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Predicting postfire erosion and mitigation effectiveness with a web-based probabilistic erosion model

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Abstract

The decision of where, when, and how to apply the most effective postfire erosion mitigation treatments requires land managers to assess the risk of damaging runoff and erosion events occurring after a fire. To meet this challenge, the Erosion Risk Management Tool (ERMiT) was developed. ERMiT is a web-based application that uses the Water Erosion Prediction Project (WEPP) technology to estimate erosion, in probabilistic terms, on burned and recovering forest, range, and chaparral lands with and without the application of mitigation treatments. User inputs are processed by ERMiT to combine rain event variability with spatial and temporal variabilities of hillslope burn severity and soil properties, which are then used as WEPP input parameter values. Based on 20 to 40 individual WEPP runs, ERMiT produces a distribution of rain event erosion rates with a probability of occurrence for each of five postfire years. In addition, rain event erosion rate distributions are generated for postfire hillslopes that have been treated with seeding, straw mulch, and erosion barriers such as contour-felled logs or straw wattles.
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1. Introduction

Since 1990, in the western United States, there has been a significant increase in the number, size, and severity of wildfires (Joint Fire Science Program, 2004). High severity fires not only consume or deeply char all vegetation, but also affect the physical properties of soil (DeBano et al., 1998). These changes alter watershed responses to rainfall causing increased runoff, erosion, and downstream sedimentation, which can threaten human life and damage property (Robichaud et al., 2000). During these past 15 years, the population living in the 'wildland-urban interface' (lands surrounding urban areas) has increased (Stewart et al., 2003), making protection of life and property a significant challenge, not only for wildland fire suppression efforts, but also for mitigation of damaging hillslope and downstream effects (DeBano et al., 1998). United States land management agencies have spent tens of millions of dollars on postfire emergency watershed stabilization measures intended to minimize flood runoff, peakflows, onsite erosion, offsite sedimentation, and other hydrologic damage to natural habitats, roads, bridges, reservoirs, and irrigation systems (General Accounting Office, 2003).

Following a fire, land managers choose which mitigation actions, if any, are needed to protect life, property, and the environment. Choices depend on 1) probability of the hazard—i.e., the probability that damaging amounts of runoff and erosion will occur; 2) lost resource value if the event occurs—i.e., monetary value of resource lost or restoration (e.g., water quality impairment, stream restoration, reservoir dredging, or road repair) that would be needed if damaged; and 3) the cost and effectiveness of potential mitigation. Although the costs or value of potentially damaged resources and postfire mitigation treatments can be determined, the probability of damaging runoff and erosion occurring and the effectiveness of mitigation treatments are not well established. Consequently, managers often must assign these probabilities and estimate treatment effectiveness based on past experience and consensus of

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opinion. Land managers need more information and effective tools to determine hazard probabilities and balance the costs and potential benefits of treatments.

Several technologies are currently used to estimate potential postfire runoff and erosion. The most common are the Soil Conservation Service Curve Number (CN) to estimate runoff (Ponce and Hawkins, 1996) and the Revised Universal Soil Loss Equation (RUSLE) to estimate erosion (Foster et al., 1996). The RUSLE models were developed for cropland applications and predict average annual erosion rather than short-term risk (Fangmeier et al., 2005). Other models, such as KINematic EROSion2 (KINEROS2) (Smith et al., 1995; Goodrich et al., 2002) and Soil Water Assessment Tool (SWAT) (Neitsch et al., 2002), have been developed for non-agricultural applications and used extensively in rangeland research. However, these tools are not easily accessed and used by land managers.

The Water Erosion Prediction Project (WEPP) is a process-based model that simulates rain splash, sheet flow, and concentrated flow erosion processes, as well as the interactions between these processes (Flanagan and Livingston, 1995; Laflen et al., 1997). WEPP, developed for agricultural use where soil and rainfall properties are easily measured and hillslopes are uniform, could not be directly applied to wildland environments where complex hillslope conditions are affected by fire or other management activities. Fire effects on hydrologic and erosion parameters are not well known, and wildfires generally take place in steep, mountainous regions where, due to orographic effects, available climate data are not representative of the area to be modeled (Scheele et al., 2001). In addition, soil properties often are less well known for these remote areas than for croplands or valleys.

Recent efforts have produced adaptations of WEPP (Elliot, 2004) that allow land managers to assess the impacts of fire and other disturbances on hydrological watershed responses in forest and rangelands. One adaptation, Disturbed WEPP, provides estimates of annual hillslope erosion in forest and range environments given various management scenarios, including prescribed fire and wildfire (Elliot et al., 2004). Annual erosion predictions from Disturbed WEPP incorporate some spatial variability of fire effects on soil and erosion processes (Robichaud and Miller, 1999), but multiple runs are needed to assess the effects of temporal variability.

The Erosion Risk Management Tool (ERMiT) was developed to address the need for an easily-used, postfire erosion prediction tool that incorporates spatial and temporal variability of fire effects, provides probabilities of postfire erosion rates needed for risk analysis, and includes erosion mitigation treatment effectiveness information (Robichaud et al., 2006). ERMiT is a web-based application that predicts event sediment delivery in probabilistic terms on burned and recovering forest, range, and chaparral lands. The objectives of this article are to describe: 1) the conceptual framework and components of the ERMiT model; 2) the variability of rainfall, soil burn severity, and soil properties (input parameters) that influence postfire erosion; and 3) how the input parameter variabilities are combined to produce a probability distribution of event-based erosion rates with and without application of mitigation treatments.

2. Components of ERMiT

2.1. WEPP

ERMiT uses WEPP technology as the runoff and erosion calculation engine. WEPP simulates both interrill and rill erosion processes and incorporates the processes of evapotranspiration, infiltration, runoff, soil detachment, sediment transport, and sediment deposition to predict runoff and erosion at the hillslope scale (Flanagan and Livingston, 1995).

2.2. CLIGEN

Through the ERMiT interface, stochastic weather files generated by CLImate GENerator (CLIGEN) (Nicks et al., 1995) are selected for use in WEPP. A CLIGEN weather file includes daily precipitation amount, duration, time-to-peak, and peak intensity; minimum, maximum, and dewpoint temperature; and solar radiation, wind velocity, and wind direction values. To

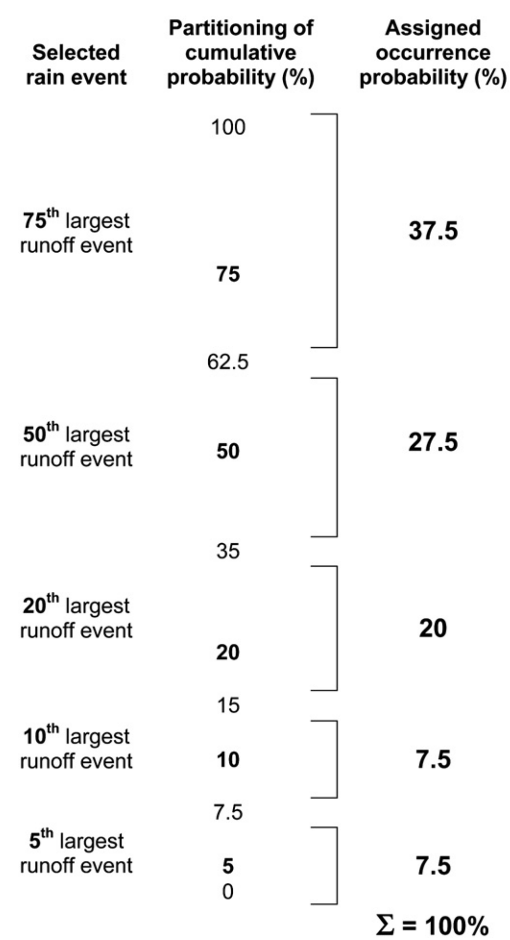


Fig. 1. Five runoff events are selected from the 100-yr weather record generated by CLIGEN. Each rain event associated with a selected runoff event is assigned an occurrence probability based on a partitioning of the 100% cumulative probability.

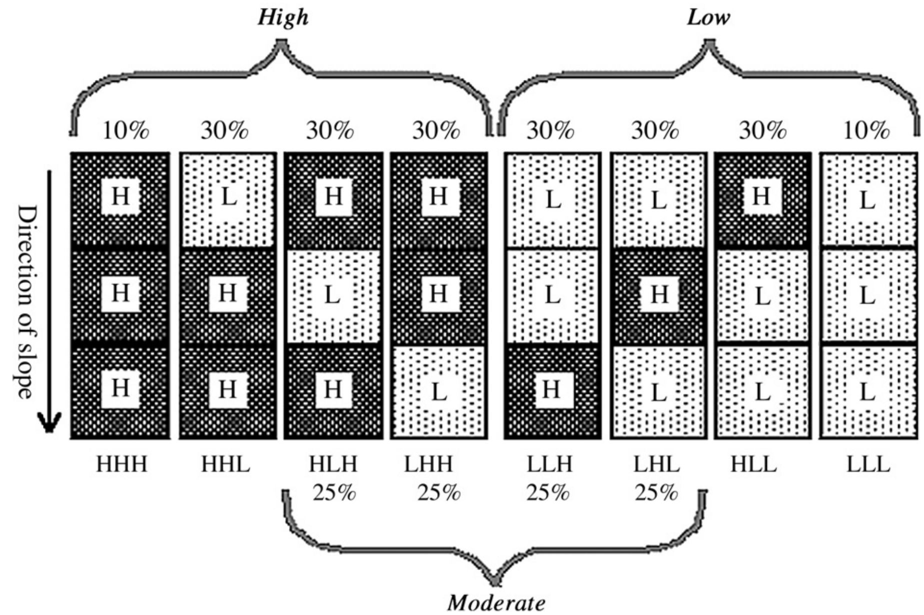


Fig. 2. Each column of three overland flow elements (OFEs) represents a soil burn severity hillslope arrangement. Based on the user-designated soil burn severity classification (high, moderate, or low), four arrangements of high (H) and low (L) soil burn severity OFEs are modeled. The assigned probability of occurrence for each hillslope arrangement is indicated within the bracket of the burn severity user designation.

generate a weather file, CLIGEN uses the climate information (statistical characterizations from historical data of monthly precipitation, minimum, maximum and dewpoint temperatures, and solar radiation; monthly probabilities of a wet day following a wet day and of a wet day following a dry day; a time-to-peak distribution, and wind data) from one of the more than 2600 weather stations located throughout the United States.

These accessible weather stations are rarely located near the remote areas being modeled by ERMiT, and the stations in mountainous regions are usually in valleys such that even a

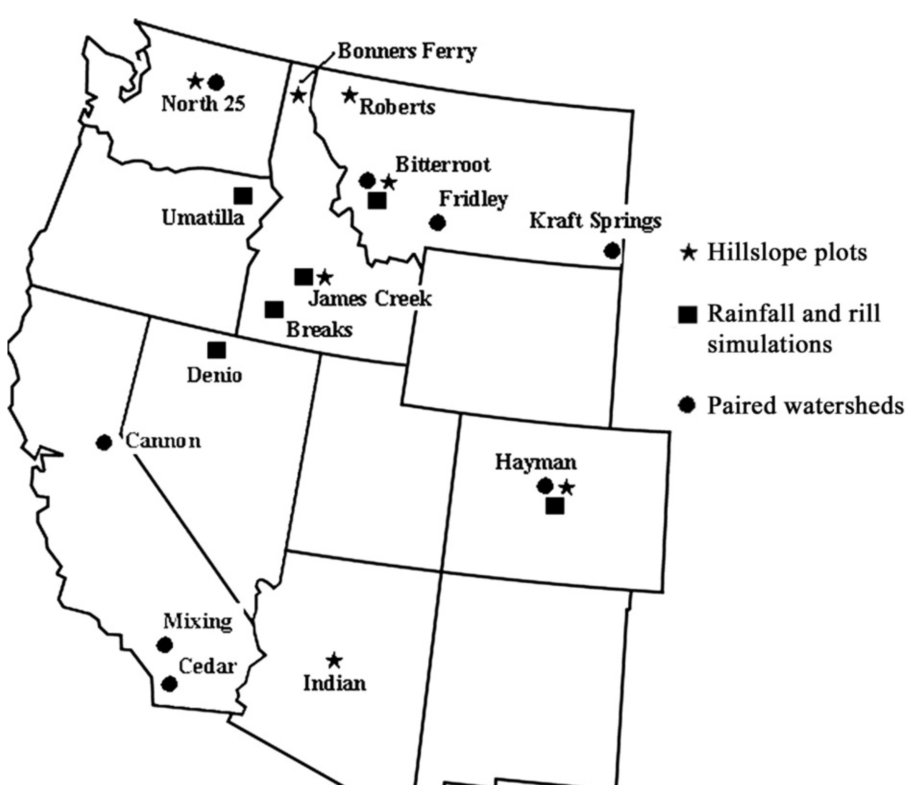


Fig. 3. Data from postfire research sites throughout the western United States have been used to parameterize and validate the ERMiT model.

nearby station may not be representative of the area to be evaluated. Consequently, users may create custom climate parameter files, based upon one of the supplied parameter files, by using the integrated Rock:Clime web interface (Scheele et al., 2001). Elevation and monthly mean minimum and maximum temperature, mean precipitation, and number of wet days may be adjusted directly by the user, or by using values provided by the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Daly et al., 1994; Elliot, 2004) data. PRISM's mean monthly precipitation data are distributed on a 2.5-min grid over the conterminous United States. A temperature lapse rate adjustment for orographic effects based on an elevation differential is available.

3. Variability of ERMiT input parameters

Weather variability as well as the spatial and temporal variability of soil parameter values (both inherent and in relation to soil burn severity) are incorporated into ERMiT. The general process used to incorporate weather and spatial variability is to 1) determine a range of parameter values (CLIGEN and field measurements), 2) select representative values from the range, and 3) assign 'occurrence probabilities' for each selected value. The computational constraints of the model require that the sum of occurrence probabilities for each source of variability adds to 100%. Thus, all possible parameter values are represented in the model by the 4 to 5 selected values, and the cumulative probability (100%) is divided among the 4 or 5 selected values.

Temporal variation, the change in soil parameter values over time due to recovery, is modeled by changes in the occurrence probabilities assigned to the selected values for each year of recovery. Details of how recovery is accommodated in ERMiT are described at the end of this section; thus, the occurrence probabilities within this section, with the exception of the recovery portion, are for the initial, postfire Year 1.

3.1. Precipitation

Rainfall intensity and duration influence two erosion processes—raindrop impact and concentrated overland flow. Since rill erosion from concentrated flow is the dominant erosion process on steep hillslopes, runoff is the driving mechanism for erosion and sediment delivery (Robichaud, 2000a). Consequently, runoff is the criterion used to select rain event records for each ERMiT run.

A 100-year weather file, generated using CLIGEN, is used to produce a 100-year runoff record for the combination of soil, cover, and burn severity conditions that has the greatest potential to generate runoff for the site. Because not all 100 years can be modeled efficiently, the maximum runoff event from each year is recorded and the years with the 5th, 10th, 20th, 50th, and 75th ranked runoff events are selected for further analysis. Weather data for one year prior to each selected year are used to maintain soil moisture patterns for the selected runoff events. Thus, the original 100-year weather record is reduced to a 6 to 10 year record. Occurrence probabilities for the rain events associated with the selected runoff events are 7.5, 7.5, 20, 27.5, and 37.5%, respectively. Because each rain event that is modeled is used to represent a range of potential rain events, occurrence probabilities were derived from the ranking of the associated runoff events and the difference between rankings (Fig. 1).

3.2. Hillslope characteristics

Topographic inputs (hillslope horizontal length and gradients for top, middle, and toe) are user-specified and fixed for each ERMiT run. The top and toe gradients (i.e., steepness) are assigned

Table 1
The postfire value ranges for interrill erodibility (K_i), rill erodibility (K_r), effective hydraulic conductivity (K_e), and critical shear (τ_c) by soil texture and high or low soil burn severity are shown

	Pre-fire cover	Soil burn severity	Clay loam	Silt loam	Sandy loam	Loam
Forest						
K_i ($\times 10^3$) (kg-s m^{-4})		Low	200 to 500	250 to 600	300 to 1200	320 to 800
		High	400 to 2000	500 to 2500	1000 to 3000	600 to 3200
K_r ($\times 10^{-4}$) (s m^{-1})		Low	0.010 to 2.5	0.020 to 3.5	0.030 to 4.5	0.015 to 3.0
		High	2.0 to 8.0	3.0 to 9.0	4.0 to 10	2.5 to 8.5
K_e (mm h^{-1})		Low	25 to 8	33 to 9	48 to 14	40 to 18
		High	13 to 2	18 to 3	22 to 5	27 to 4
τ_c (N m^{-2})		Low	4	3.5	2	3
		High	4	3.5	2	3
Range and chaparral						
K_i ($\times 10^3$) (kg-s m^{-4})	Shrub	Low	13 to 170	16 to 230	75 to 930	3.4 to 93
		High	39 to 170	49 to 230	230 to 930	11 to 93
	Grass	Low	1.9 to 15	12 to 150	50 to 650	2.6 to 63
		High	6.6 to 85	40 to 840	170 to 3,600	9.0 to 350
	Bare	Low	39 to 170	49 to 840	230 to 3,600	11 to 350
		High	39 to 170	49 to 840	230 to 3,600	11 to 350
K_r ($\times 10^{-4}$) (s m^{-1})		Low	0.38 to 6.0	0.33 to 7.8	0.090 to 7.2	0.51 to 4.6
		High	3.0 to 27	2.7 to 33	0.95 to 31	3.8 to 22
K_e (mm h^{-1})	Shrub	Low	15 to 6	22 to 8	29 to 9	22 to 8
		High	11 to 5	16 to 6	21 to 6	16 to 6
	Grass	Low	13 to 5	26 to 10	17 to 8	15 to 5
		High	10 to 4	21 to 8	14 to 7	12 to 4
	Bare	Low	10 to 4	21 to 8	14 to 7	12 to 4
		High	10 to 4	21 to 8	14 to 7	12 to 4
τ_c (N m^{-2})		Low	1.9	3.4	2.8	0.8
		High	1.5	2.7	2.2	0.6

For range and chaparral lands, user-designated pre-fire canopy cover proportions provide an additional level of classification for K_i and K_e values.

to the upper and lower 10% with the middle gradient assigned to the remaining 80% of hillslope length. Hillslope horizontal length and top, middle, and toe gradients may be obtained from field surveys, digital elevation models (DEM), topographic maps, or geographical information system (GIS) data layers.

3.3. Soil burn severity

Fire effects on erosion are not homogeneous across the landscape (Robichaud and Miller, 1999). Soil burn severity is a description of the impact of a fire on the soil and litter. High soil burn severity is associated with decreased ground cover, increased soil water repellency, decreased infiltration and increased erosion (DeBano et al., 1998; Robichaud, 2000b; Benavides-Solorio and MacDonald, 2001; Pierson et al., 2001). The soil burn severity of a fire varies widely in space, depending on the topography as well as the pre-fire fuel load, moisture conditions, weather, and the fire behavior. Areas that are drier, such as those near ridge tops, and areas with greater amounts of fuel may experience higher soil burn severity than areas that are wetter, such as riparian areas or draws. This variability in soil burn severity creates mosaic landscapes with varying portions having low, moderate, and high soil burn severity (DeBano et al., 1998).

Rainfall simulation experiments have shown that only two soil burn severity classes, high and low, can be distinguished on the basis of runoff and erosion (Robichaud, 1996; Brady et al., 2001; Pierson et al., 2001); however, most postfire burn severity classifications include three classes—high, moderate, and low. In ERMiT, each of the three user-designated soil burn severity classes is modeled with a set of four spatial arrangements of high and low burn severity overland flow elements (OFEs). Each spatial arrangement consists of three OFEs on the modeled hillslope (Fig. 2). In modeling the first postfire year, a high soil burn severity user designation will apply four spatial arrangements of 75% high (H) and 25% low (L) OFEs; a moderate soil burn severity user designation will use four spatial arrangements of 50% H and 50% L OFEs; and a low soil burn severity user designation will use four spatial arrangements of 25% H and 75% L OFEs (Fig. 2). Each spatial arrangement within each soil burn severity class is assigned a probability of occurrence. One of the four spatial arrangements on high soil burn severity hillslopes has all three OFEs assigned H, and, similarly, one of the four spatial arrangements on low soil burn severity hillslopes has all three OFEs assigned L. To reduce the impact of the less likely occurrence of hillslope conditions that are uniformly high or low soil burn severity, the spatial arrangements of all H and all L are assigned a 10% probability of occurrence while the other three arrangements for a high or low soil burn severity designation are each assigned a 30% probability of occurrence. Each of the four moderate soil burn severity OFE arrangements is assigned a 25% probability of occurrence (Fig. 2). These spatial arrangements of high and low OFEs allow ERMiT not only to simulate the spatial variability of soil burn severity across the landscape, but also to simulate situations where an area of low soil burn severity may absorb runoff or filter out sediment that is leaving an upslope area with high soil burn severity.

Table 2
Based on the user-selected soil burn severity class (high, moderate, and low), the 20 combinations of high (H) and low (L) soil burn severity overland flow elements (OFEs) and soil parameter sets are boxed

	Soil burn severity spatial arrangement of OFEs								
	-----High soil burn severity OFEs-----				----Low soil burn severity OFEs-----				
Occurrence probability	10%	30%	30%	30%	30%	30%	30%	10%	
downslope ↓	H	L	H	H	L	L	H	L	↓ downslope
	H	H	L	H	L	H	L	L	
	H	H	H	L	H	L	L	L	
Occurrence probability			25%	25%	25%	25%			
			-----Moderate soil burn severity OFEs----						

Soil parameter set and occurrence probability	High soil burn severity selected				Low soil burn severity selected			
Soil 1 (5th %ile values[a]) 10%	HHH1	LHH1	HLH1	HHL1	LLH1	LHL1	HLL1	LLL1
Soil 2 (20th %ile values[a]) 20%	HHH2	LHH2	HLH2	HHL2	LLH2	LHL2	HLL2	LLL2
Soil 3 (50th %ile values[a]) 40%	HHH3	LHH3	HLH3	HHL3	LLH3	LHL3	HLL3	LLL3
Soil 4 (80th %ile values[a]) 20%	HHH4	LHH4	HLH4	HHL4	LLH4	LHL4	HLL4	LLL4
Soil 5 (95th %ile values[a]) 20%	HHH5	LHH5	HLH5	HHL5	LLH5	LHL5	HLL5	LLL5
			Moderate soil burn severity selected					

The OFEs, listed vertically in the top portion of the table, are repeated horizontally in the lower portion of table where they are combined with the soil parameter sets. Occurrence probabilities are for the first postfire year.

[a] Values of K_i, K_r, K_e, and τ_c from the cumulative distribution function of the selected range of values (Table 1).

3.4. Soil properties

The postfire erosion potential of a soil depends on time since the fire, soil texture, soil water repellency, ground cover, soil moisture, and other factors that influence infiltration and soil erodibility. The variable effects of postfire ground cover, soil water repellency, and soil erodibility are modeled by variability in interrill erodibility (K_i), rill erodibility (K_r), effective hydraulic conductivity (K_e), and critical shear (τ_c) parameters. The ranges of K_i, K_r, K_e, and τ_c values used in ERMiT were derived from field measurements taken at postfire research sites across the western United States (Fig. 3). These parameters are grouped according to soil texture (clay loam, silt loam, sandy loam, and loam) and high or low soil burn severity categories (Table 1). Since loss of ground cover and water repellent soil conditions often occur after high severity fires (Robichaud, 2000b), the measured K_e value ranges for high soil burn severity are approximately 40% less than the low soil burn severity ranges (Table 1).

Values for hydraulic conductivity, K_e, are based on final infiltration rates obtained using rainfall simulation on 0.5 and 1.0 m^2 plots over a range of soil textures and burn severities (Robichaud, 2000b; Pierson et al., 2001). The measured final infiltration was multiplied by 0.40 for forests and by 0.30 for range and chaparral to adjust for scale effects that were determined from estimated infiltration rates on small watershed sites where runoff and erosion rates were measured. WEPP reduces K_e in direct proportion to the user-input value for ‘rock content,’ the percentage of soil volume that contains rock fragments (i.e., 20% rock will reduce K_e by 20%). WEPP imposes an upper limit for this rock content adjustment of 50%.

Interrill erodibility, K_i, value ranges were obtained from small plot rainfall simulation experiments, which because of

Table 3
The occurrence probabilities for the rain events, soil burn severity downslope spatial arrangements (H = high soil burn severity overland flow element; L = low soil burn severity overland flow element), and the soil parameter sets are combined to provide 100 occurrence probabilities associated with 100 event erosion predictions for postfire Year 1

Selected rain event [occurrence probability] (%)	Soil burn severity spatial arrangement [occurrence probability] (%)	Soil parameter set [occurrence probability] (%)	100 permutations of the three sources of variability: Combined sources of variability	Combined occurrence probability (%)
Rain event associated with the 5th largest runoff [7.5]	HHH [10]	Soil 1 [10]	(5th RO rain event)[a] (HHH) (Soil 1)	(0.075)×(0.10)×(0.10)×100=0.08
		Soil 2 [20]	(5th RO rain event) (HHH) (Soil 2)	(0.075)×(0.10)×(0.20)×100=0.15
		Soil 3 [40]	(5th RO rain event) (HHH) (Soil 3)	(0.075)×(0.10)×(0.40)×100=0.30
		Soil 4 [20]	(5th RO rain event) (HHH) (Soil 4)	(0.075)×(0.10)×(0.20)×100=0.15
		Soil 5 [10]	(5th RO rain event) (HHH) (Soil 5)	(0.075)×(0.10)×(0.10)×100=0.08
	LHH [30]	Soil 1 [10]	15 combinations	15 calculated occurrence probabilities
	HLH [30]	Soil 2 [20]		
	HHL [30]	Soil 3 [40]		
		Soil 4 [20]		
		Soil 5 [10]		
Rain event associated with the 10th largest runoff [7.5]	HHH [10]	Soil 1 [10]	20 combinations	20 calculated occurrence probabilities
	LHH [30]	Soil 2 [20]		
	HLH [30]	Soil 3 [40]		
	HHL [30]	Soil 4 [20]		
		Soil 5 [10]		
Rain event associated with the 20th largest runoff [20]	HHH [10]	Soil 1 [10]	20 combinations	20 calculated occurrence probabilities
	LHH [30]	Soil 2 [20]		
	HLH [30]	Soil 3 [40]		
	HHL [30]	Soil 4 [20]		
		Soil 5 [10]		
Rain event associated with the 50th largest runoff [27.5]	HHH [10]	Soil 1 [10]	20 combinations	20 calculated occurrence probabilities
	LHH [30]	Soil 2 [20]		
	HLH [30]	Soil 3 [40]		
	HHL [30]	Soil 4 [20]		
		Soil 5 [10]		
Rain event associated with the 75th largest runoff [37.5]	HHH [10]	Soil 1 [10]	15 combinations	15 calculated occurrence probabilities
	LHH [30]	Soil 2 [20]		
	HLH [30]	Soil 3 [40]		
		Soil 4 [20]		
		Soil 5 [10]		
	HHL [30]	Soil 1 [10]	(75th RO rain event) (HHL) (Soil 1)	(0.375)×(0.30)×(0.10)×100=1.13
		Soil 2 [20]	(75th RO rain event) (HHL) (Soil 2)	(0.375)×(0.30)×(0.20)×100=2.25
		Soil 3 [40]	(75th RO rain event) (HHL) (Soil 3)	(0.375)×(0.30)×(0.40)×100=4.50
		Soil 4 [20]	(75th RO rain event) (HHL) (Soil 4)	(0.375)×(0.30)×(0.20)×100=2.25
		Soil 5 [10]	(75th RO rain event) (HHL) (Soil 5)	(0.375)×(0.30)×(0.10)×100=1.13

Ten (first five and last five) of the 100 permutations are fully expanded to show complete permutation sets.
[a]RO rain event = rain event associated with the ranked runoff event.

their short length (0.75 and 1.0 m), are restricted to interrill erosion processes (Robichaud, 2000b; Brady et al., 2001; Pierson et al., 2001). Rill erodibility, K_r, and critical shear, τ_c, value ranges were calculated from rill detachment rates and total shear measured during concentrated flow studies done on 4-m long plots (Moffet et al., 2007-this issue).

In range and chaparral environments, field data have shown that postfire values for K_i and K_e also vary by the proportions of shrubs and grasses in the pre-fire vegetation cover (Table 1). This is accounted for by adjusting K_i soil parameter values within each soil texture–burn severity class using area-weighted means based on user-specified proportions of pre-fire shrub and grass canopy cover, such that $K_i = (K_{i\ shrub} \times \%_{shrub}) + (K_{i\ grass} \times \%_{grass}) + (K_{i\ bare} \times \%_{bare})$.

Not every burn severity–soil texture combination was represented in the field sites where soil parameters were measured. Statistical relationships between soil burn severity and soil texture were developed where data were sufficient (generally 2 to 3 soil textures) and extrapolated to soil texture–soil burn severity combinations where data were sparse. Thus, the measured burn severity effects (i.e., fire effects on K_i, K_r, K_e, and τ_c) on some soil textures were used

Table 4
The exceedance probability for each event sediment delivery prediction is computed as the sum of one plus the occurrence probabilities for all greater sediment yield predictions

Event sediment delivery prediction (t ha^{-1})	Permutation (RO rain event[a], soil burn severity OFE[b] arrangement[c], soil parameter set)	----------Occurrence probability---------- RO rain event[a] (%)	Soil burn severity OFE spatial arrangement (%)	Soil parameter set (%)	Permutation combined occurrence probability (%)	Exceedance probability for event sediment delivery prediction (%)
61.4	5, HHH, 5	7.5	10	10	0.075	1.08
52.1	10, HHH, 5	7.5	10	10	0.075	1.15
43.9	5, HHL, 5	7.5	30	10	0.225	1.38
43.2	5, HHH, 4	7.5	10	20	0.150	1.53
42.4	20, HHH, 5	20	10	10	0.200	1.73
40.7	5, LHH, 5	7.5	30	10	0.225	1.95
40.5	5, HLH, 5	7.5	30	10	0.225	2.17
39.1	10, LHH, 5	7.5	30	10	0.225	2.40
37.9	10, HHL, 5	7.5	30	10	0.225	2.63
37.0	10, HHH, 4	7.5	10	20	0.150	2.78
36.5	10, HLH, 5	7.5	30	10	0.225	3.00
35.2	5, HHH, 3	7.5	10	40	0.300	3.30
34.5	5, HHL, 4	7.5	30	20	0.450	3.75
31.8	20, LHH, 5	20	30	10	0.600	4.35
31.2	20, HHL, 5	20	30	10	0.600	4.95
30.6	20, HHH, 4	20	10	20	0.400	5.35
30.6	10, HHH, 3	7.5	10	40	0.300	5.65
30.4	20, HLH, 5	20	30	10	0.600	6.25
29.2	50, HHH, 5	27.5	10	10	0.275	6.53
25.8	5, HLH, 4	7.5	30	20	0.450	6.98
25.6	20, HHH, 3	20	10	40	0.800	7.78
24.4	10, HHL, 4	7.5	30	20	0.450	8.23
21.1	5, LHH, 4	7.5	30	20	0.450	8.67
20.6	20, HHL, 4	20	30	20	0.450	— Σ+ 1=9.88
20.3	10, LHH, 4	7.5	30	20	0.450	10.33
20.3	10, HLH, 4	7.5	30	20	0.450	10.78
19.8	50, HHL, 5	27.5	30	10	0.825	11.60
19.7	10, HHL, 3	7.5	30	40	0.900	12.50
50 values		50 permutations and occurrence probabilities				50 values
0.7	5, HLH, 1	7.5	30	10	0.225	69.58
0.0	5, HHL, 1	7.5	30	10	0.225	69.80
20 values of 0.0	Total of 100 permutations	20 permutations and occurrence probabilities				20 values of 69.80

The example illustrated above shows that an event sediment delivery of 20.6 t ha^{-1} has an exceedance probability of 9.9%. Note, only a portion of the 100 sediment delivery predictions are shown.
[a]RO rain event = rain event associated with the ranked runoff event.
[b]OFE = overland flow element.
[c]H = high soil burn severity overland flow element; L = low soil burn severity overland flow element.

Table 5
To model change over time, the occurrence probability of Soil 1 and Soil 2 (the less erodible soil parameters sets) are increased and Soil 3, Soil 4, and Soil 5 (the more erodible soil parameters sets) are decreased for each year of postfire recovery

Soil parameter set	Occurrence probability (%)				
	Year 1	Year 2 (monsoon)	Year 3	Year 4	Year 5
Soil 1	10	30 (12)	50	60	70
Soil 2	20	30 (21)	30	30	27
Soil 3	40	20 (38)	18	8	1
Soil 4	20	19 (19.5)	1	1	1
Soil 5	10	1 (9.5)	1	1	1

Year 2 variations for monsoonal climates are shown in parenthesis.

to estimate soil burn severity effects on soil texture–burn severity groups where only the unburned condition was measured. Future field measurements will be used to fill data gaps and refine current parameter estimates. The ERMiT code was designed to easily incorporate such improvements.

To capture within-class variability of K_i, K_r, K_e, and τ_c, which, in some cases, have a range of values that vary by two orders of magnitude (Table 1), values within each soil texture–burn severity range are assigned probabilities of occurrence. To do this, each K_i, K_r, and τ_c value range was converted to a cumulative distribution function (CDF) with values arranged from least to most erodible. The CDF for the K_e value range was arranged from highest to lowest hydraulic conductivity. From each CDF the 5th, 20th, 50th, 80th, and 95th percentile values (mean ± approximately two standard deviations) were assigned occurrence probabilities of 10%, 20%, 40%, 20%, and 10%, respectively. For example, all the K_i values (500,000 to 2,500,000 kg-s m^{-4}) for silt loam soil texture, forest vegetation type, burned at high severity (Table 1) were converted to a CDF, and the percentile values listed above were assigned their respective occurrence probabilities.

The selected values of K_i, K_r, K_e, and τ_c for each soil burn severity–soil texture range are grouped by percentile ranking into five soil parameter sets, such that all the 5th percentile values are grouped in 'Soil 1;' 20th percentile values are grouped in 'Soil 2;' 50th percentile values are grouped in 'Soil 3;' 80th percentile values are grouped in 'Soil 4;' and 95th percentile values are grouped in 'Soil 5.' As a result, each burn severity–soil texture class has five soil parameter sets (each with a probability of occurrence) that are used by ERMiT to generate sediment delivery predictions.

4. Combining the sources of variation

To combine soil burn severity variability with soil parameter variability, the soil parameter sets—one for high soil burn severity and one for low soil burn severity—are combined with each of the soil burn severity spatial arrangements. The resultant matrix has the most erodible/lowest hydraulic conductivity in the lower left corner and the least erodible/greatest hydraulic conductivity soil parameter set in the upper right corner as shown in Table 2. For example, given a high soil burn severity user input, the WEPP runs would include the 20 combinations of soil parameters and high/low soil burn severity OFEs boxed under 'HIGH soil burn severity selected' in Table 2. The 'Soil5' parameter set and the 'HHH' soil burn severity spatial arrangement results in WEPP modeling a hillslope using 95th percentile values of the high soil burn severity ranges for K_i, K_r, K_e, and τ_c for all three OFEs. Another combination for the same user selections would be soil parameter set 'Soil3' and soil burn severity spatial pattern 'HLH'. In this case, WEPP models a 3-OFE hillslope using 50th percentile values of the high soil burn severity ranges for K_i, K_r, K_e, and τ_c on the top and bottom OFEs, and 50th percentile values of low soil burn severity ranges for K_i, K_r, K_e, and τ_c for the middle OFE.

To include the third source of variability, the 20 groups of soil burn severity–soil parameter sets are combined with the weather data. Using the reduced CLIGEN file of 6–10 years, WEPP runs in 'continuous mode' to produce erosion predictions for those years. From these WEPP runs, the five representative single event erosion predictions are extracted from the output and paired with the assigned occurrence probabilities (Fig. 1). The occurrence probabilities for the 100 combinations of 5 rain

Table 6
With each year of postfire recovery, the occurrence probabilities and the selection of soil burn severity overland flow element (OFE) arrangements (H = high soil burn severity overland flow element; L = low soil burn severity overland flow element) are shifted toward lower soil burn severity

Hillslope burn severity OFEs	Occurrence probability (%)				
	Year 1	Year 2	Year 3	Year 4	Year 5
User selected high soil burn severity					
HHH	10	0	0	0	0
LHH	30	25	0	0	0
HLH	30	25	25	0	0
HHL	30	25	25	25	0
LLH	0	25	25	25	25
LHL	0	0	25	25	25
HLL	0	0	0	25	25
LLL	0	0	0	0	25
User selected moderate soil burn severity					
HHH	0	0	0	0	0
LHH	0	0	0	0	0
HLH	25	0	0	0	0
HHL	25	25	0	0	0
LLH	25	25	25	25	25
LHL	25	25	25	25	25
HLL	0	25	25	25	25
LLL	0	0	25	25	25
User selected low soil burn severity					
HHH	0	0	0	0	0
LHH	0	0	0	0	0
HLH	0	0	0	0	0
HHL	0	0	0	0	0
LLH	30	25	25	25	25
LHL	30	25	25	25	25
HLL	30	25	25	25	25
LLL	10	25	25	25	25

events, 4 soil burn severity spatial arrangements, and 5 soil parameter sets are calculated as the product of the occurrence probabilities due to each source of variation (Table 3). For example, the occurrence probability for the event sediment delivery prediction given the rain event associated with the 5th largest runoff (7.5% probability, Fig. 1), the HHH soil burn severity spatial arrangement (10% probability, Fig. 2), and the Soil3 soil parameter set (40% probability, Table 2) is $(0.075)\times(0.10)\times(0.40)=0.003$, or 0.3% (row 3 in Table 3).

The 100 sediment delivery predictions are paired with the combined occurrence probability, and sorted in descending order. The 'exceedance probability' for each sediment delivery prediction is computed as the sum of the occurrence probabilities for all greater sediment yield predictions (Table 4). An additional 1% is added to the sum of occurrence probabilities to avoid a zero exceedance probability (0%) being reported for the least likely combination of parameters (row 1 of Table 4).

4.1. Burned site recovery

Erosion rates generally decline with each year of postfire recovery, largely due to increases in natural ground cover and breakdown of water repellent soil conditions (Robichaud and Brown, 2000). Each ERMiT run produces sediment delivery predictions for every permutation of input parameters, and these are not changed nor is WEPP re-run to predict sediment yields during the postfire recovery years. To model the effects of recovery, ERMiT changes the occurrence probabilities of soil parameter sets and soil burn severity spatial arrangements. Over the five years of modeled recovery, the occurrence probabilities of the less erodible soil parameters (Soil 1 and Soil 2 soil parameter sets) are increased and the more erodible soil parameters (Soil 4 and Soil 5 soil parameter sets) are decreased (Table 5). In addition, the occurrence probabilities, as well as the selection of soil burn severity OFE spatial arrangements, shift toward lower erosion with each year of recovery (Table 6). These yearly adjustments to occurrence probabilities and OFE selections are based on field measurements made through postfire recovery periods. As additional recovery data are collected, this shift can be refined.

July, August, and September are the monsoon months for the southwestern US. Because monsoon rains usually come in short bursts of rainfall and do not provide dependable wet cycles, postfire recovery is slower in areas affected by monsoons than in other environments. Consequently, if rainfall data reflect monsoon rainfall characteristics (i.e., total precipitation less than 600 mm yr^{-1} and [ΣJul, Aug, Sep precipitation]/[annual precipitation] is greater than 0.3), then the Year 2 occurrence probabilities for the five soil parameter sets are adjusted (Table 5). This adjustment, based on field observations at the Indian Fire in Arizona and the Hayman Fire in Colorado (P. Robichaud, unpublished data), will predict larger Year 2 sediment deliveries for areas with monsoon rainfall characteristics than in areas with other rainfall patterns. Sediment

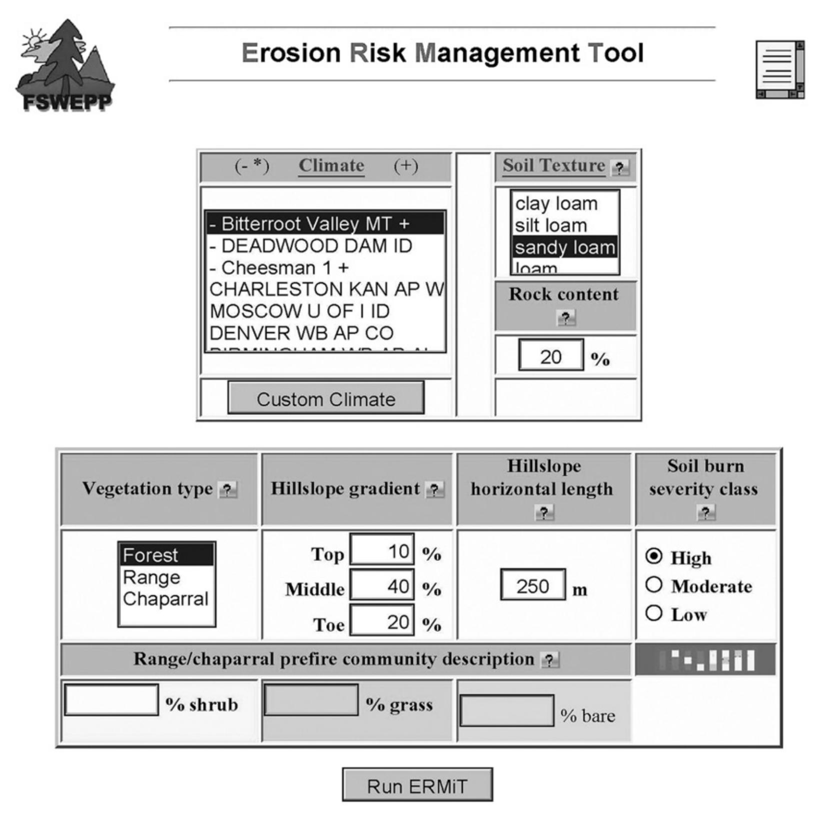


Fig. 4. The ERMiT input screen with user designations for the example scenario inserted.

delivery predictions for Year 1 and for Year 3 and beyond are calculated with the same soil parameter set occurrence probabilities for all rainfall patterns.

4.2. Example

An example ERMiT run is presented to illustrate the user interface and model output formats and to describe the sediment delivery prediction analyses. The context for this example run is the 2000 Valley Complex Fires that burned in the Bitterroot National Forest of Montana. This large wildfire burned many steep hillslopes at high severity. The water quality of the streams and rivers within the burned area is a highly valued resource that was at risk from large increases in sedimentation. This example ERMiT run is for a 250 m slope above Rye Creek, which has a sandy loam soil with 20% rock content. The hillslope gradients are 10% at the top, 40% at mid-slope, and 20% at the toe (Fig. 4).

4.3. Model output

The ERMiT output screen reports user inputs, summarizes the precipitation and runoff for the 100-year WEPP run using PRISM-modified climate data, and describes the five rain events associated with selected runoff events that were used to create the reduced climate file (Fig. 5). Below the inputs and selected rain event summaries, a graphical output shows the single-rain event, postfire, hillslope sediment delivery exceedance probabilities plotted against the predicted event sediment delivery for each of the first five postfire years (Fig. 6). The

Erosion Risk Management Tool

Bitterroot Valley MT +
Modified by Rock:Clime on January 10, 2003 from STEVENSVILLE MT 247894 0
T MAX -6.27 -2.51 2.39 8.56 13.23 17.29 22.57 21.77 15.42 8.34 -0.41 -5.31 deg C
T MIN -15.20 -12.67 -9.75 -6.34 -2.63 1.03 2.77 1.74 -2.19 -6.42 -10.51 -13.92 deg C
MEANP 116.33 89.92 95.25 72.64 89.92 72.90 32.00 48.51 45.72 50.80 76.96 93.22 mm
WET 9.34 7.09 7.36 7.33 8.86 9.58 5.71 5.96 6.43 6.44 8.18 8.74

sandy loam soil texture, **20%** rock fragment

10% top, 40% average, 20% toe hillslope gradient

250 m hillslope horizontal length

high soil burn severity on **forest**

100 - YEAR MEAN ANNUAL AVERAGES				
895.29	**mm**	annual precipitation from	9182	storms
10.31	**mm**	annual runoff from rainfall from	261	events
7.42	**mm**	annual runoff from snowmelt or winter rainstorm from	174	events

Storm Rank (return interval)	Storm Runoff (mm)	Storm Precipitation (mm)	Storm Duration (h)	10-min Peak Intensity (mm h^{-1})	30-min Peak Intensity (mm h^{-1})	Storm Date
1	43.2	69.5	3.12	133.95	95.55	July 26 year 27
5 (20-year)	**18.7**	**37.3**	**1.79**	**53.50**	**42.45**	**July 15 year 94**
10 (10-year)	**17.1**	**43.1**	**2.97**	**115.87**	**71.71**	**June 2 year 62**
20 (5-year)	**13.6**	**29.3**	**2.45**	**77.70**	**48.42**	**June 13 year 60**
50 (2-year)	**7.5**	**26.8**	**2.12**	**30.76**	**25.70**	**June 23 year 40**
75 (1⅓-year)	**3.7**	**17.2**	**1.96**	**27.19**	**20.84**	**September 12 year 37**

Fig. 5. A portion of the ERMiT output for the example scenario shows the user-designated inputs, summary statistics for the 100-yr climate generated by CLIGEN, the selected runoff events (1st ranked runoff event is shown in row one of the table, but is not one of the selected events), and rainfall parameters for the rain events associated with the selected runoff events.

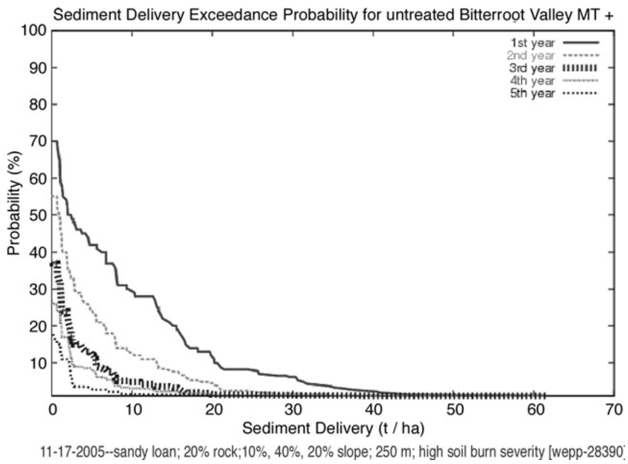


Fig. 6. The graphic portion of the ERMiT output shows single-rain event sediment delivery exceedance probabilities plotted against predicted event sediment deliveries for the untreated hillslope of the example scenario. Each of the first five postfire years is indicated by a separate line on the graph.

spacing between the plotted lines for each year provides an indication of the predicted recovery rate for the hillslope being modeled (Fig. 6). These data for the untreated hillslope are also included in the tabular output interface discussed in the following section.

5. Treatment effectiveness

The decision to apply postfire treatments to reduce runoff and erosion is based on a cost–benefit analysis—assessing the probability that damaging erosion will occur, the need for and cost of restoring damaged resources, the probability of reducing erosion with applied mitigation treatments, the costs of treatment application, and the savings realized by reducing resource damage. Using data from rainfall and rill simulations, hillslope plots, and paired catchment studies, estimates of the erosion reduction and/or sediment trapping efficiency of seeding, straw mulching, and contour-felled log/straw wattle erosion barrier treatments have been incorporated into ERMiT. In general, treatment effects are modeled by increasing the occurrence probabilities of the less erosive soil parameter sets (Soil 1, and Soil 2) and reducing the occurrence probabilities of the more erosive soil parameter sets (Soil 3, Soil 4, and Soil 5). Probabilistic predictions of single event sediment delivery with and without applied treatments are generated for five postfire years.

Beyers (2004) and Robichaud et al. (2000) reported that seeding had little measured effect in reducing first postfire year erosion; however, seeding effects are more evident in the second and subsequent years. In ERMiT, occurrence probabilities associated with the soil parameter sets are adjusted to reflect the increase in ground cover and subsequent decrease in erosion in Years 2 to 5.

Erosion reduction due to the application of straw mulch has been measured at four sites (Robichaud, unpublished data). In ERMiT, four straw mulch application rates (1, 2, 3.5, and 4.5 t ha^{-1}), which increase ground cover to 47, 72, 89, and 94%, respectively, are modeled. The sediment delivery predictions based on mulching rate are produced by adjusting the occurrence probabilities associated with the soil parameters sets, similar to the adjustments made for increases in natural ground cover during postfire recovery years.

Contour-felled log and straw wattle erosion barriers have the ability to reduce erosion by slowing runoff and trapping runoff and sediment. For modeling, straw wattles are assumed to be the same as contour-felled logs. Measured storage potential, trapping efficiencies, and performance of 3000 contour-felled logs from six research sites were used to develop a hillslope storage function based on the mean log diameter and hillslope spacing (mean distance (m) between in-line log tiers). ERMiT applies a regression relationship, based on user-specified mean log diameter (cm), spacing (m), and slope (%), to determine the potential storage capacity (PSC) for the hillslope:

$$\begin{aligned} \text{PSC} &= \frac{1342}{\text{slope}} + 0.0029 \times (\text{log diameter})^2 + \frac{272}{\text{spacing}} \\ R^2 &= 0.97 \qquad n = 3000 \text{ logs} \end{aligned}$$

where PSC is potential storage capacity (m^3 ha^{-1}). PSC is converted to a weight per unit volume based on measured sediment bulk densities (clay loam sediment = 1.1 g cm^{-3}; silt loam sediment = 0.97 g cm^{-3}; sandy loam sediment = 1.23 g cm^{-3}; and loam sediment = 1.16 g cm^{-3}).

Based on field observations, the potential storage capacity is rarely fully utilized. To compare the actual hillslope sediment storage to the potential hillslope storage capacity, the sediment trapping efficiency is calculated as the sediment stored behind the contour-felled logs divided by the sum of the sediment leaving the hillslope and the sediment stored behind the contour-felled logs. Field data suggest that sediment trapping efficiency varies with rainfall intensity. ERMiT calculates a weighted maximum 10-min rainfall intensity ($I_{10\text{-}W}$) based on the maximum 10-min rainfall intensity (I_{10}) estimated from each rain event associated with the 5th-, 10th-, 20th-, 50th-, and 75th-ranked runoff events. $I_{10\text{-}W}$ is calculated as the sum of the I_{10} for each storm multiplied by its respective occurrence probability, such that:

$$\begin{aligned} I_{10-W} = &(I_{10-5\text{th rank}} * 0.075) + (I_{10-10\text{th rank}} * 0.075) \\ &+ (I_{10-20\text{th rank}} * 0.2) + (I_{10-50\text{th rank}} * 0.275) \\ &+ (I_{10-75\text{th rank}} * 0.375) \end{aligned}$$

where $I_{10\text{-}W}$ (mm h^{-1}) is the weighted maximum 10-min rainfall intensity and $I_{10\text{-5th rank}}$, $I_{10\text{-10th rank}}$, $I_{10\text{-20th rank}}$, $I_{10\text{-50th rank}}$, and $I_{10\text{-75th rank}}$ are the maximum 10-min rainfall intensity (mm h^{-1}) estimated from each rain event associated with the 5th-, 10th-, 20th-, 50th-, and 75th-ranked runoff events, respectively. Rainfall intensity for snowmelt events is taken to be zero.

Field data were used to determine efficiency functions based on $I_{10\text{-}W}$ for two postfire years:

$$\text{Year 1}: EFF_{y1} = -0.84(I_{10-W}) + 114$$

$$\text{Year 2}: EFF_{y2} = -1.4(I_{10-W}) + 116$$

where EFF is the trapping efficiency (percent) of the erosion barriers and $I_{10\text{-}W}$ is the weighted maximum 10-min rainfall intensity (mm h−1).

The sediment trapping efficiency of erosion barriers continues to decrease with time because each sediment producing event reduces potential storage capacity for the next rain event. In addition, settlement, decay, and movement of contour-felled log and straw wattle structures cause the hillslope treatment to be less efficient with time (Robichaud, in review). After Year 2, efficiency is estimated as a percentage of the preceding year, such that:

$$\text{Year 3}: EFF_{y3} = 0.75 \times EFF_{y2}$$

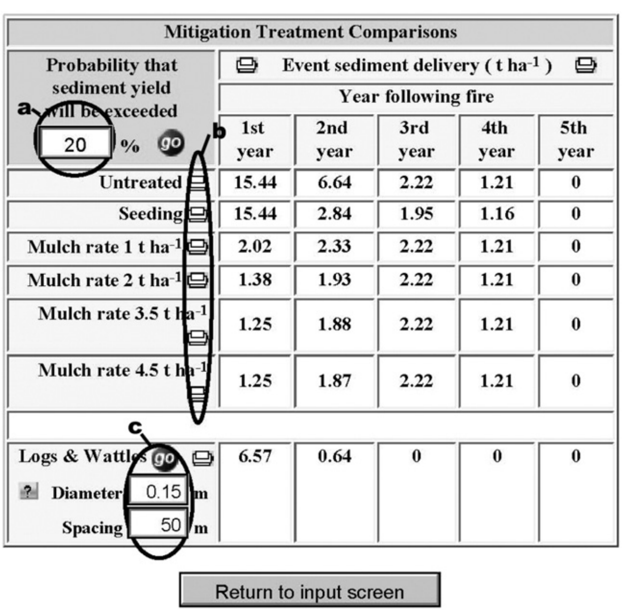
$$\text{Year 4}: EFF_{y4} = 0.55 \times EFF_{y3}$$

$$\text{Year 5}: EFF_{y5} = 0.45 \times EFF_{y4}$$

These changes in efficiencies are based on field observations of erosion barrier performance and sediment storage changes over time.

5.1. Example

In the example ERMiT run, the hillslope is evaluated to determine the risk of postfire erosion that exceeds a manageable limit for event sediment delivery. To establish output criteria, the example scenario includes hypothetical conditions set by a postfire assessment team. First, the team determined that 5 t ha^{-1} was the maximum tolerable event sediment delivery



Mitigation Treatment Comparisons					
Probability that sediment yield will be exceeded	Event sediment delivery (t ha^{-1})				
	Year following fire				
20 % go	1st year	2nd year	3rd year	4th year	5th year
Untreated	15.44	6.64	2.22	1.21	0
Seeding	15.44	2.84	1.95	1.16	0
Mulch rate 1 t ha^{-1}	2.02	2.33	2.22	1.21	0
Mulch rate 2 t ha^{-1}	1.38	1.93	2.22	1.21	0
Mulch rate 3.5 t ha^{-1}	1.25	1.88	2.22	1.21	0
Mulch rate 4.5 t ha^{-1}	1.25	1.87	2.22	1.21	0
Logs & Wattles go Diameter 0.15 m Spacing 50 m	6.57	0.64	0	0	0

Return to input screen

Fig. 7. The tabular portion of the ERMiT output shows predicted single-rain event sediment deliveries that have a 20% exceedance probability by postfire year and by treatment for the hillslope of the example scenario. Circles 'a' and 'c' indicate embedded interfaces where user inputs can modify the output table to evaluate a range of options. Circle 'b' indicates the printer icons that, when clicked, call up data tables of predicted event sediment deliveries and occurrence probabilities by postfire year.

in postfire year 1. Second, straw mulch treatment will be applied if the year 1 risk of exceeding the event sediment delivery limit (5 t ha^{-1}) is greater than 20% and straw mulch application will reduce that risk to 20% or less.

5.2. Model outputs

In the output table, the user can select (circle a, in Fig. 7) an exceedance probability and the corresponding event sediment delivery prediction is displayed by postfire year and by treatment (Fig. 7). Within this embedded interface, the user can evaluate the predicted sediment delivery over a range of occurrence probabilities without rerunning the model. In addition, by clicking on the printer icon to the right of each treatment label (circle b, in Fig. 7), a full table of predicted event sediment deliveries and their occurrence probabilities by postfire year for that treatment are displayed on screen. Contour-felled log or straw wattle erosion barrier treatments need mean diameter (m) and log spacing (m) user inputs (circle c, in Fig. 7) for event sediment deliveries to be predicted. The tabular output screen allows the predicted event sediment deliveries of the untreated hillslope to be compared to the treated hillslope for each of five postfire years to determine the potential benefit of postfire mitigation treatments (Fig. 7).

By setting the output table to 20% exceedance probability, it is possible to compare the effects of mulching at different rates. On the untreated hillslope, sediment delivery estimates with 20% exceedance probability are over 15 t ha^{-1}, which is well above the 5 t ha^{-1} tolerable limit set by the postfire assessment team. However, mulching at a rate of 1.0 t ha^{-1} lowers the sediment delivery estimate with a 20% exceedance probability to 2 t ha^{-1}, which is below the tolerable limit set by the postfire assessment team. Mulching at a higher rate does not lower the predicted event sediment delivery enough to justify the additional mulch.

6. Conclusions and management implications

ERMiT is a dynamic process-based model that can be readily updated as additional data and validation results become available. Unlike most erosion prediction models, ERMiT does not provide 'average annual erosion rates;' rather, it provides a distribution of erosion rates with the likelihood of their occurrence. Such output can help managers make erosion mitigation treatment decisions based on the probability of high sediment yields occurring, the value of resources at risk for damage, cost, and other management considerations. ERMiT is most useful when managers determine an event sediment delivery amount that can be tolerated without sustained resource damage and the probability of that event occurring. This would likely vary within a burned area. For example, short-term declines in water quality may be tolerable while damage to a unique cultural heritage site would not, and modeling the hillslopes above these two resources would likely require different user-designated exceedance probabilities and treatment criteria.

Application of postfire erosion mitigation treatments does not eliminate erosion, but treatments can reduce the hillslope response to many rain events. After wildfires, managers can use ERMiT to estimate the probabilities of erosion-producing rain events occurring, the expected event sediment deliveries, and predicted rates of recovery for the burned area. In addition, realistic expectations of treatment effectiveness will allow managers to make more cost-effective choices of where, when, and how to treat burned landscapes.

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