

State of Science

What is wrong with post-fire soil erosion modelling? A meta-analysis on current approaches, research gaps, and future directions

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ABSTRACT: In the near future, a higher occurrence of wildfires is expected due to climate change, carrying social, environmental, and economic implications. Such impacts are often associated with an increase of post-fire hydrological and erosive responses, which are difficult to predict. Soil erosion models have been proven to be a valuable tool in the decision-making process, from emergency response to long-term planning, however, they were not designed for post-fire conditions, so need to be adapted to include fire-induced changes.

In recent years, there have been an increasing number of studies testing different models and adaptations for the prediction of post-fire soil erosion. However, many of these adaptations are being applied without field validation or model performance assessment. Therefore, this study aims to describe the scientific advances in the last 20 years in post-fire soil erosion modelling research and evaluate model adaptations to burned areas that aim to include: (i) fire-induced changes in soil and ground cover; (ii) fire-induced changes in infiltration; (iii) burn severity; and (iv) mitigation measures in their predictions. This study also discusses the strengths and weaknesses of these approaches, suggests potential improvements, and identifies directions for future research.

Results show that studies are not homogeneously distributed worldwide, according to the model type used or by region most affected by wildfire. During calibration, 73% of cases involved model adaptation to burned conditions, and only 21% attempted to accommodate new processes. Burn severity was addressed in 75% of cases, whilst mitigation measures were simulated in 27%. Additionally, only a minor percentage of model predictions were validated with independent field data (17%) or assessed for uncertainties (13%). Therefore, further efforts are required in the adaptation of erosion models to burned conditions, to be widely used for post-fire management decisions. © 2020 John Wiley & Sons, Ltd.

KEYWORDS: erosion model; infiltration; burn severity; model efficiency; meta-analysis

Introduction

Wildfires are often identified as one of the main drivers of soil erosion and land degradation, inducing hydrological and geomorphological changes (Shakesby and Doerr, 2006). One direct effect of wildfires is the loss of protective cover (vegetation and/or litter), which reduces the rainfall interception, surface roughness, evapotranspiration, and infiltration capacity of soils. The soil structure can also be altered directly in moderate to high-severity wildfires due to the destruction of the organic and/or mineralogical bindings of soil particles (Larsen and MacDonald, 2007; Fernández *et al.*, 2010). After fires, the fraction of bare soil exposed to raindrop impact is increased, allowing raindrop kinetic energy to be transferred directly to the soil surface, breaking down its structure (DeBano

et al., 1998; DeBano, 2000; Robichaud *et al.*, 2000). The destruction of soil structure, both directly and indirectly by fire, favours runoff and particle detachment, increasing sediment losses (Robichaud *et al.*, 2000; Shakesby and Doerr, 2006). In some conditions, the removal of the surface cover, combined with soil fire-induced changes, can also allow the creation of soil crusts, and these can inhibit infiltration (Bradford *et al.*, 1987; Silva *et al.*, 2019). On top of this, wildfires may also induce or enhance the occurrence of soil water repellency (SWR) (Doerr and Thomas, 2000).

The magnitude and impacts of these fire-induced changes are intrinsically associated with fire severity. Higher fire severities increase the occurrence of on-site runoff and erosion, but also of off-site effects such as destructive floods and debris flows downstream from the burned area (Vieira

et al., 2015). Therefore, a proper assessment of soil burn severity is crucial for soil erosion predictions and planning post-fire mitigation measures (Fernández and Vega, 2016, 2018; Vieira *et al.*, 2018a). Besides soil erosion by water, burned areas are also affected by other processes, such as debris flows, landslides, wind erosion, gully erosion, and dry ravel (Shakesby and Doerr, 2006), however these processes are not approached in this review.

In order to mitigate post-fire soil erosion by water, there has been a development of mitigation treatments that can be classified into three major categories: protective cover layers, vegetative regrowth methods, and erosion barriers. Protective cover layers (e.g. mulch) are considered the most efficient in reducing soil erosion rates (Robichaud and Ashmun, 2013; Prats *et al.*, 2014, 2015; Keizer *et al.*, 2018; Lopes *et al.*, 2020). They reduce the kinetic energy of raindrops and impede the water flow, thereby limiting the detachment and transport of soil particles and favouring water infiltration (Ferreira *et al.*, 2005; Bautista *et al.*, 2009; Cerdà and Robichaud, 2009).

However, when an extensive area is affected by wildfire, it is difficult to specify intervention priorities to mitigate soil erosion by water or to decide whether such mitigation is required in the first place, as the hydrological and erosive response is a complex process and is highly affected by external factors. From a local point of view, burn severity, pre-fire land use, soil characteristics, or rainfall patterns increase the complexity of these decisions. On a wider scale, other factors might come into play, such as climate, terrain, or the presence of values-at-risk downstream from the burned area, which could also add complexity to these same prioritizations (Robichaud *et al.*, 2000). To address these sources of variability in a cost-effective way, erosion models arise as a powerful tool, providing crucial information to support decision-making, either for emergency responses and/or long-term planning.

The most widely used models to estimate post-fire soil erosion by water are empirically based, such as the Universal Soil Loss Equation (USLE; Wischmeier and Smith, 1978) and its revised form RUSLE (Renard *et al.*, 1997). Such wide application is related to the fact that empirical models generally require less demanding input data when compared to physically based ones (Merritt *et al.*, 2003). USLE and RUSLE models, as well as other erosion models, were developed to estimate soil erosion by water in agricultural lands, and are not adapted to take into account the impacts of wildfires on vegetation (Morrison and Kolden, 2015; Hosseini *et al.*, 2018) and soil properties (Chen *et al.*, 2013; Moody *et al.*, 2013; Fernández and Vega, 2018; Nunes *et al.*, 2018). Several modelling tools are also based on (R)USLE, such as the Soil and Water Assessment Tool (SWAT; Neitsch *et al.*, 2011), the Soil Erosion Model for Mountain Areas in Korea (SEMMA; Park *et al.*, 2012), or the revised Morgan–Morgan–Finney erosion models (MMF; Morgan, 2001). Physically based models are more complex and data demanding, such as the Pan-European Soil Erosion Risk Assessment model (PESERA; Kirkby *et al.*, 2008) or the Water Erosion Prediction Project-related models (WEPP; Nearing *et al.*, 1989; Flanagan and Nearing, 1995).

Post-fire modelling research focuses on providing accurate predictions for hydrological and geomorphological effects in fire-affected scenarios. Building a coherent knowledge database is difficult, not only because of regional differences in climate, soil properties, and wildfire characteristics, but also due to differences in research approaches and scales (Shakesby and Doerr, 2006), or even due to the model limitations in representing soil erosion processes (Nearing, 1998). The need to adapt models to post-fire conditions and validate their predictions has been emphasized in several studies (Larsen and MacDonald, 2007; Fernández *et al.*, 2010; Fernández and

Vega, 2018; Vieira *et al.*, 2018a), rather than developing a new model specifically for post-fire conditions. These model adaptations to burned conditions were typically achieved by introducing an empirical ‘fire factor’ or by adjusting input parameters such as ground cover, surface roughness, or soil hydraulic properties (Fernández *et al.*, 2010; Chen *et al.*, 2013; Vieira *et al.*, 2014, 2018a). This approach has often been used because of the current lack of knowledge and available data to accurately predict post-fire hydrological responses (Larsen and MacDonald, 2007; Moody *et al.*, 2013; Fernández and Vega, 2018; Hosseini *et al.*, 2018; Vieira *et al.*, 2018a), combined with the urgent need for managers to predict the correspondent hydrological and erosive risks (Robichaud *et al.*, 2016).

The aim of this study is to review the scientific advances of the last 20 years in post-fire soil erosion modelling, from a meta-analysis approach. The specific objectives of this work are to identify whether the authors addressed changes in (i) soil structure and ground cover, (ii) water infiltration capacity in the soil, (iii) included burn severity in their predictions, and (iv) simulated the applications of post-fire mitigation measures. The study also intends to evaluate the main modelling approaches used, the author’s model efficiency assessment whilst conducting a critical overview of those options, as well as providing guidelines for future studies.

Materials and Methods

Selection of the publications

An extensive search was conducted through the Scopus database on 27 February 2020 for articles published prior to 2019 that combined three terms (Figure 1). This search was focused on finding modelling studies that tested and/or adapted models to estimate post-fire soil erosion by water, from an existing burned area study case. This search retrieved 664 works that were screened and excluded if they met any of the following criteria:

- review and/or meta-analysis papers;
- journals without a peer-review process;
- books or book chapters;
- reports;
- editorials;
- conference proceedings;
- works in which the modelling was conducted on individual processes;
- studies modelling debris flows and landslides;
- empirical or statistical regressions;
- works that did not conduct post-fire soil erosion modelling in an existing burned area;
- works that were not written in English

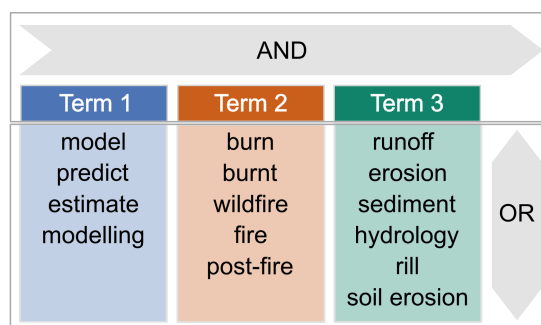


Figure 1. Combination of terms used for search in the Scopus database. [Colour figure can be viewed at wileyonlinelibrary.com]

The selected publications, as well as their reference lists, were further reviewed, resulting in a total of 41 articles (Table 1), published from 1998 to 2019, as shown in Figure 2.

Data analysis

Studies were divided into two groups according to the formulation basis of the models used: physical or empirical. Following this methodology, the selected papers were searched to find whether they addressed any of the four key variables affecting post-fire hydrological response:

- i *Changes in soil structure and ground cover.* Direct fire-induced changes as a consequence of the fire, leading to a reduction in interception and roughness due to vegetation consumption, and changes in soil structure, such as soil erodibility, porosity, aggregate stability, or organic matter (Shakesby and Doerr, 2006; Faria *et al.*, 2015). These fire-induced changes cause the soil to be less protected from splash and runoff processes, as fire-impacted soil particles are more prone to be detached and transported.
- ii *Post-fire hydrological effects related to changes in soil water infiltration.* Indirect fire-induced changes in soil infiltration capacity, such as the occurrence of SWR (Doerr and Thomas, 2000; Shakesby and Doerr, 2006), or changes in saturated hydraulic conductivity or sorptivity (Martin and Moody, 2001; Moody and Ebel, 2013). These fire-induced changes promote surface runoff generation, which increases the magnitude and energy of runoff to detach and transport soil.
- iii *Changes related to burn severity.* The degree of fire-induced changes (i, ii) has been associated with burn severity, which in turn is reflected in the magnitude of the hydrological and erosive response after fire (Shakesby and Doerr, 2006; Shakesby, 2011; Moody *et al.*, 2013; Vieira *et al.*, 2015), and the window of disturbance (MacDonald and Larsen, 2009; Vieira *et al.*, 2016).
- iv *Post-fire erosion mitigation measures.* The application of techniques that attempt to provide a reduction in flow velocity, promote infiltration, and protect soil from runoff and raindrop impact, therefore reducing soil erosion rates (Robichaud and Ashmun, 2013; Prats *et al.*, 2015).

Additionally, to fulfil the aims of this work, it was identified whether the selected studies conducted any type of model adaptation to burned areas, as well as improvements of single inputs and model components. Other aspects were also considered, such as whether the post-fire soil erosion by water data was compared to the model predictions (calibration and validation), or if the authors applied the models in unburned conditions. Furthermore, model efficiency indicators were used to classify model performance (Moriassi *et al.*, 2015), in accordance with the results obtained by the authors in each publication. To compare the efficiency among model types, the values of the most used efficiency indices across the studied cases (R^2 , NSE, RMSE) were retrieved, included in the database, and further analysed. In addition, the predicted and measured erosion values from those cases were also retrieved.

Results

Description of the dataset

From the 41 analysed research articles, 52 individual cases were identified. Amongst the empirical models, RUSLE and MMF were the most commonly used (16 and 4 cases,

respectively). In contrast, the WEPP-based (9) and PESERA (3) models were the most representative of the physically based models (Figure 3).

The database covers a wide array of scales, ranging from hillslope to regional modelling; however, most of the predictions were performed at hillslope (54%) or catchment (27%) scale (Figure 4). The vast majority of cases (50%) were developed in forest ecosystems (Figure 4), and to a lesser extent in areas with mixed land cover types (40%) and shrublands (10%). Finally, the bulk of the studies were focused on soil erosion after wildfires (92%), whereas only four cases dealt with prescribed burnings (Figure 4).

Global distribution and regional trends

The works included in the present meta-analysis were conducted in only four continents (Figure 5a), and the greatest number of study cases were found in Europe (25) and the United States (23). The distribution of studies does not correspond to the burned area distribution across the globe. According to the Global Wildfire Information System (GWIS, 2019), the continents that contribute most to the annual burned area (Figure 5b) are Africa (63%), Australia (13%), and South America (9%), in which 7, 6, and 2%, respectively, of the continental area was affected (Figure 5c).

Among the continents with more observations, a greater usage of empirical models was identified amongst the European cases (64%), whilst in the United States there was a preference for the physically based models (63%). The most often represented models were RUSLE in Europe and WEPP in the United States.

Model adaptation to burned areas

In 73% of cases (Table 2), the authors performed model adaptations to post-fire conditions. Most of these model adaptations involved the testing of equations or methods that had been applied elsewhere, and only 21% modified inputs or model components with novel equations or processes (Table 2). All of these adaptations were analysed and compiled into two main fire-induced changes groups: soil structure and ground cover, and soil water infiltration (see the online Supporting Information Table S1).

Model adaptations for soil structure and ground cover in post-fire conditions

Most of the modifications associated with soil structure and ground cover involved alterations in soil erodibility and vegetation cover, as described extensively in the online Supporting Information (Table S1). Modifications to soil erodibility in USLE-family models from our database (RUSLE and USLE-Forest) mainly aimed at incorporating burn severity and SWR, which are not explicitly considered in RUSLE (Larsen and MacDonald, 2007). These changes were based on literature and field measurements, although in general they did not result in any model efficiency improvements. Fernández and Vega (2016) and Karamesouti *et al.* (2016) also increased the erodibility factor proportionally with burn severity to adapt the PESERA model to post-fire conditions. In Fernández and Vega (2016), the authors defined erodibility classes (high, moderate, low) based on the soil losses associated with each degree of soil burn severity. However, the results of this study show that the model tends to underestimate soil erosion compared to measured values. Karamesouti *et al.* (2016) estimated erodibility classes (for pre-fire and post-fire conditions) based on

Table 1. References included in the meta-analysis database

Reference	Country	Fire type	Model	Model reference	Time step	Model basis
Benda <i>et al.</i> (2019)	USA	Wildfire	READI ^m	Benda <i>et al.</i> (2019)	Annual	Physical
Coschignano <i>et al.</i> (2019)	Italy	Wildfire	RUSLE + SCS-CN ^{o,2}	Nearing <i>et al.</i> (1989); Renard <i>et al.</i> (1997)	Annual	Empirical
Lanorte <i>et al.</i> (2019)	Italy	Wildfire	RUSLE ^o	Renard <i>et al.</i> (1997)	Annual	Empirical
Pastor <i>et al.</i> (2019)	Portugal	Wildfire	LandSoil ⁱ	Ciampalini <i>et al.</i> (2012)	3 years	Physical
Shan <i>et al.</i> (2019)	Australia	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
Thompson <i>et al.</i> (2019)	USA	Wildfire	USLE-Forest ^{o,2}	Dissmeyer and Foster (1980)	Annual	Empirical
Brown <i>et al.</i> (2018)	Portugal	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
Colson <i>et al.</i> (2018)	Spain	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
Fernández and Vega (2018)	Spain	Wildfire	RUSLE Disturbed ^{t,1}	Renard <i>et al.</i> (1997)	Annual	Empirical
			WEPP	Elliot (2004)	Annual	Physical
Hosseini <i>et al.</i> (2018)	Portugal	Wildfire	MMF ^j	Morgan (2001)	Seasonal	Empirical
Nunes <i>et al.</i> (2018)	Portugal	Wildfire	SWAT ^r	Neitsch <i>et al.</i> (2011)	Monthly	Empirical
Srivastava <i>et al.</i> (2018)	USA	Wildfire	GIS WEPP ^{t,2}	Flanagan and Nearing (1995)	Daily	Physical
Vieira <i>et al.</i> (2018a)	Portugal	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
			MMF	Morgan (2001)	Annual	Empirical
			PESERA ^k	Kirkby <i>et al.</i> (2008)	Annual	Physical
Choi and Kim (2017)	USA	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
Akbarzadeh <i>et al.</i> (2016)	Iran	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
Fernández and Vega (2016)	Spain	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
			PESERA	Kirkby <i>et al.</i> (2003)	Annual	Physical
Fox <i>et al.</i> (2016)	France	Wildfire	POSTFIRE ^l	Fox <i>et al.</i> (2016)	Event	Physical
Karamesouti <i>et al.</i> (2016)	Greece	Wildfire	PESERA	Irvine and Kosmas (2003); Kirkby <i>et al.</i> (2003)	Annual	Physical
			RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
McGuire <i>et al.</i> (2016)	USA	Wildfire	Rose ^d	Hairsine and Rose (1991, 1992a,1992b)	Event	Physical
Robichaud <i>et al.</i> (2016)	USA	Wildfire	ERMIT ^c	Robichaud <i>et al.</i> (2014)	Annual	Physical
Al-Hamdan <i>et al.</i> (2015)	USA	Prescribed/ Wildfire	RHEM ⁿ	Nearing <i>et al.</i> (2011)	Annual	Physical
Morrison and Kolden (2015)	USA	Wildfire	RUSLE	Renard <i>et al.</i> (1991)	Annual	Empirical
Surfleet <i>et al.</i> (2014)	USA	Wildfire	DHSVM ^a	Wigmosta <i>et al.</i> (1994)	Hourly	Physical
			HBV-EC ^e	Bergström (1976, 1992); Moore (1993); Lindström <i>et al.</i> (1997)	Hourly	Physical
					Seasonal/ Annual	Physical
Vieira <i>et al.</i> (2014)	Portugal	Wildfire	MMF	Morgan (2001)	Annual	Empirical
Christie <i>et al.</i> (2013)	USA	Wildfire	USLE-Forest	Dissmeyer and Foster (1980)	Annual	Empirical
			WEPP ^t	Nicks <i>et al.</i> (1995); Elliot (2004)	Annual	Physical
Rulli <i>et al.</i> (2013)	Italy	Wildfire	RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
Park <i>et al.</i> (2012)	Korea	Wildfire	SEMMA ^p	Park <i>et al.</i> (2008)	Event	Empirical
Goodrich <i>et al.</i> (2012)	USA	Wildfire	KINEROS2//	Woolhiser <i>et al.</i> (1990); Goodrich <i>et al.</i> (2012)	Event	Physical
Feikema <i>et al.</i> (2011)	Australia	Wildfire	AGWA ^h		Event	Physical
Fernández <i>et al.</i> (2010)	Spain	Wildfire	E2 ^b	Murray <i>et al.</i> (2005); Argent <i>et al.</i> (2009)	Annual	Physical
			MMF	Morgan (2001)	Annual	Empirical
			RUSLE	Renard <i>et al.</i> (1997)	Annual	Empirical
Myronidis <i>et al.</i> (2010)	Greece	Wildfire	USLE ^{o,1}	Wischmeier and Smith (1978)	Annual	Empirical
Bovolo <i>et al.</i> (2009)	Spain	Wildfire	SHETRAN ^q	Ewen <i>et al.</i> (2000)	Annual	Physical
				Flanagan and Livingston (1995); Flanagan and Nearing (1995)	Event	Physical
Dun <i>et al.</i> (2009)	USA	Prescribed	WEPP		Event	Physical
Larsen and MacDonald (2007)	USA	Wildfire	Disturbed WEPP	Flanagan and Nearing (1995); Elliot (2004)	Year	Physical
			RUSLE	Renard <i>et al.</i> (1997)	Year	Empirical
Moffet <i>et al.</i> (2007)	USA	Prescribed	WEPP	Flanagan and Nearing (1995)	Event	Physical
Spigel and Robichaud (2007)	USA	Wildfire	Disturbed WEPP	Flanagan and Nearing (1995); Elliot (2004)	Annual	Physical
Vafeidis <i>et al.</i> (2007)	Greece	Wildfire	Thornes ^s	Thornes (1985)	Event	Physical
Doten <i>et al.</i> (2006)	USA	Wildfire	DHSVM	Wigmosta <i>et al.</i> (1994)	Event	Physical
Canfield <i>et al.</i> (2005)	USA	Wildfire	HEC6 ^{t,f}	Thomas (2003)	Event	Physical
Wilson <i>et al.</i> (2001)	USA	Wildfire	HEM-GIS ^g	Lane <i>et al.</i> (1988, 1995); Wilson <i>et al.</i> (2001)	Event	Physical
Soto and Díaz-Fierros (1998)	Spain	Prescribed	WEPP	Flanagan and Nearing (1995)	Annual	Physical

- ^aDHSVM = Distributed Hydrology Soil Vegetation Model.
- ^bE2 = Catchment modelling framework.
- ^cERMiT = Erosion Risk Management Tool.
- ^dHairsine–Rose = Hairsine–Rose soil erosion model.
- ^eHBV-EC = Hydrologiska Byråns Vattenbalansavdelning – Environment Canada (version).
- ^fHEC6T = Numerical sedimentation model.
- ^gHEM–GIS = Analytical Hillslope Erosion Model integrated into a Geographical Information System.
- ^hKINEROS2/AGWA = Kinematic runoff and erosion model/Automated Geospatial Watershed Assessment.
- ⁱLandSoil = Landscape design for soil conservation under land use and climate change.
- ^jMMF = Morgan–Morgan–Finney model.
- ^kPESERA = Pan-European Soil Erosion Risk Assessment.
- ^lPOSTFIRE = Post-fire model that maps the burn scar, quantifies potential runoff risk, and estimates soil erosion rates.
- ^mREADI = Road Erosion and Delivery Index.
- ⁿRHEM = Rangeland Hydrological and Erosion Model.
- ^oRUSLE = Revised Universal Soil Loss Equation.
- ^{o1}USLE = Universal Soil Loss Equation.
- ^{o2}USLE-Forest = Universal Soil Loss Equation for Forestry.
- ^{o3}RUSLE + SCS-CN = RUSLE + Soil Conservation Service-Curve Number model.
- ^pSEMMA = Soil Erosion Model for Mountain Areas in Korea.
- ^qSHETRAN = Hydrological model for water flow, solute, and sediment transport in river catchments.
- ^rSWAT = Soil and Water Assessment Tool.
- ^sThornes model = Thornes’ (1985) soil erosion model.
- ^tWEPP = Water Erosion Prediction Project erosion model.
- ¹Disturbed WEPP.
- ²GIS WEPP = Web-based Geographical Information System – WEPP interface.

the literature. In this study, the adaptations were based on the spatial distribution of burn severity classes, leading to more realistic predictions of the spatial distribution of soil erosion. The model performance (Moriassi *et al.*, 2015), however, was unsatisfactory following the model adaptations conducted by Fernández and Vega (2016), whereas in Karamesouti *et al.* (2016) these adaptations were not evaluated.

In the case of WEPP, Moffet *et al.* (2007) focused their attention on optimizing subfactors related to soil surface to emphasize the role of rill formation and surface roughness in post-fire soil erosion by water, approximating their estimations to the mean measured soil erosion. Canfield *et al.* (2005), however, modified the characteristics of sediments and their transport in the HEC6T model, while Al-Hamdan *et al.* (2015)

highlighted the role of texture and ground cover (vegetation and stone cover) in soil erodibility and included it in the RHEM model, obtaining in both studies a good model performance (Moriassi *et al.*, 2015) as a result of these adaptations.

Nevertheless, cover inputs were the most commonly modified to represent burn severity and soil cover evolution after wildfires. Successful modifications were achieved three times with RUSLE, once with a very good (Fernández *et al.*, 2010) and other two with a satisfactory model performance (Larsen and MacDonald, 2007; Moriassi *et al.*, 2015; Vieira *et al.*, 2018a), and generally involved the adjustment of this factor for forest soils and the use of a cover factor (C) estimated in other burned areas (Borrelli *et al.*, 2016). In contrast, Vieira *et al.* (2014) and Hosseini *et al.* (2018) changed the time step

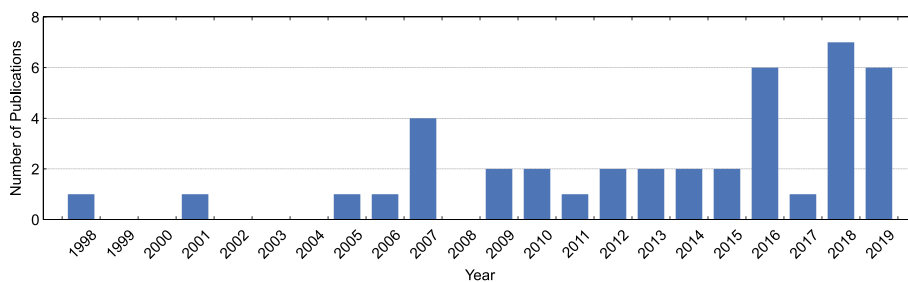


Figure 2. Number of publications per year obtained after the Scopus database search (conducted on 27 February 2020) and the application of the exclusion criteria ($n = 41$). [Colour figure can be viewed at wileyonlinelibrary.com]

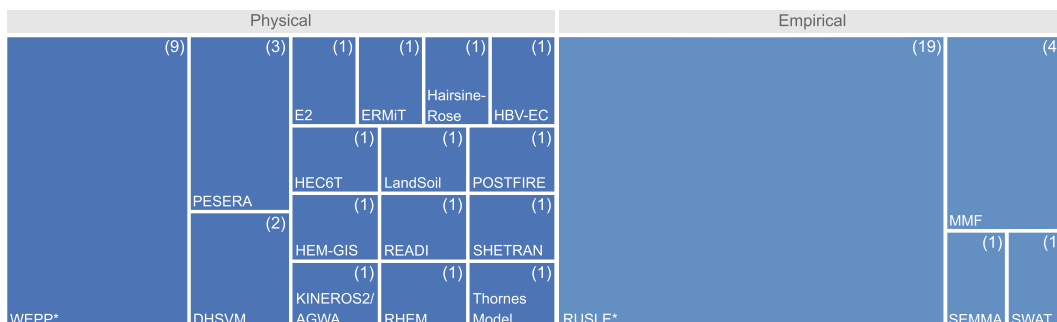


Figure 3. Number of cases in which each model was applied. * WEPP includes the WEPP, WEPP GIS, and Disturbed WEPP models; RUSLE includes the RUSLE, USLE, and USLE-Forest models. [Colour figure can be viewed at wileyonlinelibrary.com]

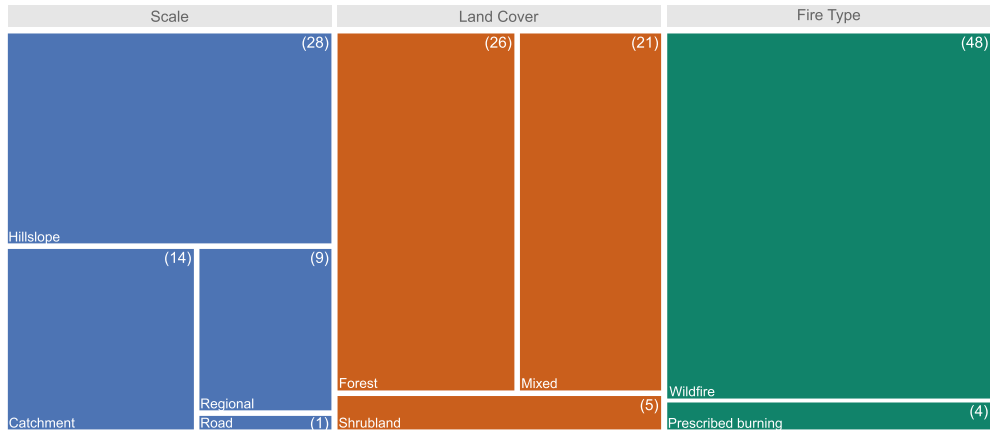


Figure 4. Number of cases per modelling scale, land cover, and fire type. [Colour figure can be viewed at wileyonlinelibrary.com]

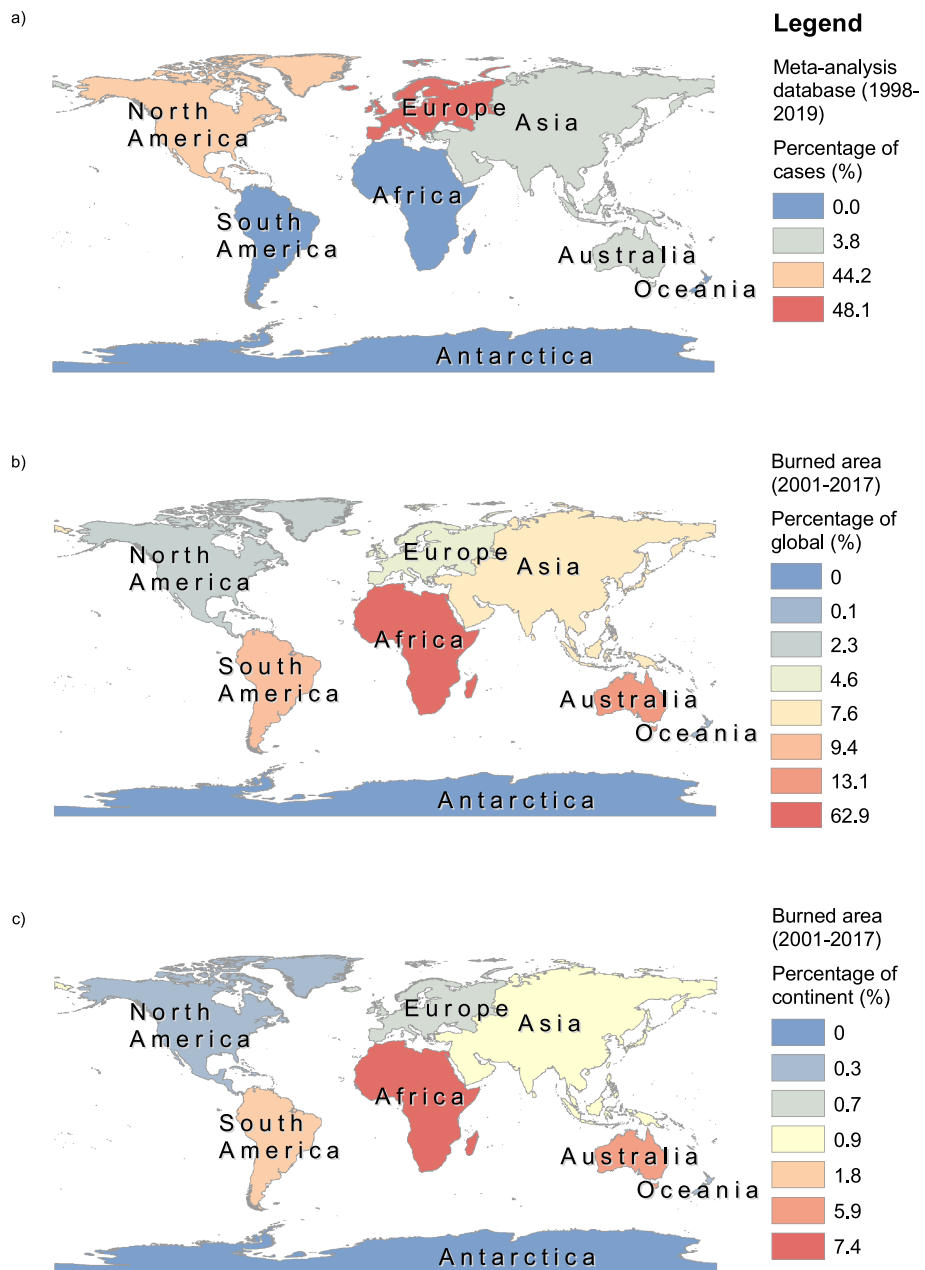


Figure 5. Distribution of: (a) meta-analysis cases per continent (1998–2019); (b) continental contribution to the global burned area (average 2001–2017); and (c) fraction of continents affected by wildfires (average 2001–2017). [Colour figure can be viewed at wileyonlinelibrary.com]

from annual to seasonal in MMF, which allowed the calculation of a seasonal *C* factor that provided a more accurate representation of vegetation recovery in burned areas. In both cases, the authors achieved overall a good model performance, according to the efficiency model indicators stated by Moriasi *et al.* (2015). Nunes *et al.* (2018) followed Vieira *et al.*'s (2014) procedures to change *C* in the SWAT model and adapted it for burned eucalyptus and pine stands.

Although less frequently, the support practice factor has also been changed to account for post-fire management. This was either implemented by: (a) estimating several mitigation scenarios with RUSLE, where each mitigation measure and slope were taken into account (Myronidis *et al.*, 2010; Rulli *et al.*, 2013); (b) considering that mulching efficiency in preventing soil erosion is highly related to ground cover with MMF (Vieira *et al.*, 2018a); or (c) considering the degree of disturbance of vegetation cover and surface after fire with RUSLE and USLE-Forest (Christie *et al.*, 2013; Karamesouti *et al.*, 2016). Only in Vieira *et al.* (2018a) were these model improvements assessed, obtaining a very good model performance (see online Supporting Information Table S1).

Model adaptations for soil infiltration in post-fire conditions

Infiltration rates were modified to account for fire-induced SWR, for the READI (Benda *et al.*, 2019), MMF (Vieira *et al.*, 2014, 2018a; Hosseini *et al.*, 2018), and SWAT (Nunes *et al.*, 2018) models. This adjustment resulted in satisfactory to good model performances (Moriasi *et al.*, 2015) for Vieira *et al.* (2014, 2018a) and Hosseini *et al.* (2018) who adapted the MMF model to simulate the hydrological effects of SWR by adjusting the soil water storage capacity (MS), and for Nunes *et al.* (2018) who calibrated this fire-induced change through curve number, while in the case of Benda *et al.* (2019) the model performance was not assessed. Wilson *et al.* (2001) with the HEM model, and Coschignano *et al.* (2019) by coupling SCS-CN with the RUSLE model, also changed the runoff curve number to account for less infiltration. Wilson *et al.* (2001) adapted it following Nearing *et al.* (1989) and Coschignano *et al.* (2019) by adjusting the curve number according to burn severity, both without any model performance evaluation.

Regarding saturated hydraulic conductivity, Moffet *et al.* (2007) optimized the parameter in the WEPP model for real conditions to decrease the gap between measured and predicted values, while McGuire *et al.* (2016), in the Harsine–Rose model, adapted the parameter considering the changes that may occur in hydraulic soil properties after wildfire and its recovery over time. In neither of these cases was the performance of the changes measured.

Other model adaptations and considerations

Besides the adaptations presented in the previous subsections, some authors tested in their studies parameterization sets for post-fire conditions, such as Feikema *et al.* (2011) in E2, Park *et al.* (2012) in SEMMA, and Robichaud *et al.* (2016) in ERMIT, achieving from satisfactory to very good model performances. The authors improved the model accuracy by considering in their sets the spatial variability of rainfall, vegetation, and soil organic layer (Park *et al.*, 2012), or burn severity spatial variations for a better prediction of potential erosion rates (Robichaud *et al.*, 2016).

Model performance was evaluated in 46% of the cases where changes were applied, and in 25% of them the modifications led to a positive model performance (from satisfactory to very good). In contrast, in only 5% of the 94 identified model adaptations did the authors conduct any type of validation afterwards (Vieira *et al.*, 2014, 2018a; Robichaud *et al.*, 2016;

Hosseini *et al.*, 2018; Nunes *et al.*, 2018), the results of which were generally positive.

Model performance evaluation and validation of predictions

In 60% of the cases (Table 2), efficiency metrics were used to assess model performance. The efficiency indices used were the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), root mean square error (RMSE), percentage bias (PBIAS), mean average error (MAE), and RMSE-observations standard deviation ratio (RSR) as presented in the online Supporting Information (Table S2). The values of the most used efficiency indices across the studied cases (R^2 , NSE, RMSE) are represented in Figure 6, whereas the predicted and measured erosion values from those cases are shown in Figure 7. The R^2 values of both physically and empirically based models showed a similar dispersion, and did not show any significant difference between model types. The NSE values indicated that physical models outperformed empirical models, primarily because empirical models had a higher number of outliers. The same behaviour was detected for the RMSE, which indicated a higher dispersion of results and more outliers within the predictions of empirical models. However, it is noteworthy that for all efficiency indices, the empirical models represent a higher number of cases than the physical.

When comparing RUSLE and WEPP predictions with other models that have been applied less often, such as Landsoil, MMF, PESERA, or RHEM, it is possible to verify that the latter have been applied to more restricted datasets (Figure 7). Furthermore, some studies formed clusters, indicating that model performances might be conditioned by local post-fire soil erosion measurements and the modelling approach (Figure 7). On top of that, the studies included in the present meta-analysis showed that only in 17% of cases were the modelled data validated (Table 2).

Discussion

Tackling post-fire soil and ground cover conditions

For modelling post-fire scenarios, several parameters should be considered regarding erosion processes (i.e. soil physical properties, the increase of bare soil area, the decrease of rainfall interception by the canopy, or the decrease of water storage capacity in the soil) (Moody *et al.*, 2013). However, some of these parameters are difficult to determine, not only due to the complex interaction of factors (Morgan, 2001), but also due to the lack of knowledge associated with hydrological processes and their link with soil properties (Larsen and MacDonald, 2007; Fernández and Vega, 2018).

Overall, most of the model adaptations for soil structure required changes in soil erodibility (see above and online Supporting Information Table S1), so that models could consider the expected increase in soil losses (e.g. Larsen and MacDonald, 2007; Fernández and Vega, 2016), and involved a decrease in ground cover to account for the reduction of the protective effect from vegetation (e.g. Rulli *et al.*, 2013; Coschignano *et al.*, 2019). However, these alterations for soil characteristics were also used to account for changes in infiltration, especially because the infiltration process is not explicitly considered in several empirical models (e.g. RUSLE). Therefore, the erodibility factor has been the main target of criticism from several researchers. Larsen and MacDonald (2007) and Moffet *et al.* (2007) suggested that

Table 2. Percentage of the total number of identified cases ($n = 52$) that address each of the research questions of the meta-analysis

Research questions		Cases (%)	
		Yes	No
Predictions	Erosion	100	0
	Runoff/discharge	46	54
	Unburned	50	50
	Model adaptation to burned areas	73	27
	Is infiltration addressed?	58	42
	Is burn severity addressed?	75	25
Model calibration	Improvement of model components	21	79
	Post-fire rehabilitation measures	27	73
	Use of efficiency indices	60	40
Efficiency assessment	Validation	17	83
	Uncertainty/sensitivity analysis	13	87
Structural	Empirical	48	52
	Physical	52	48
	Process-oriented	29	71
	Spatially distributed	42	58

the current algorithms for calculating soil erodibility are not consistent with the understanding of post-fire erosion processes. Fernández and Vega (2018) also concluded that the erodibility in the RUSLE equation does not reflect fire-induced changes in soil properties because it does not consider the influence of burn severity; while others state that the K factor does not reflect the changes in soil permeability and structure after wildfire (Moody *et al.*, 2013; Morrison and Kolden, 2015). Larsen and MacDonald (2007) and Moffet *et al.* (2007) also suggested that, to achieve greater precision, the K factor should be reformulated, and Larsen and MacDonald (2007) also suggested that soil moisture would be more properly included in the K factor, followed by an adaptation to site-specific conditions. However, despite that suggestion, soil erodibility has not yet been calibrated for soil moisture in burned conditions (Vieira *et al.*, 2018a).

Another input that has received attention from researchers is the cover factor (C) that represents the removal of vegetation. However, such input has often been considered a static parameter through the hydrological year, despite many models (e.g.

RUSLE, MMF, WEPP) being able to use smaller time steps, which allows for the accounting of seasonal or recovery-related changes in ground cover. Such consideration is particularly important in post-fire scenarios in which vegetation undergoes several seasonal transformations (Robichaud *et al.*, 2000; Shakesby and Doerr, 2006; Dun *et al.*, 2009; Morrison and Kolden, 2015). Therefore, the decrease in time step is expected to improve model predictions, as also found by Vieira *et al.* (2014), where MMF performance improved after shifting from annual to seasonal time steps. Notwithstanding, a reduction in time step implies a higher demand for field data in the rest of the model inputs.

Several authors also adapted the rainfall erosivity to local climate, which is not a post-fire model adaptation *per se*. However, this matter raised additional criticism of the application of the RUSLE model in recently burned areas. Fernández *et al.* (2010) suggested that the kinetic energy equation used in the model was possibly inadequate for the climate of NW Spain, thus explaining why the predictions overestimated post-fire soil erosion measurements. This fact was also stated by Larsen and MacDonald (2007), suggesting that the R calculated according to Wischmeier and Smith's (1978) equation would overestimate predictions due to the assumed linearity between the rainfall erosivity and sediment yields. In contrast, the same authors also suggested that if the rainfall erosivity factor is adapted to different climates, it may lead to a lower final value for the predicted soil erosion by water, with inherent implications for model performance.

Tackling post-fire infiltration

Most of the model adaptations for infiltration in post-fire environments have been focused on the reduction of infiltration rates through various methods, such as the increase of the runoff curve number or the calibration of saturated hydraulic conductivity according to field observations, such as runoff, soil cover, or burn severity (e.g. Moffet *et al.*, 2007; Nunes *et al.*, 2018). These adaptations, however, could only be applied in models that integrated a hydrological component where either infiltration was reduced or runoff was increased to account for frequently observed fire-induced changes such as SWR or changes in saturated hydraulic conductivity (Robichaud *et al.*, 2016; Ebel, 2020). In contrast, to represent the usual decrease in infiltration after fires, Vieira *et al.* (2014,

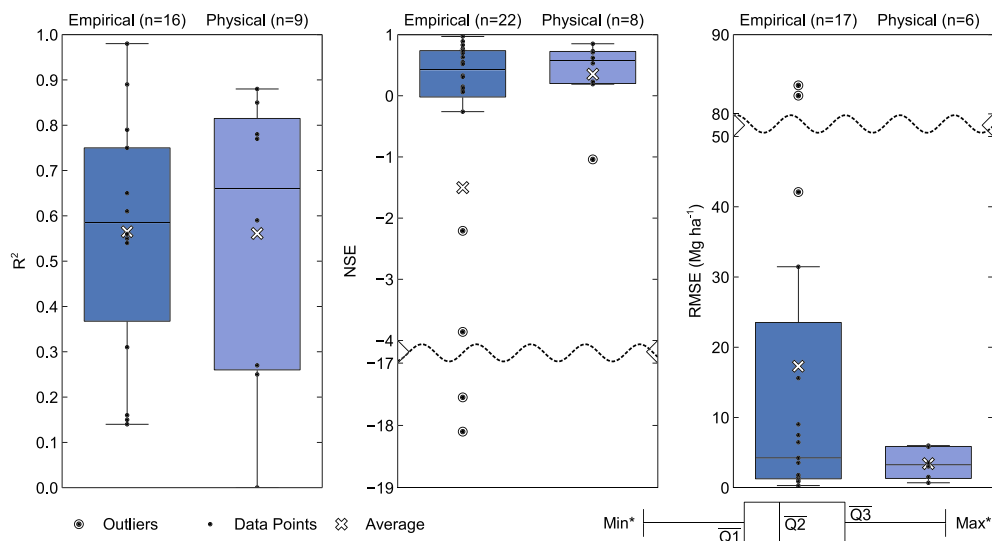


Figure 6. Values of the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), and root mean square error (RMSE) for each group of model types. The limits (Min* and Max*) were obtained by calculating the furthest point non-outlier. The quartiles were weighted geometrically over the nearest points' proximity and the number of samples. All values were obtained, including the outliers; 'n' indicates the number of cases from which the efficiency indices' values were retrieved. [Colour figure can be viewed at wileyonlinelibrary.com]

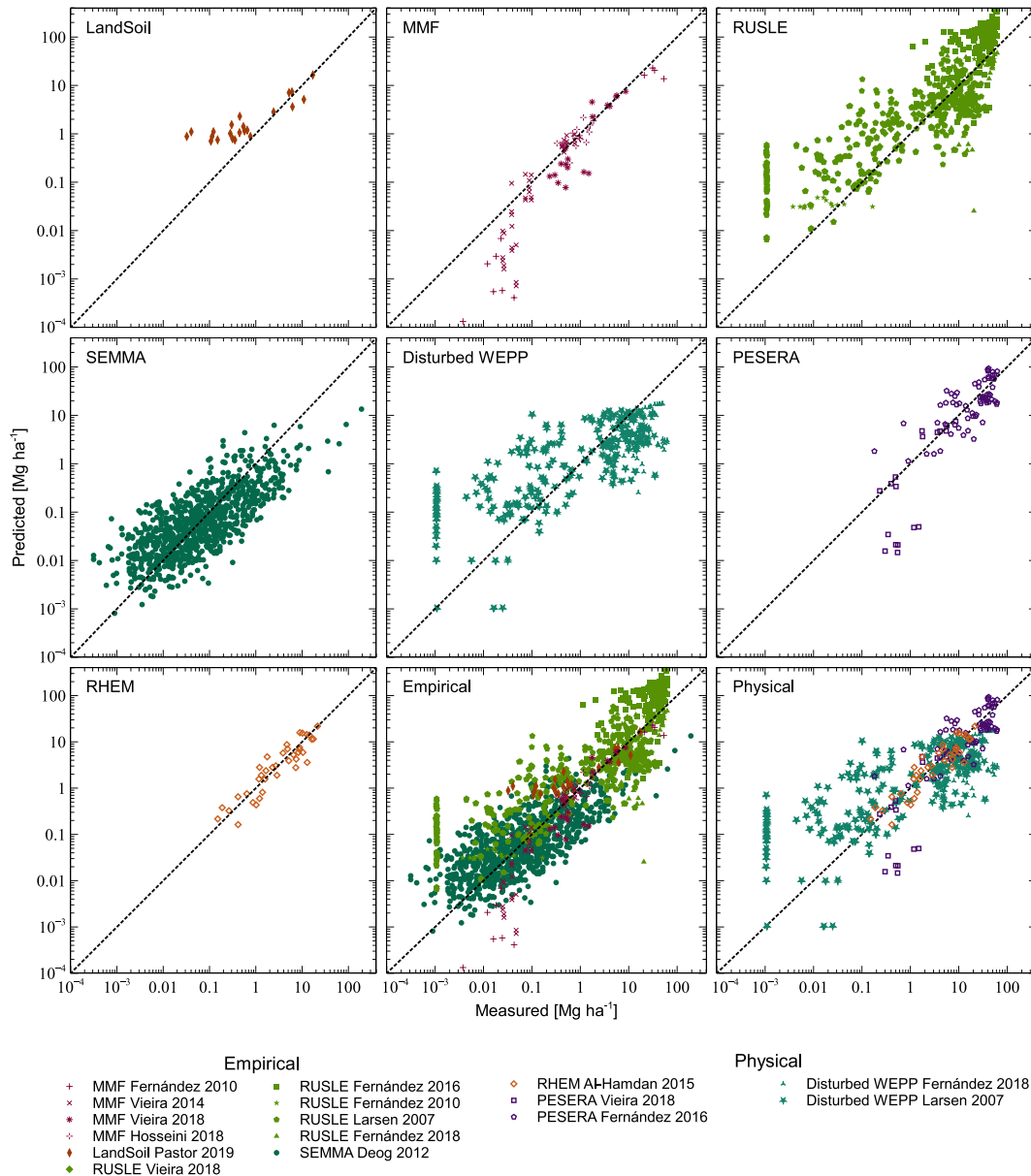


Figure 7. Representation of the predicted and measured data retrieved from the cases in which the model efficiency was assessed. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

2018a) reduced the infiltration by adapting soil moisture at field capacity (MS) according to the seasonal evolution of SWR (i.e. by reducing soil field capacity in the presence of repellent conditions). In addition to that, the effective hydrological depth of soil (EHD) was adjusted to account for ground cover dynamics, especially in the presence of mulching, which has also been shown to improve model efficiency in predicting runoff and erosion at a seasonal scale (Vieira *et al.*, 2014). Others also suggest further modifications to the EHD factor according to seasonal changes and the evolution of vegetation recovery (Fernández *et al.*, 2010; Morrison and Kolden, 2015; Hosseini *et al.*, 2018). However, there is no consensus on EHD (Morgan, 2001; Fernández *et al.*, 2010; Vieira *et al.*, 2014) due to the uncertainty of field-measured values.

Vieira *et al.* (2018a) also highlighted the importance of including runoff estimations in post-fire modelling, and suggested that is the reason why RUSLE underperforms compared to MMF and PESERA when applied to the same dataset. To circumvent that problem, Coschignano *et al.* (2019) combined a runoff curve number model with RUSLE estimations in a recently burned catchment, which is similar to the methodology used when applying SWAT; however, the absence of model

performance assessment does not allow us to determine if these changes result in any improvement.

Another model parameter that has been adjusted to accommodate changes in infiltration after fire has been the erodibility factor. For instance, Fernández and Vega (2018) concluded that the erodibility (K , RUSLE) equation does not reflect fire-induced changes in soil properties because it does not consider the influence of burn severity. Additionally, Larsen and MacDonald (2007) and Moffet *et al.* (2007) suggest that the current algorithms for calculating the K factor are not consistent with the understanding of post-fire erosion processes. Those same authors also indicate that to achieve greater precision, the K factor should be reformulated, while others state that the K factor does not reflect the changes in soil permeability and structure after wildfire (Moody *et al.*, 2013; Morrison and Kolden, 2015). In addition, the infiltration process is not explicitly considered in several empirical models such as RUSLE; however, the decline in infiltration caused by the fire-induced physical and chemical soil alterations has often been related to an increase in runoff rates in field studies at plot scale (Malvar *et al.*, 2016; Vieira *et al.*, 2018b), and has been shown to improve model efficiency in predicting runoff and erosion at seasonal scale (Vieira *et al.*, 2014).

Addressing burn severity in modelling predictions

Burn severity has become widely recognized as a key parameter determining post-fire soil erosion by water, so that its inclusion in soil erosion models is now considered fundamental for state-of-the-art emergency stabilization planning (Moody *et al.*, 2013; Morgan *et al.*, 2014; Shakesby *et al.*, 2016; Fernández and Vega, 2018). The results of the present study, shown in Table 2, indicate that past studies have identified the importance of including the impacts of burn severity in their erosion predictions but have faced difficulties in doing so, either because the parameters of the model(s) are unsuited to simulate burn impacts or because their calibration is poorly established for post-fire conditions. The latter is well illustrated by the modelling studies of Fernández *et al.* (2010) and Fernández and Vega (2016), achieving acceptable and poor model performance, respectively, with model parameterization based on standard values as opposed to extensive calibration efforts. From all the models analysed in this study, only ERMIT incorporates burn severity as an explicit model parameter. This fact could be one of the main reasons why, in some of the cases, models underestimate soil erosion for high burn severity (Soto and Díaz-Fierros, 1998; Larsen and MacDonald, 2007; Fernández and Vega, 2016, 2018). Several authors also indicated the need to develop and validate a robust burn severity classification that could be applied worldwide (Larsen and MacDonald, 2007; Vieira *et al.*, 2015; Fernández and Vega, 2016, 2018; Brown *et al.*, 2018; Colson *et al.*, 2018). Prior work also stresses the strong impact of fire severity on vegetation cover, and that an incorrect vegetation cover estimation could lead to poor modelling results (Fernández and Vega, 2016; Vieira *et al.*, 2018a).

Post-fire mitigation measures

It is known that post-fire mitigation treatments, such as the application of a protective cover or mulch (e.g. straw, wood chips, hydromulch), are an effective measure for reducing the effects of water erosion after fire (Robichaud *et al.*, 2010). Despite the attention that has been given to soil erosion modelling after fire, the present meta-analysis showed that only nine studies (Fernández *et al.*, 2010; Myronidis *et al.*, 2010; Christie *et al.*, 2013; Rulli *et al.*, 2013; Vieira *et al.*, 2014, 2018a; Karamesouti *et al.*, 2016; Robichaud *et al.*, 2016; Pastor *et al.*, 2019) considered the application of mitigation measures in their modelling predictions, mulching being the most used technique. It should be highlighted that this topic only recently became a matter of interest, since almost all these studies were published between 2010 and 2019 (Figure 2).

To account for distinct mitigation measures, modellers generally used the support practice factor (P) present in RUSLE, or a ground cover factor (e.g. C factor) to address the increase of protective ground cover in comparison to the burned areas without any treatment. Rulli *et al.* (2013) used the C and P factors according to Fernández *et al.* (2010) and Myronidis *et al.* (2010). Karamesouti *et al.* (2016) also considered the application of post-fire treatments in the P factor of the RUSLE, using values from a previous study (Kitahara *et al.*, 2000). Similar to many other studies, the performance of these model applications was not assessed due to the lack of detailed measurements.

In contrast, Vieira *et al.* (2014) improved the accuracy of predicting the efficiency of mitigation measures with MMF following the studies developed by Fernández *et al.* (2010) with this same model. This was achieved by adjusting additional parameters, such as the EHD, and by assuming a linear

relationship between mulching efficiency and ground cover (P , MMF). Vieira *et al.* (2018a) also used these assumptions and applied them in the RUSLE, MMF, and PESERA models, achieving good model performance for all three models, credited to the quality and detail of the field measurements available, especially data for runoff and erosion. For that same reason, Robichaud *et al.* (2016), with the ERMIT model, achieved significant progress in the development of a tool for post-fire mitigation planning. The background dataset from past burned areas in the United States provided the necessary calibration robustness to create mitigation scenarios with a good model performance.

The results of the analysed studies highlight the potential of modelling applications for predicting soil erosion risk and the efficiency of the possible mitigation techniques that could be applied. Nevertheless, the number of studies that aimed to develop and implement the mitigation measures in the models, with further calibration and validation of the data, are reduced. In general, the results also point to the need for sampling larger field datasets aimed at model calibration and performance improvement. For this reason, research on this matter is required for it to be considered a robust decision-making tool for managers.

Final considerations and recommendations for future studies

In recent reviews by Alewell *et al.* (2019) and Batista *et al.* (2019), the challenges and concerns of soil erosion modelling were extensively identified. Both studies consider that there is no single better model, and the accuracy of the predictions is rather related to the quality of the inputs and the calibration process. The authors also suggest caution in the applicability of results in systems other than those the calibrations were conducted for. In this matter, they indicate that spatially distributed models are only reliable when the obtained predictions are properly verified. They also raised awareness about the wrongful communication of uncertainties to practitioners, pointing out that in order to consider modelled data in decision-making, the degree of disagreement between the predictions and reality must be more clearly provided.

Considering the results of this meta-analysis, uncertainty assessment is minimal, being present in only 13% of the cases. Uncertainty analysis should be a cross-sectional assessment of the modelling process, leading to its integration in model outcomes. This practice has been widely implemented in climate and land use change research, to ensure a proper knowledge transference to land managers (Frieler *et al.*, 2015). For this reason, if researchers acknowledge the sources of uncertainties in model applications, this could be addressed in future research. Therefore, efforts should not only be invested in the assessment of parametric uncertainty, but also in structural uncertainty, considering whether the model used is suitable for modelling the desired processes. Having said that, and considering most of the authors' criticisms towards model capacities, some aspects would benefit from further research, as detailed below.

Results have shown a strong regional bias in soil erosion modelling after wildfires, pointing out that most of the studies were conducted in the northern hemisphere. Considering this fact, together with the information in Figure 5, it is clear that efforts are not being invested in the areas that are suffering most from wildfires. For this reason, further improvement of the actual models could arise as a resourceful tool for erosion risk and post-fire mitigation assessment, after validation, for areas

with limited resources. Additionally, the combined effect of climate and land use changes is also producing a shift in fire patterns, resulting in the increasing occurrence of wildfires in non-fire-prone ecosystems (Stephens *et al.*, 2013), which could benefit from this knowledge in the future.

On top of the issues analysed by Alewell *et al.* (2019) and Batista *et al.* (2019) in soil erosion modelling, post-fire modelling presents the added difficulty of including the heterogeneous effects of fire on soil hydrological properties and processes. One of these properties is SWR (Shakesby *et al.*, 2000; Shakesby, 2011), whose role has scarcely been considered in post-fire erosion modelling (Vieira *et al.*, 2014). In Vieira *et al.* (2014), an adjustment factor is provided to integrate this property in modelling and despite the good performance of this factor, the authors claim that it is required to check its suitability in more diverse scenarios. The degree of burn severity is also a component that requires a more accurate implementation in modelling for better prediction of potential soil erosion by water in relation to the degree of fire impact. This parameter has usually been considered in cover and soil erodibility factors (see online Supporting Information Table S1), resulting in predictions that frequently have not been evaluated for model improvement, so its suitability is still uncertain due to the lack of field data for validation. It is therefore essential to develop and improve the integration of burn severity in soil erosion models, describing not only the impact of fire immediately after the fire, but also throughout the window of the disturbance period, and by associating such metric with other variables that affect soil erosion. For instance, burn severity also plays a role in ground cover and the repellent properties of soil to water (Doerr *et al.*, 2006), influencing the remaining protective cover and vegetation recovery, which varies greatly during the first year after fire. For this reason, model predictions would benefit from a decrease in the time step, therefore being able to more accurately include the variations of ground cover over time in their modelling predictions. Last, it will also be important to consider in future model predictions the impact of burn severity on the infiltration process as previously evidenced by other researchers (Shakesby *et al.*, 2016).

An important gap found in this study is the lack of research case studies assessing model efficiency and/or presenting the calibration and validation approaches. This should be a priority for the future of this research topic, since validation is the most reliable method to inform the scientific community about the suitability of such a model or approach in estimating a given process, in this case post-fire soil erosion. Associated with the suggestion of more calibration and validation is also the usage of model performance metrics, which provides a direct assessment measure for given model or approach reliability to be further used under those conditions. The foremost reason for such difficulties in validating and evaluating model applications resides in the scarce post-fire field data available for model input and model prediction assessment. This data collection generally requires a substantial investment in field campaigns in fire-affected lands, either by wildfire or prescribed fires, during an uncertain window of disturbance period, which can vary from months to years (Shakesby and Doerr, 2006; Moody *et al.*, 2013). In addition, most of the studies under analysis were conducted at plot scale, which limits the reproducibility of results due to the specificity of the calibrations, regarding not only soil properties but also rainfall patterns (Bronstert and Bárdossy, 2003). Nevertheless, addressing a wider range of scales will benefit the understanding of post-fire impacts, from on-site processes (plot-to-hillslope) to off-site impacts (catchment). The same applies to post-fire mitigation measures, since this meta-analysis showed that little attention has been

given to modelling the application of post-fire erosion mitigation treatments. In recent works, Vieira *et al.* (2014, 2018a) successfully applied the RUSLE, MMF, and PESERA models in areas managed with mitigation treatments; however, they highlighted the general scarcity of data available for calibration and lack of representability among all the possible treatments that could be applied, because it has only been tested for mulching.

As already mentioned, during the meta-analysis research we encountered a small group of publications applying other models prior to the post-fire soil erosion modelling. Despite the exclusion from the database as the focus was not a real post-fire situation, we chose to discuss the potential of integrating post-fire soil erosion models with other complementary ones: integrated assessment models (IAMs). The IAMs are regarded as a potential solution to tackle complex environmental problems in multidisciplinary studies, and have been widely used to inform policy regarding climate change mitigation and adaptation (Havlík *et al.*, 2015). In this group of studies, several were found to combine fire simulations determining wildfire occurrence according to climate projections (Litschert *et al.*, 2014; Gould *et al.*, 2016), or burn severity mapping according to fuel loads (Sidman *et al.*, 2015; Elliot *et al.*, 2016; Gannon *et al.*, 2019), with post-fire soil erosion modelling. The potential of these modelling exercises is that using a similar strategy, land managers could then make informed decisions about the best land management practices to minimize the occurrence of wildfires and their post-fire risks combined, instead of separately. Nevertheless, model combination could lead to a progressive accumulation of errors, so uncertainty assessment must be conducted to prevent this from happening.

All the issues commented on above converge in the fact that more fieldwork in burned areas is still needed, for both wildfires and prescribed fires, aimed at collecting specific parameters for model testing and adaptation. In this sense, the authors of this study suggest the compilation and creation of an open access database, which will allow testing of different models and approaches with datasets collected in contrasting scenarios, as well as calibrating and validating models with independent datasets when these resources are not available. The development of studies in which several models are applied to the same dataset may also have an added value (Larsen and MacDonald, 2007; Vieira *et al.*, 2018a; Kampf *et al.*, 2020), allowing the determination of the structural uncertainty in modelling predictions. In such cases, we encourage RUSLE or WEPP to be used as reference models, since they are the most commonly used for post-fire soil erosion prediction. In addition, the authors of this study also suggest that model performance should be evaluated through the application of prediction efficiency indices; however, caution should be taken when interpreting these analyses, because they tend to valorize average predictions and could neglect extreme erosive events.

As a last consideration, if the creation of a novel post-fire soil erosion model is preferred to the option of adapting existing soil erosion models, the authors suggest that such a model should address all the fire-induced changes highlighted in this study. Furthermore, this model should be flexible in its adaptation of soil structure, soil cover, infiltration capacity, burn severity, and also account for mitigation measures during a variable window of disturbance period. This suggestion is not a model development approach *per se*, but rather a focus on key variables and processes that are specific from burned areas, and that have also been used in the application of statistical models to predict post-fire soil erosion by water (Benavides-Solorio and MacDonald, 2005; Schmeer *et al.*, 2018).

Conclusions

The main conclusions from the present meta-analysis can be summarized as follows:

- a The application of post-fire erosion models is not homogeneously distributed worldwide, according to model type used or by region most affected by wildfire.
- b Further efforts are required in the adaptation of erosion models to burned conditions, more precisely in addressing soil and infiltration changes.
- c The inclusion of systematic model efficiency metrics in post-fire modelling studies, and the separation into calibration and validation phases, will allow the scientific community to better evaluate models and their adaptations in the future.
- d A limited number of studies included post-fire mitigation effects on erosion models, and so far only the mulching and log barrier techniques have been tested regarding this matter.
- e For future studies we recommend developing and testing models that allow adjusting post-fire infiltration changes, calibrating the cover factor to the degree of burn severity, and including a wider array of post-fire mitigation measures.
- f Future studies on post-fire soil erosion modelling could consider a multidisciplinary model combination to tackle post-fire management in an integrated way.
- g Future modelling studies should include uncertainty analysis and identify ways to further improve the accuracy of predictions for better communication of the results of scientific output.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1. Model input adaptations to post-fire conditions, and correspondent model performance efficiency assessment.

Table S2. Retrieved values for the efficiency assessment indices applied in each study case.