictions would reflect local conditions and distinguish between the different treatments (untreated, treated with hydromulch and treated with needle mulch).

Upscaling with the RUSLE and PESERA models was achieved by the topographic inputs parameters included in the models, while for the revised MMF this was done according to the Modified Morgan–Duzant version of the model (Morgan and Duzant, 2008).

2.4. Model performance evaluation

Model performance was evaluated using four commonly used statistical indicators (Moriasi et al., 2007):

- Nash-Sutcliffe efficiency (NSE) – NSE determines the relative magnitude of the residual variance compared to the measured variance. NSE values greater than 0.5 indicate satisfactory model performance, whereas values below this threshold are indicative of unsatisfactory model performance (Moriasi et al., 2007).
- Coefficient of determination (R^2) – R^2 describes the proportion of data variance explained by the model. R^2 ranges from 0 to 1, with values higher than 0.5 indicating reasonable model performance (Santhi et al., 2001; Van Liew et al., 2003).
- Root mean square error (RMSE) - RMSE is an error index. According to Singh et al. (2004), RMSE values less than half the standard deviation of the measured data are considered low and inappropriate for model evaluation. RMSE values of 0 indicate a perfect fit.
- Percent bias (PBIAS) – PBIAS indicates the magnitude of model errors compared to measurements. Positive PBIAS values indicate model underestimation and negative values model overestimation (Gupta et al., 1999). PBIAS values below 25% for runoff and below 55% for soil erosion are considered reasonable (Moriasi et al., 2007).

Aside from these indicators, a Spearman's rank correlation test (rho) between measured and predicted values was also performed, to evaluate if the reduction in sample size from the calibration (n = 12) to the validation phase (n = 6) influenced model performance.

3. Results

3.1. Post-fire hydrological and erosive response in the calibration and validation plots

The burned plots produced an overall runoff amount of 603 mm (Fig. 2), which is roughly half of the rainfall amount (runoff coefficient (rc) = 44%). The effect of the needle cast resulted in a reduction in runoff, with the concurrent needle plots producing 46% less runoff than the burned plots. The hydromulch resulted in a strong runoff reduction of 76%, as compared to the burned plots.

Soil losses on the burned micro-plots were 3.7 Mg ha^{-1}, and the reduction effect of both needles and hydromulch reached 89% and 86% less erosion, as compared to the burned plots. In the case of the validation plots, the burned ones soil losses reached the 5.3 Mg ha^{-1}, and the hydromulched accounted for 1.2 Mg ha^{-1}, or 78% less.

During the entire monitoring year, the mean soil losses from the validation plots (for both treated, and untreated), show greater amounts when compared to the calibration ones. However, the increased standard deviation in the validation plots (Fig. 2) do not allow verifying significant differences between these two scales (Prats et al., 2016).

Table 2
RUSLE model parameters.

Factor	Parameter	Calibration						Validation				Methodology for parameter estimation
		M-B	M-B	M-Hm	M-Hm	M-Nm	M-Nm	SF-B	SF-B	SF-Hm	SF-Hm	
Rainfall erosivity[a]	R (MJ mm h-1 ha-1 y-1)	1064.86										Estimated according to Panagos et al. (2015).
Soil erodibility	K (Mg ha-1 MJ-1 mm-1)	0.017										Calculated according to Renard et al. (1997)
Topographic factor	LS	1.18	1.49	0.81	1.81	0.85	1.85	2.49	3.26	2.62	3.26	Calculated according to Renard et al. (1997)
Crop factor[a]	C	0.13										Estimated according to Borrelli et al. (2016) which assigned a C-factor of 0.13 to a forest area during the 2nd year after the wildfire.
Soil conservation practices	P	.8	1	0.3	0.5	0.3	0.4	0.7	0.8	0.3	0.4	Calculated from field ground cover measurements using the equation P = 1 – (GC/100).

[a] Calibrated parameters.

Table 3
MMF model parameters.

Factor	Parameter	Calibration						Validation				Methodology for parameter estimation
		M-B_{min}	M-B_{max}	M-Hm_{min}	M-Hm_{max}	M-Nm_{min}	M-Nm_{max}	SF-B_{min}	SF-B_{max}	SF-Hm_{min}	SF-Hm_{max}	
Rainfall	Annual Rainfall (R; mm yr^{-1})	1435										Recorded at the study sites (Prats et al., 2016; Vieira et al., 2016).
	Rain per rain-day (Rn; mm rain day^{-1})	11										
	Intensity of erosive rain (I, mm h^{-1})	30										
Soil	Soil moisture content at field capacity (MS; %)	19		25		30		19		25		Field measurements (Prats et al., 2016; Vieira, 2015).
	Bulk Density (BD; g cm^{-3})	0.8										
	Effective hydrological depth of soil (EHD; m)	0.090	0.096	0.120	0.132	0.087	0.092	0.075	0.079	0.128	0.133	Estimated following Vieira et al. (2014).
	Soil detachability index (K; g J^{-1})	0.7										Estimated based on soil texture, as described by Morgan (2001).
	Cohesion of the surface soil (COH; kPa)	2										
Landform	Slope (S; °)	21	29	20	31	21	33	20	26	21	26	Field measurements (Prats et al., 2016; Vieira, 2015).
Land cover	Interception (A)	0										No interception in burned areas.
	Ratio of actual to potential evapotranspiration (Et/E0)	0.7										Obtained from SWAT model output.
	Crop factor (C[a,b])	0.003	0.005	0.001	0.002	0.002		0.004		0.001		Estimated following Vieira et al. (2014).
	Soil conservation practices (P[a])	0.8	1.0	0.3	0.5	0.3	0.4	0.7	0.8	0.3	0.4	
	Percentage canopy cover (CC; %)	0										Measured in the field by Prats et al. (2016) and Vieira (2015).
	Percentage ground cover (GC; %)	0	20	50	70	60	70	20	30	60	70	
	Height of trees (PH, m)	0										

[a] In the original input table (Morgan, 2001), the C factor represented a combination of C and P parameters, which are presented separately here.
[b] Calibrated parameters.

3.2. Runoff and erosion predictions

3.2.1. Calibrated parameters

The final model calibration was delineated after selecting the combination of methodologies to calculate the R and the C factor for RUSLE and the C factor for the MMF (Table 5) that best fit the measured soil losses, according to the Nash-Sutcliffe and the R^2 model performance indicators.

The calibration results show that the R factor calculated with the Renard et al. (1997) methodology, whereas the rainfall erosivity of each event was calculated based on the Coutinho and Tomás (1995) rainfall kinetic energy clearly worsened the estimation results. In the other hand, the methodology proposed by Fernández et al. (2010), using Roose (1977) and Morgan (1995) multiplication factor together with the Panagos et al. (2015) approximate the soil losses estimations to the measured ones (Table 5).

In the case of the C factor, when using the RUSLE model, the estimations offered by Borrelli et al. (2016) presented a better fit when compared with the method defined by Renard et al. (1997) (Table 5).

However, when the C factor is applied in the MMF model, the best model fit is achieved with the Renard et al. (1997) methodology, that valued other soil parameters such as soil moisture, ground cover, surface roughness, besides the wildfire impact aspect through time as suggested by Borrelli et al. (2016) (Table 5).

3.2.2. RUSLE model

Overall, the RUSLE calibration was considered successful as NSE and R^2 values were above 0.5 (Table 6, Fig. 3b). Some underestimation of annual sediment losses was, however, found for untreated (M-B) micro-plots (pred. 2.8 vs. meas. 3.7 Mg ha^{-1}), whereas for treated micro-plots the model tended to overestimate sediment losses (M-Hm: pred. 1.2 vs. meas. 0.5 Mg ha^{-1}, for; M-Nm: pred. 1.1 vs. meas. 0.4 Mg ha^{-1}) (Table 6).

Model efficiency improved in the validation phase (NSE = 0.70; R^2 = 0.89; Table 6). Nevertheless, some there was still some overestimation (Fig. 2b) of sediment losses (PBIAS = −20.1%, RMSE = 1.6 Mg ha^{-1}), especially at the hydromulch (SF- Hm) plots (pred. 2.3 vs. meas. 1.0 Mg ha^{-1}).

3.2.3. MMF model

In general, the MMF model was able to effectively predict the hydrological response of the different micro-plots, as shown by the statistical indicators (NSE = 0.69; R^2 = 0.79; PBIAS = −0.7%) (Table 6, Fig. 3a). An underestimation of runoff amounts (Fig. 2a) was, however, found for the M-B plots (pred. 527 vs. meas. 611 mm), unlike for the M-Nm (pred. 304 vs. meas. 326 mm) and M-Hm plots (pred. 247 vs. meas. 145 mm). As regards to erosion predictions (Fig. 2b), the model was clearly able to differentiate between untreated (M-B) and treated micro-plots (M-Hm and M-Nm). On overall, model performance was considered very good since NSE and R^2 values were close to 1 (Table 6). Nevertheless, a slight underestimation of sediment losses was verified during model calibration (PBIAS = 5.2%, RMSE = 0.3 Mg ha^{-1}).

Lower model accuracy was, however, found for the validation plots (NSE = 0.77; R^2 = 0.79; Table 6), but the MMF performance was still good. The model did, however slightly overestimated sediment losses in the untreated plots (pred. 6.1 vs. meas. 5.35 Mg ha^{-1}) and highly underestimated them in the ones treated with hydromulch (pred. 0.1 vs. meas. 1.0 Mg ha^{-1}).

3.2.4. PESERA model

The calibration of PESERA was considered successful for both runoff and erosion (NSE and R^2 > 0.73; Table 6, Fig. 3a). Nevertheless, some overestimation of runoff (M-Nm: pred. 400 vs. meas. 326; M-Hm: pred. 247 vs. meas. 145 Mg ha^{-1}) and underestimation of erosion (M-Nm: pred. 0.38 vs. meas. 0.41; M-Hm: pred. 0.02 vs. meas. 0.47 Mg ha^{-1}) amounts was consistently found for the treated plots (Fig. 2). The plots

Table 4
PESERA model parameters.

Factor	Parameter	Calibration						Validation						Methodology for parameter estimation
		M-B	M-B	M-Hm	M-Hm	M-Nm	M-Nm	SF-B	SF-B	SF-Hm	SF-Hm			
Soil properties	Erodibility Class						10							Estimated based on the soil texture class, as described by Kirkby et al. (2003)
	Crusting Class						10							
	Soil Storage						10							
	Scale depth (mm)						10							Estimated from Kirkby et al. (2008)
Transport law exponents	Distance						5							Estimated according to the micro-plots hydrological and erosive response.
	Gradient			0.5					1					Estimated according to the scale effect
Runoff	Runoff threshold[a]	7		3		5		7		3				Estimated according to the micro-plots hydrological and erosive response.
Land Cover	Cover (%) (monthly values)	3	27	70	95	53	77	10	37	59	73			Measured from field measurements (Prats et al., 2016; Vieira, 2015).
Climate	Month	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Recorded at the study sites (Prats et al., 2016; Vieira et al., 2016), and nearest meteorological station (GÓIS (13I/01 G).
	Sum Rainfall (mm)	97.40	61.60	36.20	41.00	3.80	41.60	111.60	143.20	240.40	262.60	181.80	213.80	
	Av Rain/rain-day (mm)	11.99	5.13	5.90	18.36	6.44	1.90	1.49	1.71	7.48	3.86	6.13	12.43	
	SD Rain/rain-day (mm)	14.17	8.40	8.30	18.35	7.91	4.85	2.32	3.49	15.94	8.05	9.78	15.13	
	Average Temperature (°C)	10.86	12.65	10.21	13.61	13.49	18.35	18.78	18.74	17.79	14.59	9.43	8.16	
	Average Temperature amplitude (°C)	6.49	7.39	7.86	8.05	6.81	10.33	9.86	10.09	9.40	9.11	8.18	7.51	
	Sum of PET – Hargreaves (mm)	31.19	49.27	60.98	88.20	87.76	163.87	154.93	144.88	102.32	69.86	37.93	20.49	

[a] Calibrated parameters.

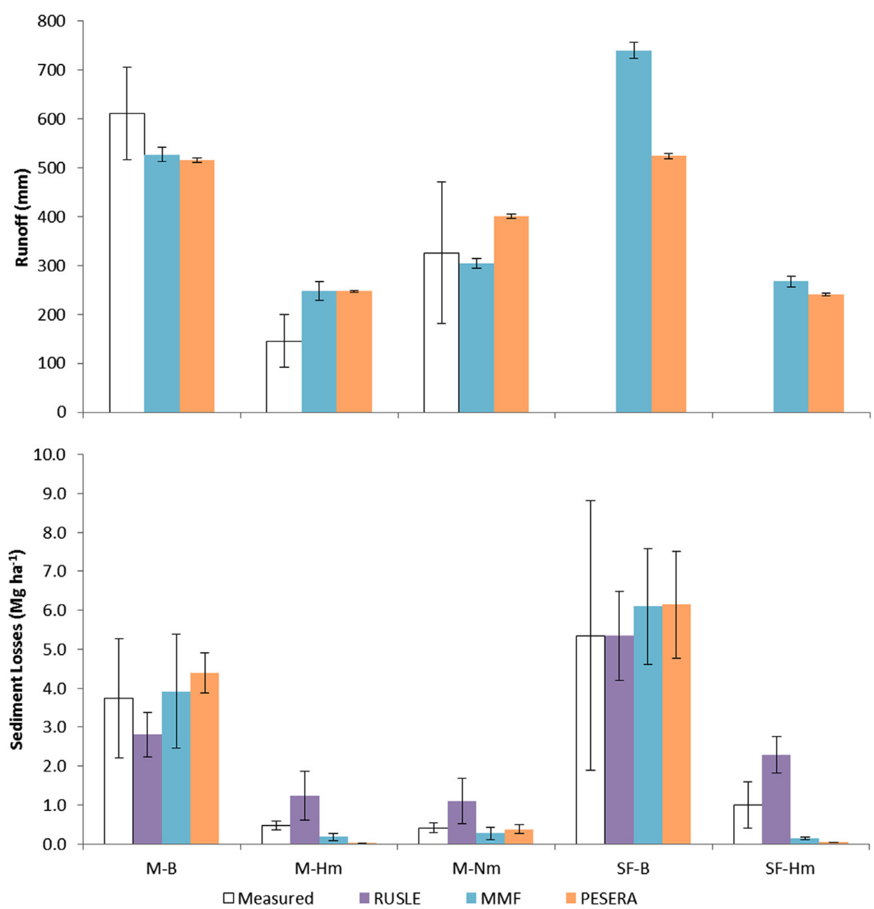

Fig. 2. Measured and predicted post-fire annual runoff and sediment losses in the different experimental plots and with the different models: RUSLE, MMF and PESERA. Maximum and minimum values are given by the error bars.

Table 5
RUSLE model performance combining several methodologies used to determine R and C factors.

	RUSLE Calibration					
C factor	R factor					
	Renard et al. (1997)		Roose (1975) and Morgan (1995)		Panagos et al. (2015)	
	NSE	R^2	NSE	R^2	NSE	R^2
Renard et al. (1997)	− 0.67	0.32	− 0.72	0.91	− 0.71	0.91
Borrelli et al. (2016)	− 7.29	0.75	0.60	0.75	**0.63**	**0.75**

	MMF Calibration	
C factor	NSE	R^2
Renard et al. (1997)	**0.97**	**0.98**
Borrelli et al. (2016)	− 2056.86	0.95

Table 6
Performance indicators of the RUSLE, MMF and PESERA models in predicting post-fire annual runoff and sediment losses, during the calibration and validation phase. Nash-Sutcliffe efficiency coefficient - NSE, coefficient of determination - R^2, Root mean square error – RMSE, percent of bias - PBIAS, Spearman's rank correlation - rho.

	Calibration			Validation		
	RUSLE	MMF	PESERA	RUSLE	MMF	PESERA
Runoff						
NSE	–	0.69	0.63	–	–	–
R2	–	0.79	0.77	–	–	–
PBIAS (%)	–	− 0.7	− 7.3	–	–	–
RMSE (mm)	–	118	130	–	–	–
rho		0.84***	0.76**	–	–	–
Sediment Losses						
NSE	0.63	0.97	0.85	0.70	0.77	0.73
R2	0.75	0.98	0.88	0.89	0.79	0.77
PBIAS (%)	− 11.7	5.2	− 3.5	− 20.1	1.9	2.6
RMSE (Mg ha^{-1})	1.06	0.30	0.70	1.62	1.43	1.53
rho	0.80**	0.80**	0.62*	1.00**	0.94*	1.00**

Significance levels: .
* = p-value < 0.05.
** = p-value < 0.01.
*** = p-value < 0.001.

with major differences between measured and predicted values being the hydromulch plots, especially in what concerns to erosion.

The difficulty of the PESERA model in simulating erosion was also noticeable at the higher spatial scale (i.e. validation plots) (Fig. 3c), nonetheless, model performance was considered reasonable (Table 6).

3.3. Comparison of model performance

The best model for predicting annual runoff at the micro plot scale was the MMF, as it reached the highest NSE and R^2 values (respectively, 0.69 and 0.89) and lowest PBIAS values (−0.7%). The PESERA performance was also good, with the statistical indicators presenting slightly lower values (Table 6).

The best erosion predictions were also achieved with the MMF (Table 6), but the model slightly underestimated sediment losses (PBIAS= 5.2%). The second best model in predicting soil erosion was PESERA (NSE = 0.85; R^2 = 0.88; PBIAS = −3.5%), followed by the RUSLE model (NSE = 0.63; R^2 = 0.75; PBIAS = −11.7%). Similar results were observed at plot scale, as the MMF performed better in predicting erosion than the other models (NSE = 0.77; R^2 = 0.79; PBIAS = 1.9%; Table 6). Reasonable predictions were also obtained with the other two models (Table 6), the PESERA (NSE = 0.73; R^2 = 0.77; PBIAS = 2.6%) performing slightly better than RUSLE (NSE = 0.70; R^2 = 0.89; PBIAS = −20.1%), as observed at micro plot scale. According to the results of the Spearman correlations (rho) sample size did not influence model performance, since high correlation values (rho > 0.62) were found between the statistical indicators of all models (Table 6).

Overall, the ability of the RUSLE, MMF and PESERA models to predict the annual runoff and sediment losses in untreated and treated plots was considered satisfactory, for both the calibration and validation phase (Table 6). Erosion predictions were better than runoff predictions for all models (Table 6).

4. Discussion

4.1. Model evaluation and comparison with other studies

Table 7 compiles the model accuracy for runoff and erosion predictions between other modelling exercises in burned areas, with the purpose of comparing them with the present work. From the reviewed modelling studies that predict post-fire soil losses at plot scale, few were found to evaluate modelling predictions with field data (Fernández et al., 2010; Fernández and Vega, 2016; Larsen and MacDonald, 2007; Vieira et al., 2014), and fewer studies did a calibration-validation exercise with an independent dataset (Vieira et al., 2014). Was also verified that model evaluation with runoff data was scarce in post-fire studies, justified by the operational difficulties in monitoring post-fire hydrological response.

The model efficiencies obtained in this study with the RUSLE model are in good agreement with the predictions of Fernández et al. (2010) for post-fire soil losses, with and without rehabilitation measures at 500 m^2 scale (Table 7). These predictions are also better than the ones from Fernández and Vega (2016) at 80–500 m^2 scale and Larsen and MacDonald (2007) at 1600 m^2 scale without any mitigation measure (Table 7). When MMF is compared, runoff predictions worsened when compared to the study of Vieira et al. (2014) at 16 m^2 scale, but are still satisfactory (< 0.6). In what concerns soil losses, MMF predictions are better than the ones obtained by Fernández et al. (2010), and in agreement with the ones obtained in Vieira et al. (2014), for post-fire soil losses with and without rehabilitation measures (Table 7). It was only possible to compare the prediction efficiency from PESERA model with the study from Fernández and Vega (2016), and in this study, the PESERA model predictions revealed to be more accurate for both calibration and validation (Table 7).

4.2. Sources of uncertainty

Predicting errors are usually attributed to errors in the model, input data, and data used for model validation (Nearing et al., 1999). In this study, one important source of error might come from the fact that the RUSLE and MMF models have a strong empirical base and were developed from slope scale data, and validated by the developers using mostly smaller scale erosion plot data derived from agricultural fields (Morgan, 2001; Renard et al., 1997). On the other hand, although PESERA might have been developed to predict soil losses over Europe and for the wide range of the European land uses, soils and climate variability (Kirkby et al., 2004), several disadvantages were found concerning the non-uniform data collection for calibration and validation from different countries (Kirkby et al., 2008). Nevertheless, these

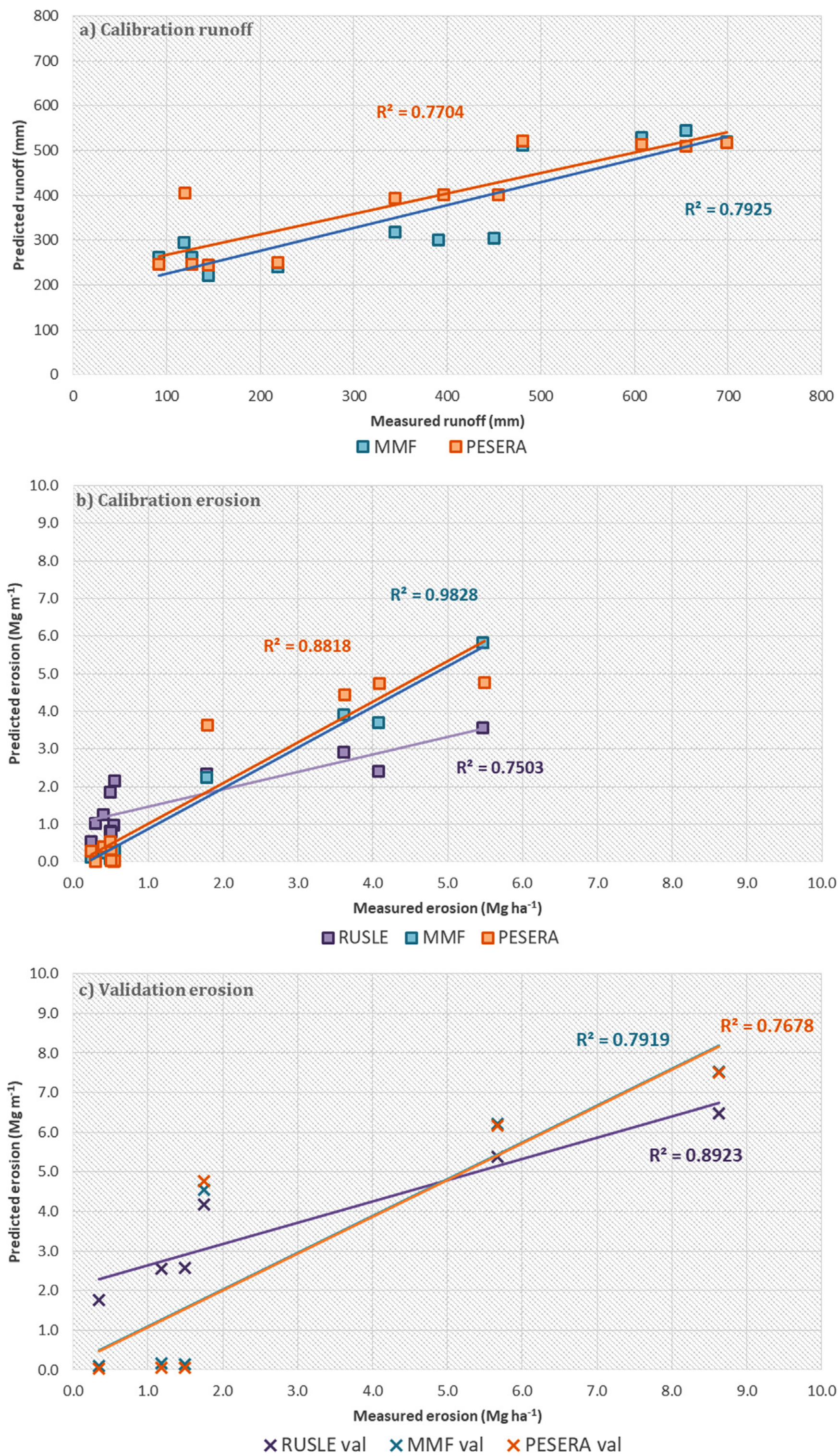

Fig. 3. Measured vs. predicted post-fire annual runoff and sediment losses in the calibration and validation phase of the RUSLE (only erosion), MMF and PESERA models.

models (alone or combined) already have been used to estimate soil losses in recently burned areas (Fernández et al., 2010; 2016; Karamesouti et al., 2016; Larsen and MacDonald, 2007; Vieira et al., 2014), leading to different model efficiency results.

4.2.1. Measurement errors

The uncertainties that are associated with field and lab measurements, such as rainfall, and sediment losses are often highlighted as the most important potential sources of measurement errors (Pietraszek, 2006; Larsen and MacDonald, 2007). The rainfall amounts used in this study can be considered as accurate, since a good agreement was found between the tipping-bucket gauges and the rainfall data from the nearest long-term climate station (GÓIS (13I/01 G), SNIRH, 2012). The same is true on the accuracy of ground cover measurements, because they were always carried out by the same observer in a systematic way, thereby reducing possible errors.

Table 7
Overview of prior studies modelling post-fire soil erosion with RUSLE, MMF and PESERA models at plot scale.

Study	Location	Land use	Model	Burn severity	Post-fire mitigation	plot size (m^2)	N° plots	Measurement range		Calibration/ Validation	NSE runoff	NSE erosion	RMSE (mm)	RMSE ($Mg\ ha^{-1}$)
								runoff (mm)	erosion ($Mg\ ha^{-1}$)					
Fernández et al. (2010)	NW Spain	Forest (pine) and shrubland	RUSLE	Moderate/ High	untreated	500	18	-	0.01 – 53.1	Calibration	-	0.87 [a]	-	6.3 [c]
					straw mulch, wood chip mulch, cut shrub barriers		10		9.31 – 44.65	Calibration	-	0.33 [a]	-	15.5 [c]
			MMF	Moderate/ High	untreated		18		0.01 – 53.1	Calibration	-	0.74 [a]	-	9.0 [c]
					straw mulch, wood chip mulch, cut shrub barriers		10		9.31 – 44.65	Calibration	-	−0.59 [a]	-	23.8 [c]
Fernández and Vega (2016)	NW Spain	Forest (pine and eucalypt) and shrubland	RUSLE	Low/ Moderate/ High	untreated	80 – 500	87	-	0.01[a] – 56.5[a]	Calibration	-	−18.1	-	83.6
			RUSLE (Fernández et al., 2010)		untreated					Calibration	-	−3.86	-	42.1
			RUSLE (Poesen et al., 1994)		untreated					Calibration	-	−17.55	-	82.3
			PESERA		untreated					Calibration	-	0.33	-	15.6
Larsen and MacDonald (2007)	Colorado Front Range, USA	Forest (pine)	RUSLE	Low/ Moderate/ High	untreated	1600	83	-	0.001 – 35.6[b]	Calibration	-	0.52 [b]	-	3.6 [d]
			Modified RUSLE		untreated					Calibration	-	0.31 [b]	-	4.3 [d]
Vieira et al. (2014)	North-Centre Portugal	Eucalypt and Pine	MMF	Low/Moderate	Treated + control	16	12	172-418	0.26 – 7.6	Calibration	0.81	0.89	78	0.9
						16	13	-	0.04 – 0.68	Validation	-	0.93	-	1.2

[a] Minimum and maximum erosion rates values observed in Verín and Barbanza sites from Fernández and Vega (2016).
[b] Maximum estimated from Larsen and MacDonald (2007) through WebPlotDigitizer (Rohatgi, 2018).
[c] Best achieved Nash Sutcliffe efficiency index and RMSE after RUSLE and revised MMF model modification.
[d] Statistics of grouped hillslope data, periods of 1–10 years after wildfire by Larsen and MacDonald (2007).

As regards sediment losses, the 1- to 2-weekly monitoring intervals (40 read outs), together with the high capacity of runoff collection tanks, provided an overview of the hydrological response of each plot. Therefore, it seems reasonable to suggest that the runoff and erosion measurements were accurate, within the limitations of a plot-based set-up (e.g. Boix-Fayos et al., 2006).

4.2.2. Modelling errors

All the applied models required adaptations to the specific post-fire conditions of the studied sites, especially for primary effects such as fire-induced changes in the soil and surface cover. The inclusion of these changes in the model inputs led to some limitations, which might have been only partially solved by the calibration approach followed in this study.

The use of rainfall erosivity values from European maps (Panagos et al., 2015), could limit the potential to refine the calibration of these models under different rainfall regimes in a long-term study case. A more direct conversion from rainfall amounts into rainfall erosivity is still required for this region (e.g. Roose, 1975 and Morgan, 1995), although the use of the long-term mean rainfall erosivity derived from Panagos et al. (2015) might be enough for a 1-year study like this one, in which more importance is given to the risk comparison between affected nearby areas.

According to several researchers, the K factor should be increased to accommodate post-fire conditions, justified by the usual decrease in soil aggregate stability and the increase in soil water repellency after fire (Larsen and MacDonald, 2007; Miller et al., 2003; Terranova et al., 2009). Fernández and Vega (2016) however, ignored these changes because they would worsen the model performance by overestimating even more the RUSLE predictions. In this study however, the soil erodibility factor (K) was calculated according to the Renard et al. (1997) methodology. Justified by Moody et al. (2013) as "a good first approximation", since this author showed that this parameter needs further research regarding post-fire conditions.

Because of the equilibrium of each formulation (RUSLE and MMF), two different C factors were used, the Borrelli et al. (2016) version in the RUSLE model that considers a generalised impact of wildfires but without taking into account burn severity, and the Renard et al. (1997) version in the MMF model as described by Vieira et al. (2014). When using RUSLE to simulate post-fire conditions for different burn severities, a C factor with the same magnitude of the Borrelli et al. (2016) values together with the Renard et al. (1997) adaptation that take into account burn severity, is still needed.

In the case of PESERA, the soil parameters were chosen according to the texture class, not considering post-fire changes, as it was done in other studies (Fernández and Vega, 2016). In this work, as the burn severity was moderate in all study sites this is not problematic, but this should be taken into consideration in other modelling exercises with various burn severities. The hydrologic and - by consequence - the erosive response among the treated and untreated plots, was calibrated through the gradient and the runoff threshold input, which led to a site-specific calibration and therefore might not mean its applicable elsewhere.

It was possible to verify that mulch treatments efficiency can be successfully predicted by using the presented methodologies. Nevertheless, some variations might arise from the chosen organic material for rehabilitation treatment, and if other techniques are used (Fernández et al., 2010), since the efficiency of the ones calibrated in this study are highly dependent on ground cover.

The fact that this study was done at an annual scale, limited the implementation of several seasonal variables, such as the soil water repellency and soil moisture, and the drastic increase in ground cover that typically occurs during the first years after the wildfire disturbance. Nevertheless, the use of mean ground cover values and soil moisture at field capacity as well as the non-inclusion of soil water repellency, still allowed good model results at an annual scale.

Finally, the reduced sample size of the validation data, and the lack of runoff results at a greater spatial scale (SF-B and SF-Hm), partially limited the evaluation of model efficiency. However, the double calibration (runoff and erosion) was an advantage for MMF and PESERA models since it improved soil losses predictions among the calibration and validation datasets.

4.3. Differences between models

As stated earlier, although the RUSLE, MMF and PESERA models have great differences in their formulation, they seem to accommodate quite well the main changes in post-fire and post-fire mitigation conditions at the annual scale. It should be highlighted, however, that the potential of these models for making accurate estimations at smaller time scales (monthly and seasonally) decreases from the physically based model to the empirical one. Therefore, the adequacy of these models depends on the objective of their implementation (i.e. post-fire management or post-fire process studies) and on the limits established for their performance.

The lack of runoff prediction within the RUSLE formulation seems to be the reason why this model performs worse in comparison to the MMF and PESERA models. Another limitation of the RUSLE model is its great dependence on empirical parameters like C and P, which have the same weight as the other input parameters when estimating soil losses. In the case of MMF and the PESERA model, runoff generation is calculated based on physical processes, and only after, soil losses are estimated based on the transport capacity of the estimated overland flow. MMF makes use of its empirical base by including the C and P factors in these soil loss estimations, while the PESERA model calculates the capacity for sediment transport based on texture and ground cover.

In past studies, RUSLE and MMF already have been successfully calibrated and validated at wider scales (16–500 m2) with field data (Table 6). The new challenge of this study, which consists in calibrating all these models at micro-plots ($0.5\,m^2$) followed by an upscaling ($10\,m^2$), could be considered successful. Since models performed reasonably well at greater spatial scales as observed by the validation results. For the MMF model however, this was only possible after including the scale component (Eq. (3)) in the runoff estimations, as done by Morgan and Duzant (2008).

4.4. Data and parameter availability for post-fire model application

The application of each model for burnt areas also depends on the availability of baseline data and parameter estimations. Many of these parameters can be easily obtained from pan-European datasets, as described below:

- topographic variables can be obtained from the EU-DEM (García et al., 2015), using different methodologies (e.g. Zhang et al., 2013);
- meteorological data can be obtained at the daily scale from the gridded E-OBS (Haylock et al., 2008).
- topographic and meteorological parameters for RUSLE (LS and R) are already mapped for Europe (Panagos et al., 2015);
- pre-fire vegetation cover is available from the CORINE Land Cover 2012 (Büttner, 2014);
- burn scar and severity maps are routinely provided by the EFFIS service (e.g. Sedano et al., 2013).

Estimations of cover values (C factor) for burnt areas should be determined for each fire. Although this and previous works provide several indicative values (Fernández et al., 2010; Vieira et al., 2014), more research is needed to derive them for different burn severities given their importance for post-fire erosion (Fernández et al., 2010; Fernández and Vega, 2016; Larsen and MacDonald, 2007; Vieira et al., 2015), or risk attenuation due to the system's response (e.g. natural needle mulch). Vegetation cover for MMF and PESERA models can be estimated from vegetation cover indices (Huete et al., 1999), as shown by Van Eck et al. (2016), however it is difficult to separate between canopy and ground cover using satellite imagery. This is also a problem when estimating the P factor for the RUSLE and MMF models, as this is calculated from ground cover.

Soil parameters are available from the SoilGrids database (Tóth et al., 2017). However, the parameters on this database do not fully match the ones required by MMF and PESERA, so robust relationships should be established, such as the one followed by Tavares Wahren et al. (2016) using neural networks, to improve model performance in a Mediterranean forest. For RUSLE, the soil erodibility factor (K) has been mapped for Europe by Panagos et al. (2014) and even considers a correction for soil stone content; however, these values should still be adjusted for post-fire conditions as described earlier.

Given the multiplicity of possible model parameterizations, the use of these models for operational purposes in Mediterranean Europe still requires some work. This study shows that micro-plot experiments can be used to calibrate models in areas dominated by inter-rill erosion, which seems to be the case in most burned areas in the Mediterranean (Shakesby, 2011). Given the large amount of published micro-plot data and the easiness of replicating these experiments, micro-plots can provide rough estimates on model parameters with higher uncertainty.

4.5. Model selection for burned areas

The models used in this work are quite different; RUSLE is a simple empirical model, while both MMF and PESERA are process-based models, and therefore more complex than the former given its monthly time-step. The selection of an appropriate model depends on a variety of factors, as discussed by Beven (2012):

- Data availability - all the models have been parameterized and tested for burned areas in the Iberian Peninsula. PESERA and especially MMF have been applied more often and are possibly more robust. On the other hand, RUSLE is easier to apply since most parameters are readily available.
- Prediction ability - this work has shown that all models can satisfactory simulate post-fire erosion, and the effects of mulching.
- Model limitations - the biggest limitation of RUSLE is that it can only predict soil erosion for small landscape units. In contrast, the PESERA and MMF models are capable of simulating both runoff and erosion, and with some modifications route water and sediment along the catchments.

When strictly considering the objective of this work, i.e. identifying the best model for designing erosion mitigation and rehabilitation measures, the RUSLE model would appear as an interesting solution for non-modellers, since it is easier to apply, it has a number of readily available parameters, and provides satisfactory results. Care should, however, be taken when conducting parameterization and validation exercises with inputs that have been used in other locations, due to climate and soil variability. The MMF and PESERA models are also valuable tools since they can be used as components to route water and sediments to streams, making them particularly useful if included in a tool for assessing the risk of water contamination after fire, a recurrent concern for water managers in burnt areas due to the increase in suspended sediments (Smith et al., 2011). Moreover, their process-based nature allows them to easily handle situations outside their calibration range, making them particularly suitable for research purposes and scenario analysis (Beven, 2012).

That being said, it is not necessarily true that land managers need to select a single model for a specific area. The usefulness of a versatile suite of simple and complex models has been demonstrated for the management of coastal ecosystems (Nunes et al., 2011), and the same approach can be applied for burned areas. As an example, RUSLE can be used for fast and simple hillslope applications (e.g. prioritization of areas-at-risk), while MMF or PESERA can be selected to assess the links between forest ecosystems and the stream network in a GIS environment, for testing different management scenarios (e.g. rehabilitation measures, plowing), similarly to what SWAT model does (Arnold et al., 1998).

5. Conclusions

In this study, three erosion models with different levels of complexity (empirical, semi-empirical and physically-based), were used to predict the hydrological and erosive response in burned forest areas, following a moderate severity fire in North-Central Portugal. The effectiveness of different mulching techniques (hydromulch vs. natural pine needle mulch) in reducing post-fire runoff and soil erosion in fire-affected areas was evaluated using the RUSLE, MMF and PESERA models by comparison to untreated conditions, and the following conclusions can be retrieved:

1. All the models were reasonably able to predict the hydrological and erosive response in burned areas (NSE > 0.6), although MMF and PESERA provide a hydrological parameterization that seem to benefit soil erosion estimations (NSE > 0.8 for calibration, and NSE > 0.7 for validation).
2. Results also showed that all these models can be calibrated at a small spatial scale ($0.5\,m^2$) but provide accurate results at greater spatial scales ($10\,m^2$).
3. From this work, the RUSLE model seems to be efficient for fast and simple applications due to its simplicity and reduced data requirements (e.g. risk areas prioritization).
4. MMF or and PESERA models would be valuable as a base of a tool for assessing the risk of water contamination in fire-affected aquatic ecosystems as well as for testing different land use management scenarios.
5. The results in this study provide indicative values for model application in burned areas, however are limited to a moderate burn severity wildfire, Therefore, care should be taken when applying the inputs in other conditions.
6. More work is needed to derive parameters for different burn severities, and different post-fire mitigation measures given their importance for post-fire erosion.

Acknowledgments

This study was carried out in the framework of the EU-funded RECARE project (ENV.2013.6.2-4, http://recare-project.eu), and by the Portuguese EROSFIRE II project (PTDC/AGR-CFL/70968/2006) project. Vieira D.C.S. was a recipient of a grant from FCT (SFRH/BPD/114898/2016, UID/AMB/50017), as well as Serpa D. (SFRH/BPD/92650/2013), and Prats. S.A. (SFRH/BPD/97851/2013), Keizer J.J. (IF/01465/2015), and Nunes J.P. (IF/00586/2015).

Thanks are due for the finantial suport to MARETEC (UID/EEA/50009/2013) from the FCT, and the finantial support to CESAM (UID/AMB/50017-POCI-01-0145-FEDER-007638) through national funds (PIDDAC), and the co-funding by the FEDER, within the PT2020 Partnership Agreement and Compete 2020.

References

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment — Part 1: model development. J. Am. Water Resour. Assoc. 34, 73–89.

Beven, K.J., 2012. Rainfall-Runoff Modelling: The Primer, 2nd ed. Wiley-Blackwell, Hoboken. http://dx.doi.org/10.1002/9781119951001.

Boix-Fayos, C., Martínez-Mena, M., Calvo-Cases, A., Arnau-Rosalén, E., Albaladejo, J., Castillo, V., 2006. Causes and underlying processes of measurement variability in field erosion plots in Mediterranean conditions. Earth Surf. Process. Landf. 32, 85–101. http://dx.doi.org/10.1002/esp.1382.

Borrelli, P., Panagos, P., Langhammer, J., Apostol, B., Schütt, B., 2016. Assessment of the

cover changes and the soil loss potential in European forestland: first approach to derive indicators to capture the ecological impacts on soil-related forest ecosystems. Ecol. Indic. 60, 1208–1220. http://dx.doi.org/10.1016/j.ecolind.2015.08.053.
Büttner, G., 2014. CORINE land cover and land cover change products. In: Manakos, I., Braun, M. (Eds.), Land Use and Land Cover Mapping in Europe. Remote Sensing and Digital Image Processing 18 Springer, Dordrecht.
Cardoso, J.C., Bessa, M.T., Marado, M.B., 1971. Carta dos solos de Portugal (1:1.000.000). Serviço de Reconhecimento e de Ordenamento Agrário. Secretaria de Estado da Agricultura, Lisboa, Portugal.
Cardoso, J.C., Bessa, M.T., Marado, M.B., 1973. Carta dos solos de Portugal (1:1.000.000). Agron. Lusit. 33, 461–602.
Carvalho-Santos, C., Nunes, J.P., Monteiro, A.T., Hein, L., Honrado, J.P., 2016. Assessing the effects of land cover and future climate conditions on the provision of hydrological services in a medium-sized watershed of Portugal. Hydrol. Process. 30, 720–738. http://dx.doi.org/10.1002/hyp.10621.
Certini, G., 2005. Effects of fire on properties of forest soils: a review. Oecologia 143 (1), 1–10. http://dx.doi.org/10.1007/s00442-004-1788-8.
Chen, L., Berli, M., Chief, K., 2013. Examining modeling approaches for the rainfall-runoff process in wildfire-affected watersheds: using San Dimas experimental forest. J. Am. Water Resour. Assoc. 49, 851–866. http://dx.doi.org/10.1111/jawr.12043.
Coutinho, M.A., Tomás, P., 1995. Characterisation of raindrop size distributions at the Vale Formoso Experimental erosion centre. Catena 25, 187–197.
DeBano, L.F., Neary, D.G., Ffolliott, P.F., 1998. Fire's Effects on Ecosystems. Wiley, New York.
Esteves, T.C.J., Kirkby, M.J., Shakesby, R.A., Ferreira, A.J.D., Soares, J.A.A., Irvine, B.J., Ferreira, C.S.S., Coelho, C.O.A., Bento, C.P.M., Carreiras, M.A., 2012. Mitigating land degradation caused by wildfire: application of the PESERA model to fire-affected sites in central Portugal. Geoderma 191, 40–50. http://dx.doi.org/10.1016/j.geoderma.2012.01.001.
Fernández, C., Vega, J.A., 2016. Evaluation of RUSLE and PESERA models for predicting soil erosion losses in the first year after wildfire in NW Spain. Geoderma 273, 64–72. http://dx.doi.org/10.1016/j.geoderma.2016.03.016.
Fernández, C., Vega, J., Vieira, D.C.S., 2010. Assessing soil erosion after fire and rehabilitation treatments in NW Spain: performance of RUSLE and revised Morgan–Morgan–Finney models. Land Degrad. Dev. 21 (1), 58–67. http://dx.doi.org/10.1002/ldr.965.
Ferreira, de B.A., 1978. Planaltos e montanhas do norte da Beira - estudo de geomorfologia. Centro de Estudos Geográficos, Lisboa.
García J.C., Antonio J., Garzón A., 2015. Date: EU-DEM Upgrade Documentation EEA User Manual EU-DEM Upgrade 12.
González-Bonorino, G., Osterkamp, W.R., 2004. Applying RUSLE 2.0 on burned forest lands: an appraisal. J. Soil Water Conserv. 59, 36–42.
Gupta, H.V., Sorooshian, S., Yapo, P.O., 1999. Status of automatic calibration for hydrologic models: comparison with multilevel expert calibration. J. Hydrol. Eng. 4 (2), 135–143.
Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from ambient air temperature. American Society of Agricultural Engineers (Microfiche collection) (USA). fiche no. 85-2517.
Haylock, M.R., Hofstra, N., Klein Tank, A.M.G., Klok, E.J., Jones, P.D., New, M., 2008. A European daily high-resolution gridded dataset of surface temperature and precipitation. J. Geophys. Res. (Atmos.) 113, D20119. http://dx.doi.org/10.1029/2008JD010201.
Huete, A., Justice, C., van Leeuwen, W., 1999. MODIS Vegetation Index (MOD13). Algorithm Theoretical Basis Document. University of Arizona, Tucson.
Hungerford, R.D., 1996. Soils-Fire in Ecosystem Management Notes: Unit II-I. U.S. Department of Agriculture, Forest Service, National Advanced Resource Technology Center, Marana, AZ.
Hyde, K., Dickinson, M.B., Bohrer, G., Calkin, D., Evers, L., Gilbertson-Day, J., Nicolet, T., Ryan, K., Tague, C., 2012. Research and development supporting risk-based wildfire effects prediction for fuels and fire management: status and needs. Int. J. Wildland Fire 22, 37–50. http://dx.doi.org/10.1071/WF11143.
Karamesouti, M., Petropoulos, G.P., Papanikolaou, I.D., Kairis, O., Kosmas, K., 2016. Erosion rate predictions from PESERA and RUSLE at a Mediterranean site before and after a wildfire: comparison & implications. Geoderma 261, 44–58. http://dx.doi.org/10.1016/j.geoderma.2015.06.025.
Keizer, J.J., Doerr, S.H., Malvar, M.C., Prats, S.A., Ferreira, R.S.V., Oñate, M.G., Coelho, C.O.A., Ferreira, A.J.D., 2008. Temporal variation in topsoil water repellency in two recently burnt eucalypt stands in north-central Portugal. Catena 74, 192–204.
Kirkby, M.J., Gobin, A., Irvine, B.J., 2003. Pan European Soil Erosion Risk Assessment.
Kirkby, M.J., Jones, R.J.A., Irvine, B., Gobin, A., Govers, G., Cerdan, O., Van Rompaey, A. J.J., Le Bissonnais, Y., Daroussin, J., King, D., Montanarella, L., Grimm, M., Vieillefont, V., Puigdefabregas, J., Boer, M., Kosmas, C., Yassoglou, N., Tsara, M., Mantel, S., Van Lynden, G.J., Huting, J., 2004. Pan-European Soil Erosion Risk Assessment: The PESERA Map, Version 1 October 2003. Explanation of Special Publication Ispra 2004No.73 (S.P.I.04.73). European Soil Bureau Research Report No.16, EUR 21176, 18pp. and 1 map in ISO B1 format. Office for Official Publications of the European Communities, Luxembourg.
Kirkby, M.J., Irvine, B.J., Jones, R.J.A., Govers, G., Team, P., 2008. The PESERA coarse scale erosion model for Europe. I. — Model rationale and implementation. Eur. J. Soil Sci. 59 (6), 1293–1306.
Larsen, I.J., MacDonald, L.H., 2007. Predicting postfire sediment yields at the hillslope scale: testing RUSLE and Disturbed WEPP. Water Resour. Res. 43, 11.
Maia, P., Pausas, J.G., Arcenegui, V., Guerrero, C., Pérez-Bejarano, A., Mataix-Solera, J., Varela, M.E.T., Fernandes, I., Pedrosa, E.T., Keizer, J.J., 2012a. Wildfire effects on the soil seed bank of a maritime pine stand—the importance of fire severity. Geoderma 191, 80–88. http://dx.doi.org/10.1016/j.geoderma.2012.02.001.
Maia, P., Pausas, J.G., Vasques, A., Keizer, J.J., 2012b. Fire severity as a key factor in post-fire regeneration of Pinus pinaster (Ait.) in central Portugal. Ann. For. Sci. 69, 499–507. http://dx.doi.org/10.1007/s13595-012-0203-6.
Miller, J.D., Nyhan, J.W., Yool, R.S., 2003. Modeling potential erosion due to the Cerro Grande fire with a GIS-based implementation of the revised Universal soil loss equation. Int. J. Wildland Fire 12 (1), 85–100.
Moody, J.A., Shakesby, R.A., Robichaud, P.R., Cannon, S.H., Martin, D.A., 2013. Current research issues related to post-wildfire runoff and erosion processes. Earth Sci. Rev. 122, 10–37. http://dx.doi.org/10.1016/j.earscirev.2013.03.004.
Morgan, R.P.C., 1995. Soil Erosion and Conservation. Longman Group Limited, London, UK.
Morgan, R.P.C., 2001. A simple approach to soil loss prediction: a revised Morgan–Morgan–Finney model. Catena 44, 305–322.
Morgan, R.P.C., Duzant, J.H., 2008. Modified MMF (Morgan–Morgan–Finney) model for evaluating effects of crops and vegetation cover on soil erosion. Earth Surf. Process. Landf. 32, 90–106. http://dx.doi.org/10.1002/esp.1530.
Morgan, R.P.C., Morgan, D.D.V., Finney, H.J., 1984. A predictive model for the assessment of erosion risk. J. Agric. Eng. Res. 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. Trans. ASABE 50 (3), 885–900.
Nearing, M.A., Govers, G., Norton, L.D., 1999. Variability in soil erosion data from replicated plots. Soil Sci. Soc. Am. J. 63, 6.
Neary, D.G., Ryan, K.C., DeBano, L.F., 2005. Wildland fire in ecosystems. Effects of fire on soil and water. USDA Forest Service, Rocky Mountain Research Station. General Technical Report RMRS-GTR-42-vol 4, Ogden, UT.
Nunes, J.P., Ferreira, J.G., Bricker, S.B., O'Loan, B., Dabrowski, T., Dallaghan, B., Hawkins, A.J.S., O'Connor, B., O'Carroll, T., 2011. Towards an ecosystem approach to aquaculture: assessment of sustainable shellfish cultivation at different scales of space, time and complexity. Aquaculture 315, 369–383. http://dx.doi.org/10.1016/j.aquaculture.2011.02.048.
Nunes, J.P., Naranjo Quintanilla, P., Santos, J.M., Serpa, D., Carvalho-Santos, C., Rocha, J., Keizer, J.J., Keesstra, S.D., 2017. Afforestation, subsequent forest fires and provision of hydrological services: a model-based analysis for a Mediterranean mountainous catchment. Land Degrad. Dev. http://dx.doi.org/10.1002/ldr.2776.
Panagos, P., Meusburger, K., Ballabio, C., Borrelli, P., Alewell, C., 2014. Soil erodibility in Europe: a high-resolution dataset based on LUCAS. Sci. Total Environ. 479–480 (1), 189–200. http://dx.doi.org/10.1016/j.scitotenv.2014.02.010.
Panagos, P., Ballabio, C., Borrelli, P., Meusburger, K., Klik, A., Rousseva, S., Tadić, M.P., Michaelides, S., Hrabalíková, M., Olsen, P., Aalto, J., Lakatos, M., Rymszewicz, A., Dumitrescu, A., Beguería, S., Alewell, C., 2015. Rainfall erosivity in Europe. Sci. Total Environ. 511, 801–814. http://dx.doi.org/10.1016/j.scitotenv.2015.01.008.
Pietraszek, J.H., 2006. Controls on Post-fire Erosion at the Hillslope Scale. Colorado State University, Colorado Front Range.
Pimentel, N.L., 1994. As formas do relevo e a sua origem. In: Brito, R.S. (Ed.), Portugal Perfil Geográfico. Editorial Estampa, Lisboa, pp. 29–50.
Poesen, J.W., Torri, D., Bunte, K., 1994. Effects of rock fragments on soil erosion by water at different spatial scales: a review. Catena 23 (1–2), 141–166. https://doi.org/10.1016/0341-8162(94)90058-2
Prats, S.A., Martins, M.A.S., Malvar, M.C., Ben-Hur, M., Keizer, J.J., 2014. Polyacrylamide application versus forest residue mulching for reducing post-fire runoff and soil erosion. Sci. Total Environ. 468–469, 464–474. http://dx.doi.org/10.1016/j.scitotenv.2013.08.066.
Prats, S.A., Malvar, M.C., Vieira, D.C.S., MacDonald, L.H., Keizer, J.J., 2016. Effectiveness of hydro-mulching to reduce runoff and erosion in a recently burnt pine plantation in central Portugal. Land Degrad. Dev. http://dx.doi.org/10.1002/ldr.2236.
Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C., (co-ordinators), 1997. Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). Agriculture Handbook n-703. USDA. Natural Resources Conservation Service, Washington, DC.
Ritchie, J.T., 1972. A model for predicting evaporation from a row crop with incomplete cover. Water Resour. Res. 8, 1204–1213.
Robichaud, P.R., Ashmun, L.E., 2012. Tools to aid post-wildfire assessment and erosion-mitigation treatment decisions. Int. J. Wildland Fire 22, 95–105. http://dx.doi.org/10.1071/WF11162.
Robichaud, P.R., Elliot, W.J., Pierson, F.B., Hall, D.E., Moffet, C.A., 2007. Predicting postfire erosion and mitigation effectiveness with a web-based probabilistic erosion model. Catena 71, 229–241.
Robichaud, P.R., Ashmun, L.E., Sims, B.D., 2010. Post-Fire Treatment Effectiveness for Hillslope Stabilization. General Technical Report, RMRS-GTR-240. U. S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO.
Robichaud, P.R., Lewis, S.A., Wagenbrenner, J.W., Ashmun, L.E., Brown, R.E., 2013. Post-fire mulching for runoff and erosion mitigation. Part I: effectiveness at reducing hillslope erosion rates. Catena 105, 75–92.
Rohatgi, A., 2018. WebPlotDigitizer. Version: 4.1. 〈https://automeris.io/WebPlotDigitizer〉 (Accessed 17 April 2018).
Roose, E., 1977. *Vingt années de mesure de l'érosion en petites parcelles en Afrique de l'Ouest*. Travaux et documents Orstom, n° 78. Éditions Orstom, Paris, pp. 108.
Rulli, M.C., Offeddu, L., Santini, M., 2013. Modeling post-fire water erosion mitigation strategies. Hydrol. Earth Syst. Sci. 17 (6), 2323–2337. http://dx.doi.org/10.5194/hess-17-2323-2013.
San-Miguel-Ayanz, J., Durrant, T., Boca, R., Libertà, G., Branco, A., de Rigo, D., Ferrari, D., Maianti, P., Vivancos, T.A., Schulte, E., Loffler, P., 2017. Forest Fires in Europe, Middle East and North Africa 2016. EUR 28707 EN, Publications Office, Luxembourg, 2017, ISBN 978-92-79-71292-0, doi: 10.2760/17690.
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. J. Am. Water Resour. Assoc. 37 (5), 1169–1188.
Santín, C., Doerr, S.H., 2016. Fire effects on soils: the human dimension. Philos. Trans. R. Soc. B 371, 20150171. http://dx.doi.org/10.1098/rstb.2015.0171.
Sedano, F., Kempeneers, P., San Miguel, J., Strobl, P., Vogt, P., 2013. Towards a pan-European burnt scar mapping methodology based on single date medium resolution optical remote sensing data. Int. J. Appl. Earth Obs. Geoinf. 20, 52–59. http://dx.doi.org/10.1016/j.jag.2011.08.003.
Shakesby, R.A., 2011. Post-wildfire soil erosion in the Mediterranean: review and future research directions. Earth Sci. Rev. 105, 71–100. http://dx.doi.org/10.1016/j.earscirev.2011.01.001.
Shakesby, R.A., Doerr, S.H., 2006. Wildfire as a hydrological and geomorphological agent. Earth Sci. Rev. 74, 269–307. http://dx.doi.org/10.1016/j.earscirev.2005.10.006.
Shakesby, R.A., Moody, J.A., Martin, D.A., Robichaud, P.R., 2016. Synthesising empirical results to improve predictions of post-wildfire runoff and erosion response. Int. J. Wildland Fire 25, 257–261. http://dx.doi.org/10.1071/WF16021.
Singh, J., Knapp, H.V., Demissie, M., 2004. Hydrologic modeling of the Iroquois River watershed using HSPF and SWAT. ISWS CR 2004-08. Champaign, Ill.: Illinois State Water Survey. ⟨www.sws.uiuc.edu/pubdoc/CR/ISWSCR2004-08.pdf⟩. (Accessed 14 February 2018).
Smith, H.G., Sheridan, G.J., Lane, P.N.J., Nyman, P., Haydon, S., 2011. Wildfire effects on water quality in forest catchments: a review with implications for water supply. J. Hydrol. 396, 170–192. http://dx.doi.org/10.1016/j.jhydrol.2010.10.043.
SNIRH, 2012. Sistema Nacional de Informação de Recursos Hídricos. ⟨http://snirh.pt⟩ (Accessed 1 March 2012).
Soto, B., Díaz-Fierros, F., 1998. Runoff and soil erosion from areas of burnt scrub: comparison of experimental results with those predicted by the WEPP model. Catena 31, 257–270.
Terranova, O., Antronico, L., Coscarelli, R., Iaquinta, P., 2009. Soil erosion risk scenarios in the Mediterranean environment using RUSLE and GIS: an application model for Calabria (southern Italy). Geomorphology 112 (3–4), 228–245. http://dx.doi.org/10.1016/j.geomorph.2009.06.009.
Tóth, B., Weynants, M., Pásztor, L., Hengl, T., 2017. 3D soil hydraulic database of Europe at 250 m resolution. Hydrol. Process. 31, 2662–2666. http://dx.doi.org/10.1002/hyp.11203.
Turco, M., Llasat, M.C., von Hardenberg, J., Provenzale, A., 2014. Climate change impacts on wildfires in a Mediterranean environment. Clim. Change 125, 369–380. http://dx.doi.org/10.1007/s10584-014-1183-3.
Turco, M., Bedia, J., Di Liberto, F., Fiorucci, P., von Hardenberg, J., Koutsias, N., et al., 2016. Decreasing Fires in Mediterranean Europe (https://doi.org/). PLoS ONE11 3, e0150663. http://dx.doi.org/10.1371/journal.pone.0150663.
Van Eck, C.M., Nunes, J.P., Vieira, D.C.S., Keesstra, S., Keizer, J.J., 2016. Physically-based modelling of the post-fire runoff response of a forest catchment in Central Portugal: using field versus remote sensing based estimates of vegetation recovery. Land Degrad. Dev. 27, 1535–1544. http://dx.doi.org/10.1002/ldr.2507.
Van Liew, M.W., Arnold, J.G., Garbrecht, J.D., 2003. Hydrologic simulation on agricultural watersheds: choosing between two models. Trans. ASAE 46 (6), 1539–1551.
Verkaik, I., Rieradevall, M., Cooper, S.D., Melack, J.M., Dudley, T.L., Prat, N., 2013. Fire as a disturbance in mediterranean climate streams (https://doi.org/). Hydrobiologia 719, 353–382. http://dx.doi.org/10.1007/s10750-013-1463-3.
Viedma, O., Moity, N., Moreno, J.M., 2015. Changes in landscape fire-hazard during the second half of the 20th century: agriculture abandonment and the changing role of driving factors. Agric. Ecosyst. Environ. 207, 126–140. http://dx.doi.org/10.1016/j.agee.2015.04.011.
Vieira, D.C.S., 2015. Understanding and Modelling Hydrological and Soil Erosion Processes in Burnt Forest Catchments (Ph.D. thesis). University of Aveiro.
Vieira, D.C.S., Prats, S.A., Nunes, J.P., Shakesby, R.A., Coelho, C.O.A., Keizer, J.J., 2014. Modelling runoff and erosion, and their mitigation, in burned Portuguese forest using the revised Morgan-Morgan-Finney model. For. Ecol. Manag. 314, 150–165. http://dx.doi.org/10.1016/j.foreco.2013.12.006.
Vieira, D.C.S., Fernández, C., Vega, J.A., Keizer, J.J., 2015. Does soil burn severity affect the post-fire runoff and interrill erosion response? A review based on meta-analysis of field rainfall simulation data. J. Hydrol. 523, 452–464. http://dx.doi.org/10.1016/j.jhydrol.2015.01.071.
Vieira, D.C.S., Malvar, C., Fernández, M.C., Serpa, D., Keizer, J.J., 2016. Annual runoff and erosion in a recently burn Mediterranean forest – The effects of plowing and time-since-fire. Geomorphology 270, 172–183. http://dx.doi.org/10.1016/j.geomorph.2016.06.042.
Wahren, F.T., Julich, S., Nunes, J.P., Gonzalez-Pelayo, O., Hawtree, D., Feger, K.-H., Keizer, J.J., 2016. Combining digital soil mapping and hydrological modeling in a data scarce watershed in north-central Portugal. Geoderma 264, 350–362. http://dx.doi.org/10.1016/j.geoderma.2015.08.023.
Wischmeier, W.H., Smith, D.D., 1978. Predicting rainfall-erosion losses- a guide to conservation planning. USDA, Washington, D.C, pp. 58 (Agriculture Handbook. No. 537).
Wohlgemuth, P.M., Beyers, J.L., Hubbert, K.R., 2009. Rehabilitation strategies after fire: the California, USA experience. In: Cerdà, A., Robichaud, P.R. (Eds.), In Fire Effects on Soils and Restoration Strategies. Science Publishers, Inc, Enfield, NH, USA, pp. 511–535.