**CSIRO** PUBLISHING

*International Journal of Wildland Fire* **2016**, *25*, 337–350
http://dx.doi.org/10.1071/WF14171

# Validation of a probabilistic post-fire erosion model

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**Abstract.** Post-fire increases of runoff and erosion often occur and land managers need tools to be able to project the increased risk. The Erosion Risk Management Tool (ERMiT) uses the Water Erosion Prediction Project (WEPP) model as the underlying processor. ERMiT predicts the probability of a given amount of hillslope sediment delivery from a single rainfall or snowmelt event on unburned, burned and recovering forest, range and chaparral hillslopes and the effectiveness of selected mitigation treatments. Eight published field study sites were used to compare ERMiT predictions with observed sediment deliveries. Most sites experienced only a few rainfall events that produced runoff and sediment (1.3–9.2%) except for a California site with a Mediterranean climate (45.6%). When sediment delivery occurred, pooled Spearman rank correlations indicated significant correlations between the observed sediment delivery and those predicted by ERMiT. Correlations were $\rho = 0.65$ for the controls, $\rho = 0.59$ for the log erosion barriers and $\rho = 0.27$ (not significant) for the mulch treatments. Half of the individual sites also had significant correlations, as did 6 of 7 compared post-fire years. These model validation results suggest reasonable estimates of probabilistic post-fire hillslope sediment delivery when compared with observations from eight field sites.

**Additional keywords:** erosion prediction, FS WEPP, post-fire assessment, probabilistic model.

Received 24 September 2014, accepted 18 January 2016, published online 29 February 2016

## Introduction

Wildfire is a natural component of many healthy forest ecosystems and is often the cause of landscape changes within and downstream of the burned area. However, land management and social issues related to fire suppression and post-fire response have become more prominent as the frequency of large wildfires has increased, often driven by climate change and high levels of fuel accumulation due to past wildfire suppression policies (Mouillot and Field 2005; Running 2006; Westerling *et al.* 2006) and a generally wetter climate over the past 50 years (Zhang *et al.* 2007). Conversely, many areas are experiencing widespread drought conditions (Westerling *et al.* 2006), which can also lead to increased fire activity in the western US. Resource managers and the general public are concerned with both the direct effects of the flame front and the hydrological consequences of the fire. Post-fire peak runoff and erosion can be orders of magnitude larger than pre-fire values owing to the loss of surface cover and fire-induced changes in soil properties (Robichaud *et al.* 2000; Moody *et al.* 2013). Direct and indirect fire effects impact large numbers of people as source water for municipal water supplies and exurb community developments are encompassed by areas increasingly at risk of wildfire (Miller *et al.* 2011; Emelko and Sham 2014).

Immediately after a wildfire, it is common practice for land managers to rapidly assess the threat to lives, properties and valued resources from potential post-fire increases in runoff and erosion (Robichaud *et al.* 2007*b*; Robichaud and Ashmun 2013; Miller *et al.* 2015). These assessments are used to guide the development of recommendations to mitigate predicted increases in runoff and erosion. On federal lands in the US, post-fire assessments and treatment recommendations are done by interdisciplinary Burned Area Emergency Response (BAER), and Burned Area Emergency Stabilisation and Rehabilitation (ESR) teams using a well-defined protocol (USDA Forest Service 2004; USDI 2006). Australia's state agencies follow a similar protocol, whereas Canadian provinces use smaller team approaches (Robichaud and Ashmun 2013).

Our research at the USDA Forest Service to date has focused on understanding the causes of increased runoff and erosion after wildfires and developing modelling tools to predict the potential increased risk of flooding and sediment delivery (Robichaud *et al.* 2007*a*, *b*; Cerdà and Robichaud 2009; Robichaud *et al.* 2010*a*; Wagenbrenner *et al.* 2010; Elliot 2013). In addition, we have evaluated the effectiveness of various treatments in mitigating post-fire runoff and erosion (Robichaud *et al.* 2010*b*). Although most of our research and model

**Table 1. Characteristics of the post-fire field study sites providing observed rainfall and sediment delivery data**

| Fire name | Location | Latitude, longitude (degrees) | Elevation (m) | Year burned | Years observed | Post-fire treatment(s) | Reference |
|---|---|---|---|---|---|---|---|
| Cannon | Central California | 38.45, −119.47 | 2325 | 2002 | 2002–06 | Log erosion barriers | Robichaud *et al.* 2008 |
| Cedar | Southern California | 32.88, −116.76 | 755 | 2003 | 2004–09 | Hydromulch; hydromulch strips | Robichaud *et al.* 2013 |
| Fridley | Southern Montana | 45.51, −110.78 | 1940 | 2001 | 2002–05 | Log erosion barriers | Robichaud *et al.* 2008 |
| Hayman[A] | | | | | | | |
| Logs<br>Mulch | Central Colorado | 39.18, −105.36;<br>39.22, −105.34 | 2440;<br>2430 | 2002 | 2002–10 | Log erosion barriers;<br>Straw mulch; hydromulch | Robichaud *et al.* 2008, 2013 |
| Mixing | Southern California | 33.68, −116.73 | 1615 | 1999 | 2000–04 | Log erosion barriers | Robichaud *et al.* 2008 |
| North 25 | Central Washington | 47.99, −120.34 | 1565 | 1998 | 1999–2002 | Log erosion barriers | Robichaud *et al.* 2008 |
| Valley | Western Montana | 45.91, −114.02 | 1725 | 2000 | 2001–06 | Log erosion barriers | Robichaud *et al.* 2008 |

[A] The location and elevation for the two sites at Hayman were different.

development has been based in the western US, our modelling tools have been successfully adapted and used throughout the world (Robichaud *et al.* 2009; Robichaud and Ashmun 2013). However, a systematic validation of our tools is needed to determine the reliability of the predictions for specific applications. In particular, we focus on the post-fire erosion predictions with and without common rehabilitation treatments in the western US. If the model predictions are reliable in the western US, then by modifying key input parameters such as soil erodibility and local climate, the model will be useable in other fire-prone areas worldwide as calibration is not needed.

Validating probabilistic prediction models is challenging because traditional parametric statistical analyses are not suitable (Soise *et al.* 2008); hydrologic datasets often have many zero values with the occasional large sediment event resulting in skewed distributions and uneven sample sizes between treatments, sites and years. Modelling soil erosion is subject to significant uncertainties (Quinton 1997; Brazier *et al.* 2000), yet land managers need to make important and timely predictions to mitigate potential runoff and erosion. Soil erosion modelling technology has advanced greatly in the past 30 years (Morgan 2011), yet questions still arise as to the models' ability to capture the dynamic erosion process (Beven and Brazier 2011). Past erosion model validation studies focussed on average values from all rainfall events or average annual values where the data may have come from natural rainfall or from rainfall simulation (Nearing 1998; Laflen *et al.* 2004; Larsen and MacDonald 2007; Beven and Brazier 2011).

In order to make probabilistic erosion predictions following wildfire, we developed the Erosion Risk Management Tool (ERMiT; Robichaud *et al.* 2007*a*, *b*). The purpose of the current paper is to present a novel validation of ERMiT, using an event-based approach. Event-based field data for validation were taken from eight study sites with 4 or more years of post-fire rainfall, runoff and erosion data located in the western US (Table 1). The objectives of this paper are to: (1) compare observed sediment delivery from small watersheds with estimates generated by ERMiT; (2) assess how well ERMiT predicts sediment delivery reduction with post-fire log erosion barriers, straw mulch and hydromulch treatments immediately post-fire, and during 4 or more years of vegetation recovery; and (3) evaluate how well ERMiT reflects the range of variability observed in sediment delivery.

## Methods

### Probabilistic post-fire erosion model

The Erosion Risk Management Tool (ERMiT, version 2014.04.07, Robichaud *et al.* 2014*a*) is a customised interface to the Water Erosion Prediction Project (WEPP, version 2010.1, available at http://www.ars.usda.gov/Research/docs.htm?docid=18084 (accessed 28 January 2016)) model, a distributed physically based hydrology and erosion model (Laflen *et al.* 1997) to predict event-based sediment yields. ERMiT processes inputs and creates outputs for the WEPP model through our Forest Service WEPP online interface (Elliot 2004). ERMiT predicts the probability of a given depth of runoff and sediment delivery from stochastically generated rainfall or snowmelt events on unburned, burned and recovering forest, range and chaparral hillslopes (Robichaud *et al.* 2007*a*, *b*; Robichaud *et al.* 2014*a*). Unlike most erosion prediction models, ERMiT was not designed to predict annual values or average values, but rather the probability associated with the delivery of a given amount of sediment, or more specifically, the sediment delivery exceedance probability. Sediment delivery exceedance probability can be thought of as 100% minus the cumulative probability percentage. For example, ERMiT will typically internally carry out up to 200 runs incorporating the variability in climate, soils and location associated with sediment delivery for a given site (Robichaud *et al.* 2007*a*). If the cumulative predicted probability for 80% of the runs is 5 Mg $\text{ha}^{-1}$, then there is a 20% (100% − 80% = 20%) probability that erosion for the conditions modelled that sediment delivery will exceed 5 Mg $\text{ha}^{-1}$. To define the events for subsequent runs, ERMiT carries out an initial run of 100 years for the highest-severity condition. The exceedance probabilities for sediment delivery are calculated for 20-, 10-, 5-, 2- and 1.5-year events for the most severe condition (most erodible high-severity soil for the entire hillslope). The years in which these events occur are then selected for the subsequent internal ERMiT analyses incorporating the soil and spatial variability attributes with the selected rainfall and/or snowmelt events of the location to predict exceedance probabilities for a wide range of possible sediment

**Table 2. Input data for the ERMiT model runs for each study site**
High soil burn severity was always selected

| Fire name | Nearest CLIGEN station | PRISM annual precipitation$^A$ (mm) | Soil texture | Surface soil rock content (%) | Slope length (m) | Slope steepness: top, mid, toe (%) | Treatment: mulch rate (Mg ha$^{-1}$) or log diameter and spacing (m) |
|---|---|---|---|---|---|---|---|
| Mulch sites | | | | | | | |
| Cedar | El Capitan Dam, CA | 467 | Sandy loam | 20 | 300 | 7, 9, 10 | 2.2 |
| Hayman | Cheeseman, CO | 476 | Sandy loam | 20 | 139 | 33, 27, 30 | 2.2 |
| Log sites | | | | | | | |
| Cannon | Bridgeport, CA | 644 | Silt loam | 20 | 247 | 44, 44, 38 | 0.18, 25 |
| Fridley | Livingston, MT | 798 | Silt loam | 20 | 263 | 40, 37, 30 | 0.21, 17 |
| Hayman | Cheeseman, CO | 478 | Sandy loam | 20 | 139 | 33, 27, 30 | 0.17, 12 |
| Mixing | Beaumont, CA | 589 | Sandy loam | 20 | 87 | 24, 24, 19 | 0.22, 14 |
| North 25 | Wenatchee, WA | 742 | Sandy loam | 20 | 222 | 50, 39, 30 | 0.17, 25 |
| Valley | Stevensville, MT | 522 | Loam | 30 | 127 | 46, 39, 30 | 0.18, 10 |

$^A$Annual precipitation is displayed as monthly amounts within ERMiT.

delivery events. Not all events produce runoff; if there is no runoff, then there is no sediment delivery. In many cases, the predicted amount of sediment delivered will be zero as is often observed in field studies (Covert *et al.* 2005; Elliot *et al.* 2006; Robichaud *et al.* 2008; Elliot and Glaza 2009; Robichaud *et al.* 2013).

A 100-year stochastic weather file for a given site is used by WEPP to produce a 100-year runoff record for the combination of soil and burn severity conditions that have the greatest potential to generate runoff or sediment delivery for the site. Field-derived values from other sites (Robichaud and Miller 1999) for interrill erodibility ($K_i$), rill erodibility ($K_r$), effective hydraulic conductivity ($K_e$) and critical shear ($\tau_c$) derived from rainfall simulation and rill simulation studies (Robichaud *et al.* 2010*a*, 2010*b*; Wagenbrenner *et al.* 2010) along with observed spatial variability in burn severity are used by ERMiT to develop a probability distribution of potential erosion rates. From this distribution, ERMiT can provide an erosion rate associated with a given probability exceedance. ERMiT is also able to generate sediment delivery predictions on hillslopes that were treated with mulch, seed and log erosion barriers (Robichaud *et al.* 2007*a*).

For validation, ERMiT model inputs (climate, soil, vegetation, hillslope length and gradient, and soil burn severity) were selected to closely match the observed site characteristics. Although burn severity is a user input to ERMiT, all of our field validation sites were located in areas burned at high severity; thus, we are not evaluating how well ERMiT predicts sediment delivery across the range of burn severities or for unburned watersheds. The nearest climate station was chosen for each site from the WEPP weather station database (Scheele *et al.* 2001). The monthly precipitation depths were then adjusted using the 4-km database from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Daly *et al.* 1997) with our RockClime interface for input into WEPP's stochastic weather generator (Scheele *et al.* 2001; Elliot 2004) (Table 2). In all cases, the precipitation was considerably greater on the study site than for the nearest weather station. Thus, the number of wet days per month was increased by half the amount of the adjusted monthly precipitation to account for the wetter climates as suggested by Bayley *et al.* (2010).

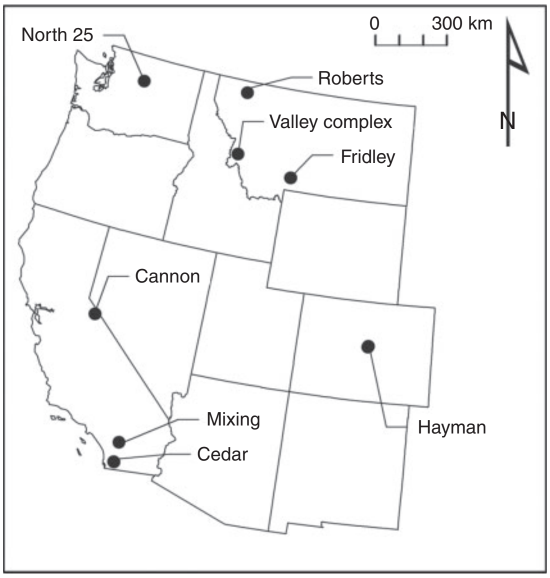

**Fig. 1.** Location of post-fire study sites in the western US used for comparison with ERMiT predictions (Robichaud *et al.* 2008, 2013).

### Field data collection

Observed field data were collected from eight paired watershed studies (two different study sites within the Hayman Fire area) in the western US (Fig. 1) for periods ranging from 4 to 7 years after burning (Robichaud *et al.* 2008, 2013). Site characteristics are briefly summarised in Table 1. There were eight control watersheds, six watersheds treated with log erosion barriers, one treated with straw mulch, two treated with hydromulch, and one treated with hydromulch applied in contoured strips (referred to as half-hydromulch). The studies were designed to measure runoff and sediment yields from adjacent paired small (1- to 13-ha) watersheds, all burned at high severity. Each site consisted of either one burned watershed treated with log erosion barriers and one burned, untreated control watershed or two watersheds treated with different mulch treatments and a control. As no pre-fire or pre-treatment runoff, peak flow or sediment delivery data were available, it was assumed that the paired watersheds behaved similarly before treatment. Details of the experimental setup, data records and results can be found in Robichaud *et al.* (2008, 2013).

The largest runoff or sediment delivery event for each year was identified in the field-observed dataset. This resulted in a total of 50 events for comparison, two of which had some snowmelt contribution. Runoff can result from both rainfall and snowmelt. Snowmelt runoff is usually so much less than rainfall that it seldom generates any hillslope erosion. However, we considered snowmelt as a potential driver of soil erosion in the present study because rain-on-snow events or unusually high spring temperatures can melt snow fast enough to cause surface runoff. Combined, the sites yielded a total of 114 plot-years of sediment delivery data, with some sites having up to up to 7 years of post-fire hydrological observations. The sediment delivery from each rainfall event from each year was compared with a predicted sediment delivery from ERMiT in the relevant post-fire year for a similar event. Field-site data from post-fire years 6 or 7 were compared with ERMiT year 5 data, as ERMiT only predicts to post-fire year 5.

The soil textural class and surface soil rock content were obtained from site observations and the Natural Resource Conservation Service soil series descriptions (NRCS 2009). All sites were forested, except for the Cedar site in California, which was chaparral vegetation before the wildfire. Each site experienced fire severe enough to result in high soil burn severity conditions as defined by Parsons *et al.* (2010). Hillslope lengths and gradients for top, middle and toe of the slope were obtained from site observations, contour maps or digital elevation models and the treatments selected were based on measurements made on site (e.g. log erosion barrier diameter and spacing, mulch application rates; Table 2).

## Statistical analysis

In order to validate ERMiT, the following were evaluated: (1) observed 10-min rainfall intensities with associated return periods greater than 2 years (National Oceanic and Atmospheric Administration (NOAA) Atlas 2 and 8; http://www.nws.noaa.gov/oh/hdsc/noaaatlas2.htm; accessed 20 May 2015) were compared to the rainfall intensities predicted by ERMiT; (2) the number and proportion of observed rainfall events that produced sediment were compared to those predicted by ERMiT; (3) for each year, the largest observed sediment delivery event and its calculated occurrence probability (1 ÷ return period) was compared to the predicted sediment delivery from ERMiT for that probability; (4) for just those events that resulted in sediment delivery, the observed sediment deliveries and exceedance probabilities were compared to ERMiT values; and (5) the distributions of the probability of observed and predicted sediment delivery were compared.

The attributes of the observed data and the predicted values do not lend themselves to traditional statistics and parametric analytical methods because the observed datasets have many zero values, with the occasional large value and few values in between. Even though sites generally experience declining erosion in the years following a wildfire, a large rainfall event several years after the fire can result in a large amount of sediment delivery. Sites have varying soil, climate and topographic characteristics, all of which interact along with recovery to influence sediment delivery, which was evident in the observed data and in the ERMiT predictions. Observed sediment delivery events for each site in the first post-fire year ranged from 2 to 26 Mg ha$^{-1}$; the distributions of the observed data are skewed, with a small number of observations in each year. ERMiT datasets have a more consistent distribution of values from zero to the largest predicted sediment delivery event, and generally a larger number of values in each dataset (because of the probabilistic nature of the dataset). The proportion of observed events that resulted in sediment delivery was calculated for each year and overall at each fire (Table 3). These values were compared with the initial 100-year model data (Table 4).

### Large rainfall intensity and event comparison

We plotted the observed 10-min rainfall intensities ($I_{10}$) of events with a return period of 2 years or more against the predicted $I_{10}$ values from ERMiT and calculated the coefficient of determination ($R^2$) between the values. For each of the largest observed rainfall events (i.e. $I_{10}$ with a return period of 2 years or more), we determined the ERMiT sediment delivery event with the nearest rainfall intensity, and recorded the predicted sediment delivery in the appropriate year since the fire. This allowed the comparison of the observed and predicted large-sediment-delivery data. Although the two probabilities are not exactly the same, this approach provides a reasonable method for comparing the rainfall events with the largest sediment delivery in a given year, because rainfall intensity is known to be a driver of post-fire erosion (Robichaud 2005; Moody and Martin 2009). If the largest sediment delivery event for the year was due to snowmelt only, then we assumed a 2-year ERMiT sediment delivery event (50% exceedance probability) for comparison.

The sediment yield from the largest rainfall event (highest $I_{10}$) from each site–treatment–year combination was paired with a comparable event and associated sediment delivery prediction from ERMiT. These 114 paired values (observed and predicted) were compared with a non-parametric correlation analysis (Proc Corr Spearman in SAS) (SAS Institute 2003). Rank-sum correlation coefficients were calculated between the observed and predicted sediment delivery data by fire, by year since fire and by treatment (Table 5).

The Kolmogorov–Smirnov (KS) two-sample test (Siegel and Castellan 1988) was used to assess the statistical significance of differences in the observed and predicted large-sediment-delivery data. The KS test was chosen because it is a simple non-parametric test suitable for assessing the significance of differences in data distributions; there is no assumption of normality or equal variance required.

### Adjusted exceedance probabilities comparison

One of the first outputs of ERMiT is the number of rainfall events and the number of runoff or sediment delivery events (rainfall or snowmelt-only) for a 100-year simulation period (Table 4). These data were used to calculate the proportion of events that are likely to produce runoff or sediment delivery, and are summarised with the proportion of observed runoff events in Table 4. The proportion of events that were predicted to generate

**Table 3. Observed rainfall event count for runoff and sediment delivery events and the total number of rainfall events in a given year at the eight study sites**

The percentage chance of a runoff and sediment delivery-producing event based on observed rainfall events is calculated for each fire and post-fire (PF) year

| | PF year 1 | | PF year 2 | | PF year 3 | | PF year 4 | | PF year 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Fire name | Runoff and sediment delivery ÷ total rainfall events | % | Runoff and sediment delivery ÷ total rainfall events | % | Runoff and sediment delivery ÷ total rainfall events | % | Runoff and sediment delivery ÷ total rainfall events | % | Runoff and sediment delivery ÷ total rainfall events | % |
| Cannon | 2/42 | 4.8 | 0/61 | 0 | 0/37 | 0 | 1/66 | 1.5 | 0/33 | 0 |
| Cedar | 26/48 | 54.2 | 16/35 | 45.7 | 11/27 | 40.7 | 9/25 | 36 | 13/25 | 52 |
| Fridley | 5/98 | 5.1 | 1/120 | 0.8 | 0/109 | 0 | 2/121 | 1.7 | 0/130 | 0 |
| Hayman | | | | | | | | | | |
| logs | 4/38 | 10.5 | 9/68 | 13.2 | 0/50 | 0 | 0/88 | 0 | 0/89 | 0 |
| mulch | 5/43 | 11.6 | 7/64 | 10.9 | 1/42 | 2.4 | 1/61 | 1.6 | 2/69 | 2.9 |
| Mixing | 10/48 | 20.8 | 5/55 | 9.1 | 1/38 | 2.6 | 1/54 | 1.9 | 5/44 | 11.4 |
| North 25 | 4/79 | 5.1 | 0/60 | 0 | 0/79 | 0 | 1/52 | 1.9 | 0/65 | 0 |
| Valley | 4/100 | 4 | 3/86 | 3.5 | 1/48 | 2.1 | 0/51 | 0 | 0/48 | 0 |

**Table 4. The ERMiT-predicted number of runoff events from rainfall or snowmelt and total number of rainfall events from the initial 100-year model run and the observed runoff events from rainfall and snowmelt and total rainfall events**

| | ERMiT output (100 years) | | | | | Observed (5 years) | | | |
|---|---|---|---|---|---|---|---|---|---|
| Fire name | Runoff events from rainfall ($n$) | Runoff events from snowmelt ($n$) | Total rainfall events ($n$) | Annual total rainfall events ($n$ year$^{-1}$) | Runoff events (%) | Runoff events from rainfall and snowmelt ($n$) | Total rainfall events ($n$) | Annual total rainfall events ($n$ year$^{-1}$) | Runoff events (%) |
| Cannon | 96 | 561 | 7904 | 79 | 8.3 | 3 | 239 | 48 | 1.3 |
| Cedar | 855 | 23 | 5172 | 52 | 17.0 | 75 | 160 | 32 | 46.9 |
| Fridley | 571 | 291 | 15 822 | 158 | 5.5 | 8 | 578 | 116 | 1.4 |
| Hayman | | | | | | | | | |
| logs | 506 | 65 | 9092 | 91 | 6.3 | 13 | 333 | 67 | 3.9 |
| mulch | 535 | 62 | 9092 | 91 | 6.6 | 16 | 279 | 56 | 5.7 |
| Mixing | 957 | 186 | 5174 | 52 | 22.1 | 22 | 239 | 48 | 9.2 |
| North 25 | 199 | 530 | 11 606 | 116 | 6.3 | 5 | 335 | 67 | 1.5 |
| Valley | 298 | 151 | 12 148 | 121 | 3.7 | 8 | 333 | 67 | 2.4 |
| **Total** | 4017 | 1869 | 76 010 | 760 | | 150 | 2496 | 499 | |
| **Mean** | 502 | 233 | 9501 | 95 | 9.5 | 19 | 312 | 62 | 8.9 |

runoff or sediment delivery via ERMiT was used to adjust the ERMiT exceedance probability calculations so we could compare only the runoff or sediment delivery-producing data. For example, at the Hayman logs site, ERMiT predicted that 6.3% of the time, there was runoff or sediment delivery, or that 93.7% of the time, the model did not produce runoff or sediment. Therefore, we multiplied the runoff event exceedance probabilities for this site by 0.063 to determine the predicted chance of runoff or sediment delivery occurring. These event probabilities were plotted against their associated sediment delivery to generate predicted sediment delivery-exceedance probability curves.

Similarly, from our observed data, we knew the number of rainfall events that occurred and the number that generated runoff or sediment delivery each year on each site (Table 3). These data were used to assign occurrence probabilities (the probability of the event occurring $= n$ runoff or sediment delivery events ÷ total rainfall events) to each of the runoff or sediment delivery events. For example, at the Hayman logs site in year 1, there were 38 rainfall events, 4 of which produced runoff or sediment delivery. The probability of the largest event was calculated as 1/38, the next largest as 2/38, and so on, with the probability of the smallest runoff or sediment delivery event as 4/38 and the probability of no runoff or sediment at all as $1 - (4/38) \times 100\%$, or 89.5%. These probabilities were plotted against their associated sediment delivery alongside the ERMiT sediment delivery-probability curves. The distance between our observed points and the ERMiT curves indicates how well ERMiT is predicting sediment delivery compared with our observed sediment delivery.

### Distribution comparison

To evaluate the full range of observed and ERMiT-predicted sediment delivery data on a comparable scale, we weighted the observed and predicted sediment deliveries by multiplying them by their associated probabilities of occurrence. Although there

**Table 5. Observed and predicted sediment delivery by fire, by year since fire and by treatment for all fires**

The calculated Spearman rank correlation ($\rho$) is shown for each. Correlations are significant at $P < 0.05$ and are in bold

| | Number of observations | Mean observed sediment delivery (Mg $ha^{-1}$) | Mean ERMiT-predicted sediment delivery (Mg $ha^{-1}$) | Spearman rank correlation coefficient (*P* value) |
|---|---|---|---|---|
| Fire name | | | | |
| Cannon | 10 | 2.52 | 0.98 | **0.73** (**0.02**) |
| Cedar | 18 | 0.86 | 2.56 | −0.17 (0.51) |
| Fridley | 14 | 1.41 | 1.41 | **0.65** (**0.01**) |
| Hayman[A] | | | | |
| Logs | 16 | 4.14 | 1.39 | **0.74** (**0.0009**) |
| Mulch | 24 | 5.56 | 0.55 | **0.53** (**0.008**) |
| Mixing | 12 | 0.21 | 1.04 | 0.35 (0.27) |
| North 25 | 8 | 0.05 | 0.13 | 0.54 (0.17) |
| Valley | 12 | 0.18 | 1.02 | 0.56 (0.06) |
| Year | | | | |
| 0 or 1 | 25 | 3.08 | 1.76 | **0.55** (**0.005**) |
| 2 | 18 | 2.91 | 2.18 | **0.57** (**0.01**) |
| 3 | 18 | 0.75 | 0.36 | **0.68** (**0.002**) |
| 4 | 18 | 1.79 | 0.55 | **0.60** (**0.008**) |
| 5 | 14 | 3.01 | 1.80 | **0.68** (**0.008**) |
| 6 | 14 | 0.63 | 0.06 | **0.59** (**0.03**) |
| 7 | 7 | 1.09 | 0.22 | 0.66 (0.10) |
| Treatment | | | | |
| Control | 50 | 2.34 | 1.56 | **0.65** (**<0.0001**) |
| Logs | 36 | 0.96 | 0.49 | **0.59** (**0.0002**) |
| Mulch | 28 | 2.81 | 1.10 | 0.27 (0.16) |

[A] The observed precipitation and the runoff and sediment delivery events selected for the log and its control site were not the same as the mulched (hydromulch and straw) and its control site.

were a far greater number of ERMiT-predicted sediment delivery values, weighting them by the percentage chance of occurrence allowed us to consider all values. The range and pertinent statistics of both the observed and predicted sediment delivery data are presented with box-and-whisker plots.

## Results

The relationship between observed and predicted $I_{10}$ values is statistically significant ($R^2 = 0.69$; $P < 0.0001$; Fig. 2) indicating the climate drivers behind ERMiT are producing acceptable rainfall attributes across the variety of locations we studied and across a range of moderate to high rainfall intensity. ERMiT slightly overestimated $I_{10}$ values and also the occurrence of rainfall or snowmelt-only sediment delivery at each site only by 0.9 to 12.9%, except for Cedar (–29%). However, the mean percentage of ERMiT predicted runoff or sediment delivery events (9.5%) closely matches the observed runoff or sediment delivery events (8.9%) (Table 4).

Of the 122 plot-years of data analysed in the large-sediment-delivery comparison, we measured zero sediment delivery 49 times, and ERMiT had an overall accuracy of 75% for predicting zero or non-zero sediment delivery events. Mean observed sediment delivery was 2.06 Mg $ha^{-1}$ compared with 1.12 Mg $ha^{-1}$ predicted by ERMiT; medians were 0.08 and 0 Mg $ha^{-1}$ respectively. Observed sediment delivery ranged from 0 to 24.5 Mg $ha^{-1}$ and ERMiT predictions ranged from 0 to 17.7 Mg $ha^{-1}$.

Observed and predicted sediment delivery data were significantly correlated overall at Spearman's $\rho = 0.60$ ($P < 0.0001$), indicating that although the data did not follow a strong 1 : 1 predictive relationship, there was a significant trend as both sets of data increased concurrently. The Cannon, Fridley and both Hayman sites also revealed significant correlations between the observed and predicted sediment delivery (Table 5). Correlations by year between the observed and predicted sediment

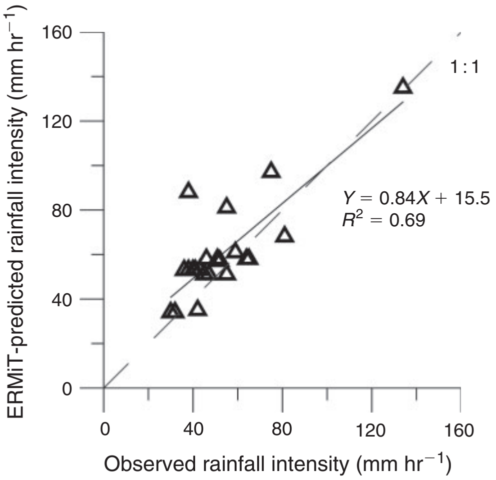

**Fig. 2.** Scatterplot of ERMiT-predicted 10-min rainfall intensity compared with measured rainfall intensities for rainfall events with a return period of 2 years or more ($n = 25$). The solid black line is the linear regression equation; the dashed grey line is the 1 : 1 line for reference.

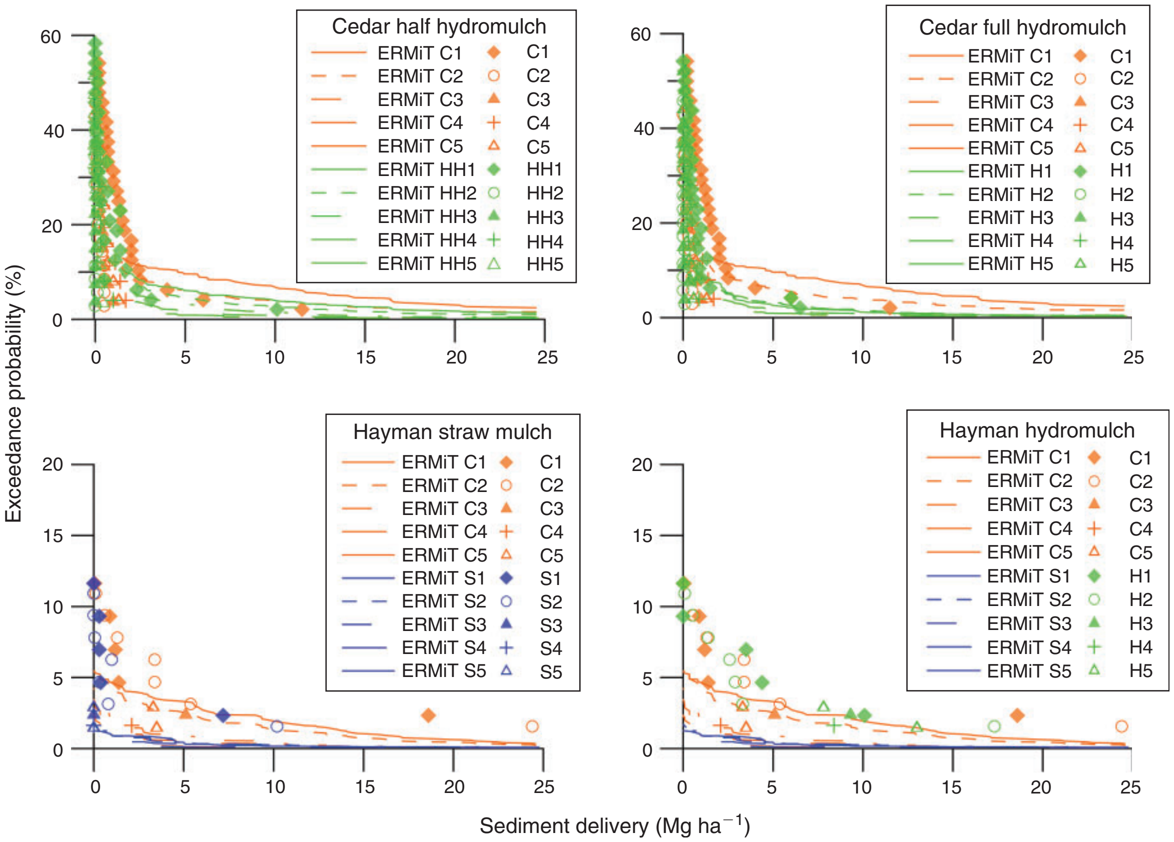

**Fig. 3.** ERMiT sediment delivery prediction curves and observed sediment delivery data for only those rainfall events that produced runoff at the two fire sites that were treated with hydromulch or straw mulch. The ERMiT curves at each site were adjusted by a proportional factor to account for the percentage of time that runoff occurred in the modelled 100 years (all values in Table 4). The *y*-axes scales are different for these two sites because of the difference in exceedance probability of sediment delivery. In the legends, C, control; H, hydromulch; HH, half hydromulch; S, straw; numbers 1–5 refer to the post-fire year.

delivery were all significant, with the exception of year 7, ranging from $\rho = 0.55$ to 0.68 (Table 5) with no apparent association with increasing time since fire. Stronger correlations were found between the observed and predicted sediment delivery data with the control plots ($\rho = 0.65$) and log erosion barriers ($\rho = 0.59$) treatments than with a combined class of hydromulch and straw mulch treatments ($\rho = 0.27$) (Table 5).

The Kolmogorov–Smirnov two-sample test (KS = 0.08, $P = 0.08$) suggests that the underlying distributions of the observed and predicted sediment delivery data are not statistically different. This two-sample test does not provide insight on what is or is not different between the two datasets (i.e. median, mean, range, skewness, etc.). Therefore, we can only generally interpret this result to indicate some degree of similarity between the two sets of values.

To further investigate the relationship between the observed and predicted sediment delivery data, we plotted the predicted ERMiT sediment delivery curves on the same graph as all of our observed sediment delivery data (Figs 3 and 4). These figures represent the exceedance probabilities of sediment delivery from observed rainfall events compared to ERMiT predictions. Observed values that are above or to the right of the ERMiT curves indicate that the probability of that particular sediment delivery event was greater than what was predicted ERMiT for this site. Observed values below or to the left of the ERMiT curves indicate that ERMiT overpredicted the probability of a particular sediment delivery event. For most fires and in most years, the observed data points fall within a reasonable range of the ERMiT curves.

Cedar sites experienced more sediment delivery events than any other site (Table 3), yet most of the sediment delivery values were quite low, especially after the first post-fire year (Fig. 3). Thus, our calculated probability of a sediment delivery event occurring was fairly high, but the amount of sediment associated with the high probabilities was ~1 Mg ha$^{-1}$ or smaller. The Hayman mulch site had a couple of large sediment delivery events in the first 2 post-fire years (Fig. 3), which were not predicted by ERMiT. In general, the observed sediment delivery on the sites treated with log erosion barriers were closely predicted by ERMiT (Fig. 4). Even at the Cannon site in year 4 (a 100-year rainfall event), the sediment delivery was close to the ERMiT sediment delivery curves with a low probability (2%, Fig. 4).

Probability-weighted sediment delivery (i.e. the probability of that event occurring × the sediment delivery, % Mg ha$^{-1}$) varied for the observed and ERMiT-predicted values and overlapped best in years where there was more than just a single observed sediment delivery event (Figs 5 and 6). Approximately

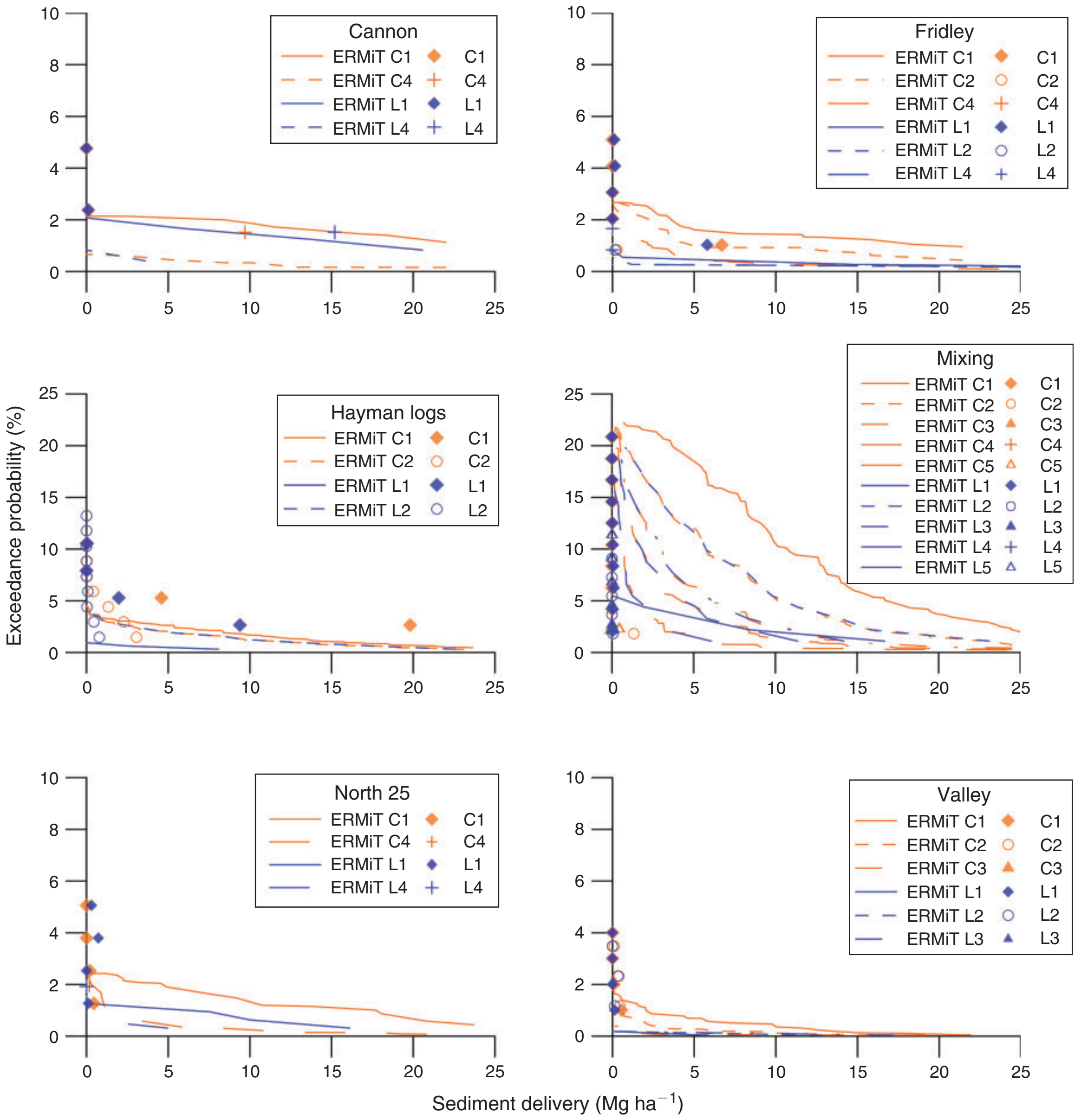

**Fig. 4.** ERMiT sediment delivery prediction curves and observed sediment delivery data for only those rainfall events that produced runoff at the six fire sites that were treated with log erosion barriers (logs). The ERMiT curves at each site were adjusted by a proportional factor to account for the percentage of time that runoff occurred in the modelled 100 years (all values in Table 4). The $y$-axes scales are different to better show the difference in exceedance probability of observed and predicted sediment delivery. In the legends, C, control; L, logs; numbers 1–5 refer to the post-fire year.

40% of the observed sediment delivery events occurred in the first post-fire year (out of the 5 years measured) and there was an overlap between the range of sediment delivery values predicted by ERMiT and the observed sediment delivery 78% of the time (Figs 5 and 6). Predicted and observed data from the control plots overlap 59% of the time, and data from the combined treatment plots overlap 46% of the time suggesting ERMiT is somewhat more accurate for predicting sediment delivery for sites without treatments. These figures are also meaningful to show the trend in decreasing sediment delivery in later post-fire years, as well as the effect of the mulch or log treatment in reducing sediment delivery both in the observed and predicted ranges.

## Discussion

### *Evaluation of model performance*

Data presented in the tables and figures in this paper reflect the large variability of sediment delivery following wildfire by site, treatment and by post-fire year, which ERMiT was specifically developed to address. Our primary interest was not to evaluate how well ERMiT predicts a single observed sediment delivery

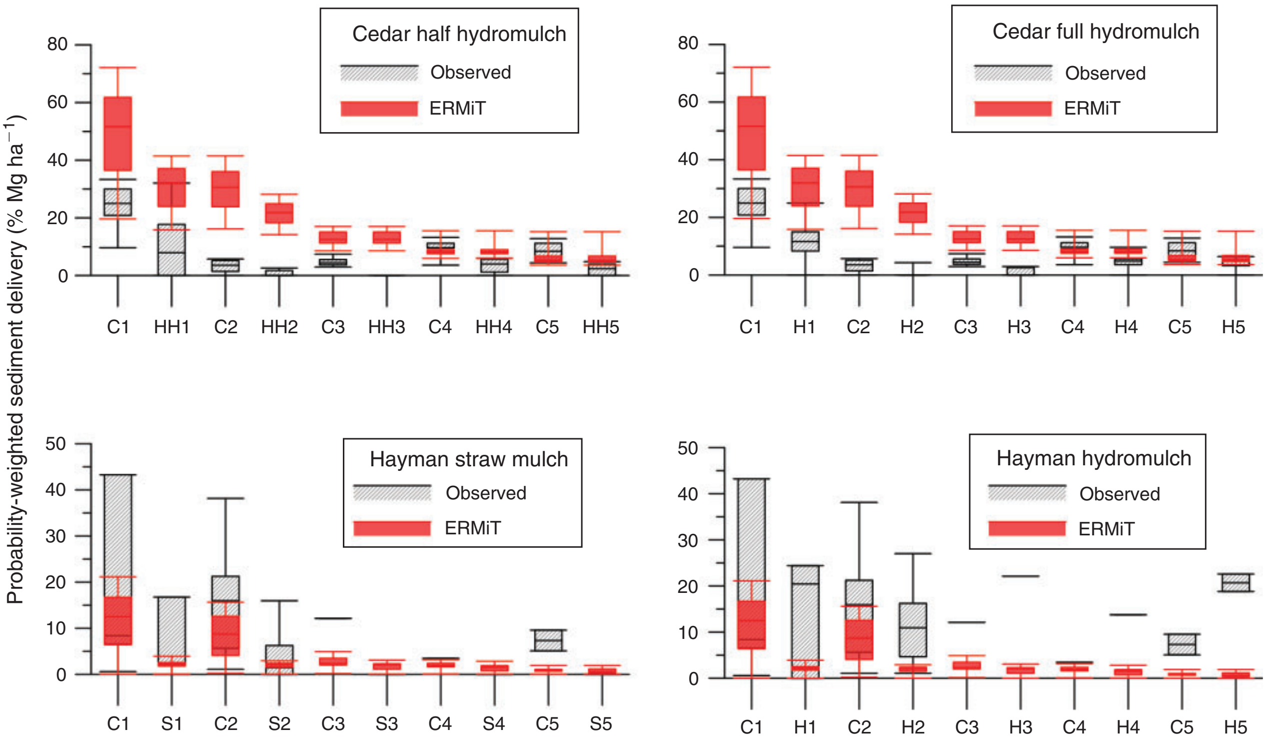

**Fig. 5.** Box-and-whisker plot of the probability-weighted sediment delivery for both the observed and ERMiT predicted data at the mulched sites. The top and bottom of the box represent the first and third quartiles of the data, the line represents the median, and the whiskers represent the maximum and minimum values. The *y*-axes scales are different to better show the distribution of probability-weighted sediment delivery. In the legends, C, control; H, hydromulch; HH, half hydromulch; S, straw mulch; numbers 1–5 refer to the post-fire year.

value (e.g. the large event correlation analysis presented in Table 5), but rather how well ERMiT reflects the range of variability observed in sediment delivery following wildfire.

Significant erosion does not happen after every wildfire. Of the 3 million ha that burn annually in the US, a very small percentage is at risk of erosion after the fire. Robichaud *et al.* (2014*b*) suggest that out of the 'large' fires (>400 ha) analysed by Forest Service BAER teams during the 2000s, 642 received treatments whereas 130 'large' fires received no treatment, showing that BAER teams justified treatments on 80% of these large fires. Observations from our monitored sites (5 years of data) and ERMiT's predictions (100 years of modelled climate predictions) suggest that the mean chance of a runoff or sediment delivery is 8.9 and 9.5% respectively (Table 4). Thus, the evaluation of erosion risk needs to be carefully determined, as it is vital for prescribing treatments to burned areas that have high erosion potential and downstream values-at-risk (Robichaud and Ashmun 2013).

Most rainfall events do not produce sediment (Table 4), and of the less than 10% of observed rainfall events that resulted in sediment delivery, the distribution was nearly equally split between sediment delivery less than and more than 1 Mg ha$^{-1}$. Even with outlier events such as the 100-year-return interval rainfall event ($I_{10}$ of 134 mm h$^{-1}$) that occurred at the Cannon site in year 4 (Fig. 4, Cannon), which had a sediment delivery of 10–15 Mg ha$^{-1}$ (Robichaud *et al.* 2008), ERMiT closely predicted the low probability (2%) and the correct year.

Relationships between observed and predicted sediment delivery in the large-sediment-delivery analysis and when compared with the full range of rainfall data indicate ERMiT's probabilistic approach is reasonable for the wide range of observed sediment delivery (Figs 5 and 6). There is an overlap in sediment delivery ranges 78% of the time in the first year, which is the most critical year in post-fire recovery and mitigation because natural vegetation has not had a chance to become established and the soils are unprotected and easily eroded.

### *Evaluation by site*

Correlations between the observed and predicted sediment delivery values were significant at four of our eight study sites (Table 5). Four sites with a poor correlation had very low observed sediment delivery (Cedar, Mixing, North 25 and Valley, 0.05–0.21 Mg ha$^{-1}$) where ERMiT's soil erodibility for sandy loam (Cedar, Mixing and North 25 sites) and loam (Valley) soils predicted more sediment delivery than observed. Erodibility values may be too high for this soil type, and the hydraulic parameters of the soils may need to be adjusted in future releases of the model. Foltz *et al.* (2011) also found sandy loam soils in the Sierra Nevada Mountains to be less erodible than other granitic soils.

Comparison of large-sediment-delivery events revealed ERMiT's predictions of sediment delivery were generally lower than observed sediment delivery (Table 5), particularly on the

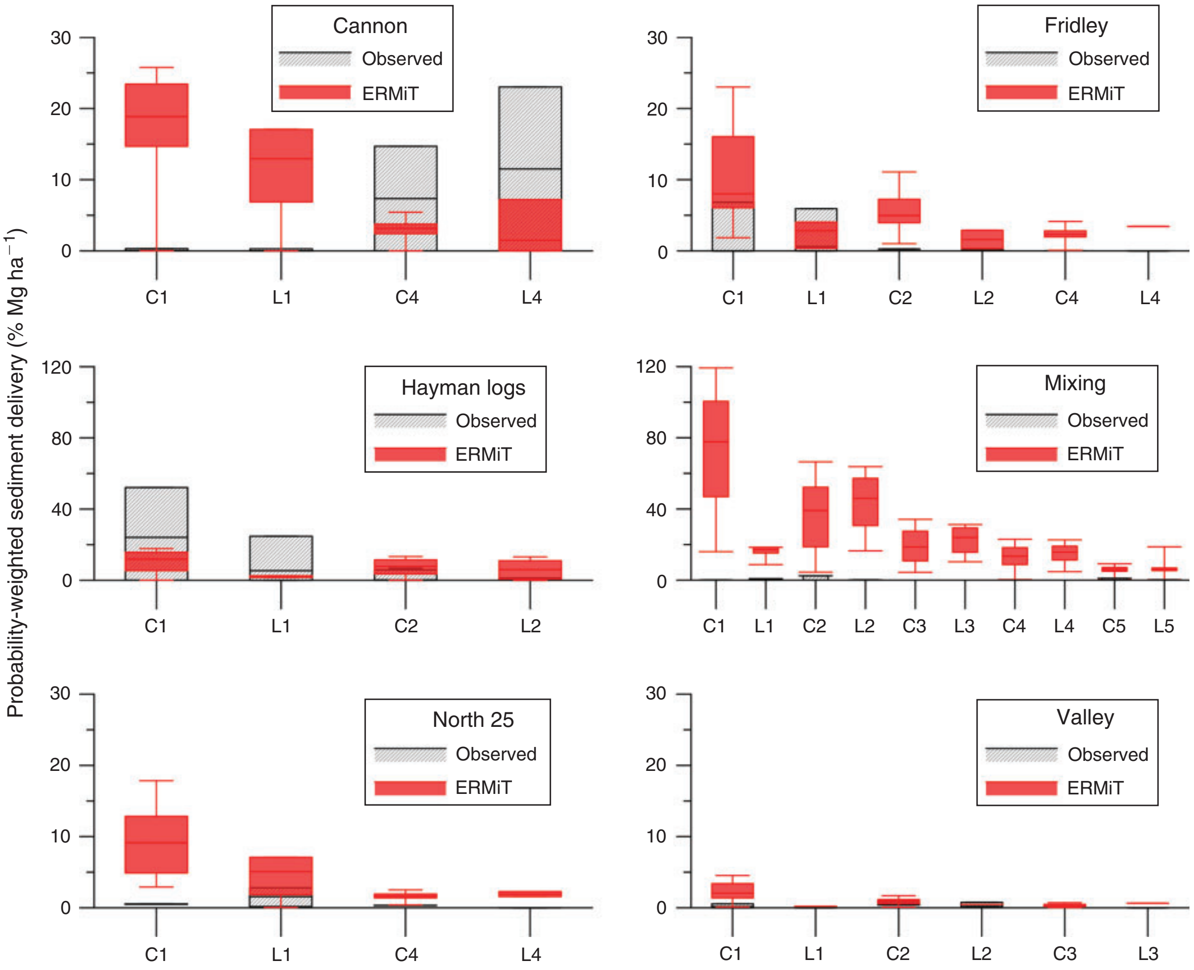

**Fig. 6.** Box-and-whisker plot of the probability-weighted sediment delivery for both the observed and ERMiT-predicted sediment delivery for the log erosion barriers sites. The top and bottom of the box represent the first and third quartiles of the data, the line represents the median, and the whiskers represent the maximum and minimum values. The *y*-axes scales are different to better show the distribution of probability-weighted sediment delivery. In the legends, C, control; L, logs; numbers 1–5 refer to the post-fire year.

Hayman sites. The five largest observed sediment delivery values were all from the Hayman sites, and of the 17 sediment delivery events greater than 5 Mg ha$^{-1}$, 14 were from Hayman sites (two others were from the Cannon site year 4, one event from the Cedar site). Hayman experienced the highest rainfall intensities of all sites (Robichaud *et al.* 2008, 2013), with the exception of the 100-year rainfall following the Cannon Fire. One hypothesis for the underpredictions on the Hayman sites is that they may be caused by high-intensity rainfall events that are typical of the Colorado Front Range (Moody and Martin 2009). This area is reputed to experience high rainfall intensities, and the observed data show unexpectedly high sediment delivery from moderate rainfall events (Moody and Martin 2001; Wagenbrenner *et al.* 2006). It is also possible that the Pikes Peak Batholith granitic soils that are prevalent in this area are more erodible than the sandy loam soil assumed by the ERMiT. In an unpublished study, L. MacDonald (pers. comm.) found that ERMiT underpredicted post-fire sediment delivery observed on hillslope-scale plots. In a study of road erosion in this area, Welsh (2008) noted that the WEPP Road (a WEPP online interface that allows users to easily describe numerous road erosion conditions) technology underpredicted sediment delivery rates from roads by approximately a factor of three. Thus, it may be necessary to consider an alternative set of soil files for this physiographic region.

Another interesting result was that the mean predicted and observed sediment delivery values were the same for the Fridley site (1.41 Mg ha$^{-1}$; Table 5). ERMiT overpredicted the five observed sediment delivery values that were less than the mean and underpredicted the three observed values that were greater than the mean, yet the site averages were equal. This result is consistent with what Nearing (1998) found from more than 3000 comparisons of predicted versus observed erosion data. Nearing concluded, ‘Evaluation of various soil erosion models with large data sets have consistently shown that these models tend to over-predict soil erosion for small measured values, and under-predict soil erosion for larger measured values.’ This trend was consistent across model types (empirical or physically based) and regardless of whether the soil erosion values came from individual rainfall events or annual total rainfall or means. Nearing attributed the over- and under-predictions to the difficulty in representing the random component between replicates.

Larsen and MacDonald (2007) also found an overprediction of small sediment delivery ($<1$ Mg ha$^{-1}$ year$^{-1}$) and an underprediction of larger sediment delivery with the Revised Universal Soil Loss Equation (RUSLE) and Disturbed WEPP, which they attributed to difficulty in assigning correct soil parameters in burned conditions and the rate of recovery of the forested environments as well as the temporal and spatial variability inherent in the processes that control post-fire sediment delivery. In the same study, they also found better agreement between measured sediment delivery values and model sediment delivery predictions when mean values were compared rather than individual measurements, which is similar to what we observed.

The Cedar site had the most observed sediment delivery events (36–54%) and produced sediment throughout a particularly wet first winter season (Robichaud *et al.* 2013). ERMiT probability-weighted sediment delivery predictions were generally too high for this low-erosion site (Fig. 5) along with the mean ERMiT sediment delivery (Table 5). On this geologically young site, the rock outcropping likely resulted in the large number of runoff or sediment delivery events as there is little infiltration on these areas. Such conditions are common throughout the Sierra Nevada Range and have been problematic in other hydrologic modelling studies (Buckley *et al.* 2014; Brooks *et al.* 2016). ERMiT does not have the ability to model rock outcrops, which typically have high runoff combined with low sediment delivery especially in the out years (3 or more years post-fire).

Observed sediment delivery values were measured at the outlet weir (Robichaud *et al.* 2008, 2013), whereas ERMiT predicts sediment delivery from an eroding hillslope. In the small watersheds, much of the sediment would be routed through at least a short length of channel between the hillslope and the watershed outlet. These short channel lengths were observed to be an area of deposition on some sites for some rainfall events, but were an area of scour on others. Channel effects may have contributed to increased sediment from the large runoff events on the Hayman sites (Table 5) compared with all the other sites and we did observe channel down-cutting on the Hayman sites.

ERMiT has been programmed to have a slower recovery in monsoonal climates, which sometimes have harsh winters and a short growing season (i.e. Hayman). Observed sediment delivery in years 3, 4 and 5 at Hayman indicates that recovery might be slower than predicted (Figs 3 and 4) as sediment delivery as high as 6.5 Mg ha$^{-1}$ was observed 7 years after the fire at the Hayman mulch site (Robichaud *et al.* 2013). Other sites did recover more quickly, which is why field data collection was limited to 4 years following fire at the North 25 and Fridley Fires, and 6 years following the Mixing, Valley and Cedar Fires. Another study site that further demonstrated high variability in recovery is the Robert Fire in northwestern Montana after a moderate- to high-severity fire where straw mulch was applied. The same paired watershed design was applied at this site (P. Robichaud, unpubl. data); no runoff or sediment delivery was produced during the 4 years of monitoring because extensive vegetation recovery provided ample ground cover before any large rainfall events.

### *Evaluation by treatment*

When the data were pooled, observed and ERMiT predicted sediment delivery distributions were significantly correlated for all years and for all treatments (Table 5). Correlations were strongest for the control sites ($\rho = 0.65$), likely owing to a wider range of sediment deliveries on the control sites compared with the treated, and reasonable predictions of large and small sediment delivery values. There is also an additional level of predictability on the control sites, without the introduced treatment parameters for the model to consider. Mulches are redistributed by wind or water, or decomposed over time, and log erosion barriers can fill or leak around the sides or bottom; treatment effectiveness varies with time and runoff rate, and this variability is difficult to incorporate into a model.

Correlations between the paired predicted and observed sediment delivery values were lowest for the mulch treatment sites ($\rho = 0.27$; Table 5). ERMiT underpredicted sediment delivery from the mulched sites, in particular the hydromulch treatment (Fig. 3, Hayman), which was attributed to variability in the original mulch distribution, and subsequent redistribution of mulch by wind or water and decomposition (Robichaud *et al.* 2013). Robichaud *et al.* (2013) found that the observed sediment delivery from the Hayman hydromulch site was not statistically different from the control site owing to the short persistence of the hydromulch. Currently, ERMiT does not have separate treatment categories for hydromulch and straw mulch, which are known to function differently over time (Robichaud *et al.* 2013).

ERMiT predictions for sediment delivery from the control study sites ($\rho = 0.65$) were slightly better than the predictions for the log-treated sites ($\rho = 0.59$). When logs break down and decay, they are less effective in the years after installation (Robichaud *et al.* 2008). ERMiT's log-treatment decay rate (Robichaud *et al.* 2007*b*) may be decaying the logs too slowly (Fig. 6, Cannon). When the probability-weighted sediment delivery ranges of observed and predicted ERMiT values were used (Figs 5 and 6) rather than single values in the correlation analysis, we observed that ERMiT overpredicted at the Cedar site (40%) and underpredicted at the Hayman sites for the mulch sites in the out years (50%) (Fig. 5). Yet with the log-treated sites, sediment deliveries at the Cannon and Mixing sites were overpredicted each year (Fig. 6) for similar soils (sandy loam). This suggests that even though a more erodible sandy loam soil may be needed for the Hayman sites as previously discussed, a less erodible sandy loam may be required for the Sierra Nevada sites.

Overall, treatment effectiveness was reasonably predicted by ERMiT; the observed and predicted probability-weighted sediment delivery for log erosion barriers and mulch treatments overlap 46% of the time. ERMiT was somewhat more accurate for predicting sediment delivery for log erosion barriers than mulch treatments.

## *User implications*

The ERMiT model is useful in the decision-making process because it gives land managers a likelihood (or not) of sediment delivery events occurring and evaluates the benefits of various erosion mitigation treatments. BAER teams were generating unrealistic predictions of hillslope sediment delivery ranging from 2 to 15 500 Mg ha$^{-1}$ based on the Universal Soil Loss

Equation (USLE), gross erosion estimates from past events, and professional judgment (Robichaud *et al.* 2000). Users should be cautioned that ERMiT may overpredict sediment delivery on some steep slopes or for large rainfall events, but in general will deliver reasonable estimates. The degree of uncertainty in these model predictions is low enough to base treatment prescriptions on ERMiT sediment delivery estimates.

To apply ERMiT outside the US, local climates need to be formatted into input files (CLIGEN format) for WEPP. This has been done for ~30 climates (Australian, southern European countries, Chile; http://forest.moscowfsl.wsu/FSWEPP/CliGen; accessed 16 Nov 2015), and guidelines for generating stochastic climate impact files for ERMiT in new locations are available. Additionally, key field-measured input parameters (as described in Robichaud *et al.* 2010*a*; Wagenbrenner *et al.* 2010) such as saturated hydraulic conductivity, interrill erodibility, rill erodibility and soil critical shear are likely different for different soil types and past land use (e.g. less erodible in the historically heavily used lands in the southern Mediterranean countries). Small watershed studies similar to the ones described here would be useful to validate sediment delivery predictions.

Moody *et al.* (2013) suggest more knowledge of key hydrological processes and inputs is necessary to enhance predictive capability, whereas Nyman *et al.* (2013) suggest examining larger spatial scales to better capture input variability. However, the above ERMiT validation exercise has shown that characteristics of rainfall, soil erodibility, fire effects, treatment effectiveness and vegetation recovery are all important processes in erosion prediction.

## Conclusion

The Erosion Risk Management Tool, ERMiT, is a probabilistic post-fire erosion model. ERMiT provides post-fire hillslope sediment delivery predictions based on topography, soil burn severity, soil texture, local climate and erosion mitigation treatments. Overall accuracy of 75% for predicting zero or non-zero sediment delivery events when compared with eight field study sites suggests ERMiT's predictions are reasonable and defensible. ERMiT-predicted rainfall intensities correlated significantly with observed intensities ($R^2 = 0.69$) and the large variability observed in sediment delivery from mostly short-duration, high-intensity rainfall events was modelled reasonably well (Kolmogorov–Smirnov $KS = 0.08$, $P = 0.08$) within ERMiT, with the exception of two southern California sites with Mediterranean climates. Every rainfall event does not produce sediment delivery; in fact, most sites experienced only a few rainfall events that produced runoff and sediment (1.3–9.2%) with overlapping predicted sediment delivery ranges (78% of the time overall, 59% of the time for the controls, and 46% of the time for the combined treatments). Significant pooled Spearman rank correlation coefficients ($\rho = 0.60$ overall, $\rho = 0.55$ to 0.68 in post-fire years 1–6, $\rho = 0.65$ for the controls, $\rho = 0.59$ for the log erosion barriers, and $\rho = 0.27$ (not significant) for the mulch treatments) provide confidence in ERMiT's predictions of treatment effectiveness and recovery after the fire. Our probabilistic modelling approach was designed to allow land managers to predict post-fire sediment delivery from burned areas, which typically have only a few large events and numerous 'no sediment'-producing rainfall events. ERMiT delivers realistic expectations for erosion occurrence prediction and an estimated quantity of sediment with and without common hillslope mitigation treatments.

## Acknowledgements

We are grateful for the support of our modelling tools from the USDA Forest Service Rocky Mountain Research Station, the Joint Fire Science Program, a cooperative effort of the USDA Forest Service and Department of Interior, and the Forest Service National Fire Plan.

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