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Predicting post-fire hillslope erosion in forest lands of the western United States

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Abstract. Many forests and their associated water resources are at increasing risk from large and severe wildfires due to high fuel accumulations and climate change. Extensive fuel treatments are being proposed, but it is not clear where such treatments should be focussed. The goals of this project were to: (1) predict potential post-fire erosion rates for forests and shrublands in the western United States to help prioritise fuel treatments; and (2) assess model sensitivity and accuracy. Post-fire ground cover was predicted using historical fire weather data and the First Order Fire Effects Model. Parameter files from the Disturbed Water Erosion Prediction Project (WEPP) were combined with GeoWEPP to predict post-fire erosion at the hillslope scale. Predicted median annual erosion rates were 0.1–2 Mg ha^{-1} year^{-1} for most of the intermountain west, ~10–40 Mg ha^{-1} year^{-1} for wetter areas along the Pacific Coast and up to 100 Mg ha^{-1} year^{-1} for north-western California. Sensitivity analyses showed the predicted erosion rates were predominantly controlled by the amount of precipitation rather than surface cover. The limited validation dataset showed a reasonable correlation between predicted and measured erosion rates ($R^2 = 0.61$), although predictions were much less than measured values. Our results demonstrate the feasibility of predicting post-fire erosion rates on a large scale. The validation and sensitivity analysis indicated that the predictions are most useful for prioritising fuel reduction treatments on a local rather than interregional scale, and they also helped identify model improvements and research needs.

Additional keywords: ground cover, modelling, sensitivity analysis, WEPP.

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Introduction

Many forests in the western USA are more susceptible to large, high-severity wildfires because of increased fuel accumulations from fire suppression (Agee 1993; Keane *et al.* 2002) and climate change (Flannigan *et al.* 2000; Westerling *et al.* 2006). Areas burned at high severity are of particular concern because of their high potential for flash floods and surface erosion (Forrest and Harding 1994; Neary *et al.* 2005). Post-fire increases in runoff and erosion can severely degrade water quality and reduce reservoir capacities (Tiedemann *et al.* 1979; Moody and Martin 2001; Neary *et al.* 2005).

To combat this risk, the USDA Forest Service and other land-management agencies have initiated fuel reduction programs, but the areas needing treatment far exceed the available funding (GAO 1999; Sampson *et al.* 2000; GAO 2007). Hence, there is a need to assess and compare the relative priority for fuel reduction treatments on a spatially explicit basis. Previous large-scale erosion mapping projects have utilised conceptual empirical models such as the Universal Soil Loss Equation or the Revised Universal Soil Loss Equation (RUSLE) (MacDonald *et al.* 2000; Miller *et al.* 2003; Brough *et al.* 2004), or locally derived categorical equations (e.g. Fox *et al.* 2006). However, it is questionable whether these largely empirical models should be extrapolated to conditions for which they have not been calibrated (Larsen and MacDonald 2007).

The primary objective of this project was to develop and apply a spatially explicit procedure for predicting first year post-fire surface erosion rates across a large geographic area. The study area consisted of the forests and shrublands in the continental western United States, and our modelling goal was to use existing data and procedures that could be consistently applied across the entire region. A series of additional objectives were identified during model development and application, and these included: (1) evaluating the sensitivity of predictions to key input parameters; (2) validating predicted values against measured values; (3) identifying key limitations to the consistency and accuracy of the predicted values; and (4) identifying specific modelling and research needs.

The following sections successively present our modelling approach, the development and compilation of the input data, modelling results, a sensitivity analysis and a discussion of key issues and possible improvements. The effect of uncertainties in the input parameters on model predictions can be evaluated through the exposed mineral soil equation and the results of the sensitivity analysis, but the absolute quantification of input and prediction errors is hampered by the lack of field data for the diverse landscapes found in the forested lands of the western US. Nevertheless, the approach and results presented here are already providing guidance to resource managers through several different risk-assessment projects. We hope the results and ideas presented in this paper will further stimulate efforts to better predict post-fire effects in fire-prone areas.

Modelling approach

Soil erosion due to water depends primarily on the amount of surface cover, slope length, slope steepness and the amount and intensity of rainfall (Renard *et al.* 1997; Pietraszek 2006). Soil texture and topographic convergence are other important parameters (Renard *et al.* 1997; Benavides-Solorio and MacDonald 2005). For convenience and simplicity, the term 'erosion' in the present paper is used to refer to both the predicted soil loss at the hillslope scale (~1–15 ha) and measured sediment yields at scales of 0.01–4 ha.

The focus of this paper is on surface erosion from rainsplash, sheetwash and rilling, as these are the most common and widespread causes of post-fire erosion (Moody and Martin 2001; Pietraszek 2006). In certain geographic areas, such as the rapidly rising mountains of southern California, debris flows and dry ravel can be important (Krammes 1960; Gabet 2003; Wohlgemuth 2003), and empirical prediction models have been developed for debris flows in some areas (Cannon 2001). At larger scales, channel erosion can be the dominant sediment source (e.g. Moody and Martin 2001), but the data and models needed to predict post-fire channel erosion are still in the developmental stage (Montgomery and Dietrich 1989; Istanbulluoglu *et al.* 2002; Moody and Kinner 2006).

Given the present state-of the-art and geographic variability in erosion processes, the most widely used models for predicting post-fire erosion are based either on RUSLE (Renard *et al.* 1997) or the Water Erosion Prediction Project (WEPP) (Flanagan and Nearing 1995; Laflen *et al.* 1997). Key inputs for both models are climate, soils, ground cover and topography. RUSLE is a conceptual empirical model that is widely used in agricultural areas; its applicability to forested areas is uncertain because of its focus on overland flow and the datasets used for calibration and validation were primarily from agricultural and rangeland plots (Renard *et al.* 1997).

WEPP is a process-based model that predicts runoff and sediment yields from planar hillslopes and small watersheds up to 2.5 km^2, and these predictions are based on up to 100 years of stochastically generated climatic data (Flanagan and Nearing 1995). The surface hydrology component of WEPP uses climate, soils, topography and vegetation input files to predict infiltration, runoff volume and peak discharge for each simulated storm. Climate, soils and vegetation inputs are also used to predict vegetative growth, litter accumulation and litter decomposition. WEPP uses these inputs and predictions to calculate both rill and interrill erosion as well as sediment deposition (Flanagan and Nearing 1995). The physically based nature of WEPP means that several hundred parameters must be specified to run the model.

Online interfaces, such as Disturbed WEPP (Elliot 2004) and the Erosion Risk Management Tool, ERMiT (Robichaud *et al.* 2007*a*), have been developed to facilitate the use of WEPP in forested areas. The Disturbed WEPP interface (http://forest.moscowfsl.wsu.edu/fswepp/, accessed 14 August 2011) was designed to simulate different forest conditions and management scenarios, including sites burned at high and low severity (Elliot 2004). To run Disturbed WEPP, the user needs only to specify a few key input parameters, including soil texture class, vegetation type, a climate station from the WEPP database and a hillslope profile. The interface then generates all of the additional parameters needed to run the WEPP model (Elliot 2004), and Disturbed WEPP has been used to model post-fire erosion in forested areas (Soto and Diaz-Fierros 1998; Larsen and MacDonald 2007; Spigel and Robichaud 2007).

The relative accuracy of RUSLE and WEPP for predicting post-fire erosion was evaluated by comparing measured and predicted values for 83 hillslopes of 0.01–0.5 ha from nine different fires in the Colorado Front Range (Larsen and MacDonald 2007). The predicted values using Disturbed WEPP ($R^2 = 0.25$) were more accurate than RUSLE ($R^2 = 0.16$), but neither model was able to accurately predict erosion rates from individual hillslopes. The high spatial variability between plots meant the model predictions were much more accurate for the mean erosion rate from groups of hillslopes burned at similar severity in a given fire, and Disturbed WEPP was again more accurate than RUSLE (R^2 of 0.66 *v.* 0.54 respectively) (Larsen and MacDonald 2007). Spigel and Robichaud (2007) also found similar results by comparing the mean erosion rates rather than from individual plots after the 2000 Bitterroot Valley fires in Montana. These results imply that average erosion rates are easier to model rather than trying to account for all the small-scale variations after wildfires within surface conditions, soil characteristics and other factors in each plot. Given these results and the greater potential accuracy of physically based models for predicting results outside the areas or conditions for which they were calibrated, the present study used the WEPP model to predict post-fire erosion rates.

The need to predict post-fire erosion rates across large areas necessitated the use of the Geo-spatial interface for the Water Erosion Prediction Project (GeoWEPP) (Renschler 2003). GeoWEPP facilitates the use of WEPP across large areas by converting GIS data into WEPP inputs, running WEPP and then compiling the results into a spatial map (Renschler 2003). Like WEPP, GeoWEPP only predicts runoff and erosion from watersheds smaller than 2.5 km^2 because it does not route sediment through perennial stream channels. The present project used the March 2004 version of GeoWEPP and the April 2005 version of WEPP.

The primary inputs for GeoWEPP are climate data, plant–management files ('land use or land cover files' in GeoWEPP), a soils map, and a Digital Elevation Model (DEM) (Fig. 1). The various plant–management and soil input files developed for burned areas and used in the Disturbed WEPP interface were

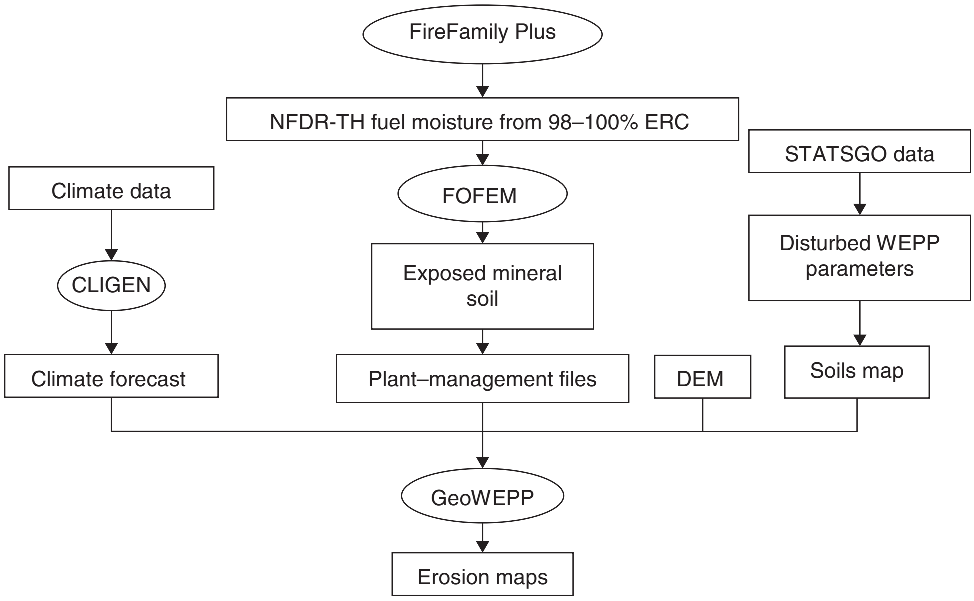

Fig. 1. Schematic of the modelling process. Rectangles indicate input or output data, and the ovals are the models used in this project. Each step was evaluated by examining key parameters and their effects on model outputs. For climate and exposed mineral soil, see Fig. 5; for DEM and slope, see Figs 6 and 7; and for soils, see Fig. 8. (NFDR-TH, National Fire Danger Rating Thousand-Hour fuel moisture values; ERC, Energy Released Component; STATSGO, State Soil Geographic; FOFEM, First Order Fire Effects Model; WEPP, Water Erosion Prediction Project; CLIGEN, Stochastic Climate Generator; DEM, Digital Elevation Model; GeoWEPP, The Geo-spatial interface for the Water Erosion Prediction Project.)

used to create the different sets of input parameters needed by the underlying WEPP model. To maximise the comparability and consistency of the results, the same sets of input files were applied across the study area. These sets of input files allowed us to spatially vary the soil type, rock content and vegetative cover as described below.

Using this procedure, we were able to predict potential erosion in the first year after burning for most areas covered by forests and dense shrublands in the western USA (Fig. 2), or a total area of ~650 000 km^2. The resulting maps are available through http://environmental-rs-modeling.com/erosion_maps.html (accessed 18 August 2011), and these predictions are already being used to identify the relative risk to municipal water supplies and aquatic resources in parts of Colorado, Washington, Oregon and California. Some of the modelling issues identified in this project have led to revisions in the underlying WEPP model, and the approach developed here is being considered for similar projects in other areas.

Development and compilation of input data

Subdividing the study area

The continental western USA was divided into 27 zones following the delineation being used by the LANDFIRE project (Fig. 2) (The National Map LANDFIRE 2005; Rollins 2009). This multiagency project is generating maps and data on vegetation, wildland fire regimes and fuel assessments across the entire USA and it provided the seamless soils and topographic data layers used in the present project (The National Map LANDFIRE 2005; The Nature Conservancy *et al.* 2005; Rollins 2009). The spatial input data layers were converted to Universal Transverse Mercator (UTM) coordinates as GeoWEPP requires a coordinate system with positive values. The results were projected back to the original LANDFIRE Albers projection for viewing purposes.

Climate data

Climate input files were generated by CLIGEN (Nicks *et al.* 1995), which is the stochastic weather generation program within WEPP (Flanagan and Nearing 1995). The climate database in WEPP has more than 2000 weather stations in the USA, including 739 stations in the study area. The data for each station include the monthly means and statistical distributions of maximum and minimum temperatures, number of wet days, and the frequency distributions of precipitation amounts and intensities. CLIGEN uses these data to generate climate input files with up to 100 years of daily temperature and precipitation data (Nicks *et al.* 1995; Yu 2002; Robichaud *et al.* 2007*a*).

GeoWEPP automatically identifies the climate station in the WEPP database nearest each watershed outlet. Mean annual post-fire erosion rates were calculated for the first 5 years of the 100 years of simulated daily weather data in order to reduce computational time while still averaging some of the interannual climatic variability. The validity of this truncation was tested as part of the sensitivity analysis.

Cover percentage and plant–management input files

An important step in the modelling process was to predict the amount of surface cover after a wildfire, as field studies have shown the amount of surface cover (or conversely the amount of bare mineral soil) is a dominant control on post-fire erosion

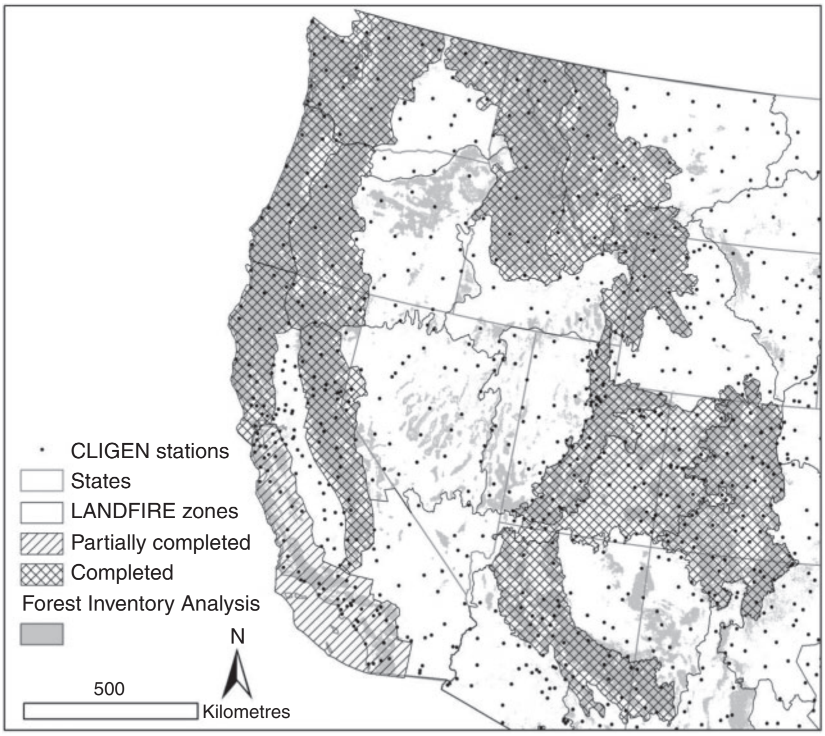

Fig. 2. LANDFIRE zones showing the areas that were successfully modelled. The grey areas are forested according to the Forest Inventory Analysis (Zhu and Evans 1994).

rates under a given climatic regime (Dissmeyer and Foster 1981; Robichaud and Brown 1999; Benavides-Solorio and MacDonald 2005; Larsen *et al.* 2009). The amount of exposed mineral soil after burning (EM) is a key parameter in the plant–management input files, and this was predicted using an empirical equation from FOFEM (First Order Fire Effects Model) (Reinhardt *et al.* 1997; Reinhardt 2003) (Fig. 1). Surface cover was then calculated as 100 minus EM percentage.

FOFEM predicts EM percentage after burning from National Fire Danger Rating Thousand-Hour (NFDR-TH) fuel moisture values and fuel types. The FOFEM database includes typical fuel loading values for different vegetation types, but it cannot provide fuel moisture values because these vary over time and space. We therefore had to calculate and map NFDR-TH fuel moisture values for an assumed probability of severe fire weather (i.e. the conditions under which an area would likely burn).

NFDR-TH fuels are defined as dead plant material with a diameter of 7.6–20 cm; the name signifies that it takes 1000 h for these fuels to gain or lose 63% of their initial moisture content (Fosberg *et al.* 1981). Daily NFDR-TH fuel moisture values can be calculated from weather data for the previous 7 days and the initial 1000-h fuel moisture content (Ottmar and Sandberg 1985). The required weather data are daily minimum and maximum temperatures, daily minimum and maximum relative humidities, and the duration of any precipitation events. These data are collected by stationary and mobile RAWS (Remote Automated Weather Stations) (National Fire and Aviation Management 2005). Daily maps of the NFDR-TH fuel moisture values are generated by the US National Interagency Fire Center. These maps are produced by identifying the 12 fire weather stations nearest to each 1-km grid cell, and then weighting each of the 12 stations by an inverse distance squared algorithm (L. Bradshaw, USDA Forest Service, pers. comm., 2005).

Cumulative frequency distributions of archived weather data were used to calculate NFDR-TH fuel moisture values for 987 fire weather stations located within the study area that had at least 8 years of data from one location. The assumed NFDR-TH fuel conditions at the time of burning were at 98–100% ERC (Energy Released Component) (K. Ryan, USDA Forest Service, pers. comm., 2005), where ERC is the energy released per unit area of flaming front. The ERC values depend on the NFDR-TH fuel moisture values and fuel type as defined below and in Burgan *et al.* (1998).

Twenty different fuel types were defined to represent the major plant communities in the USA (e.g. short-needle pine with normal dead fuel loads, hardwoods, or California mixed chaparral) (Burgan *et al.* 1998). Ten of these fuel types were needed to represent the forest and shrubland communities in the study area, and digital maps of these fuel types are available at a 1-km^2 resolution (Burgan *et al.* 1998) (Table 1). The NFDR-TH fuel moistures at 98–100% ERC were calculated for each of these 10 fuel types for each fire weather station using the FireFamily Plus software package (USDA Forest Service 2002) (Fig. 1). NFDR-TH fuel moisture maps were generated for each fuel type with the same inverse distance squared interpolation algorithm used to map daily fuel moistures. The GIS layer of fuel types (Burgan *et al.* 1998) was used to determine which fuel type was appropriate for each 1-km^2 cell in the study area, and the

Table 1. Summary of the spatial data inputs used in this project

Spatial grid layers	Resolution	Source
STATSGO soil layers	30 m	The National Map LANDFIRE (2005)
Digital elevation model	30 m	The National Map LANDFIRE (2005)
Forest inventory analysis	1 km	Zhu and Evans (1994)
Fuel type map	1 km	Burgan *et al.* (1998)

appropriate NFDR-TH fuel moisture for that fuel type was clipped from the 10 NFDR-TH fuel moisture maps. The clipped fuel moisture maps were then merged into a single map of predicted NFDR-TH fuel moisture values at 98–100% ERC.

Some areas that were barren according to the GIS map of fuel types (Burgan *et al.* 1998) had woody vegetation according to the Forest Inventory Analysis (FIA) as derived from AVHRR (Advanced Very High Resolution Radiometer) satellite data (Zhu and Evans 1994) (Table 1). The vegetation in these areas was assumed to be represented by fuel type G (short-needle pine with heavy dead fuel loads), as this fuel type adequately predicts ERC for many forests in the USA (Hall *et al.* 2003). The spatially explicit NFDR-TH fuel moisture values were used to predict EM percentage using Eqn 1 (Brown *et al.* 1985):

$$\mathrm{EM} = 94.3 - 4.96 \times \text{NFDR-TH} \tag{1}$$

The predicted EM values were used to assign a surface cover percentage to each 30-m grid cell in the study area.

As the modelling goal was to predict post-fire erosion in the first year after burning, a series of WEPP plant–management input files without growth and decomposition were developed to maintain constant surface cover over the 5 years of simulated weather (normally WEPP would simulate vegetation recovery over time). Plant–management files were developed for each 2.5% increment of surface cover, and for each file, the initial cover variables were specified to obtain the desired cover percentage. The presumed lack of regrowth in the first year after burning is justified as most areas burn in the summer or fall (autumn), shortly before the wet or summer monsoon season, and in at least some areas, sediment production per unit rainfall erosivity is unchanged for the first 2 years after burning (Shakesby *et al.* 1996; Larsen *et al.* 2009).

Soils data

Soil data layers from the LANDFIRE project (Rollins 2009) were used to develop the soil input layers used in this project (Table 1). The LANDFIRE soil layers were derived from STATSGO (STATe Soil GeOgraphic) data (USDA 1991), and included: maximum soil depth; rock fragments percentage (>2.0 mm); sand percentage; silt percentage; and clay percentage. The sand, silt and clay layers were used to classify each soil pixel into one of the four soil texture classes in Disturbed WEPP (sandy loam, loam, silt loam and clay loam). Disturbed WEPP estimates other input parameters (e.g. effective hydraulic conductivity, soil albedo and rill erodibility) from the soil texture class, and only four classes are used because there are not enough data from forested areas to justify a more detailed classification (Elliot *et al.* 2000).

The soil parameters in Disturbed WEPP also vary according to whether a site burned at high or low severity. Burn severity was classified from the map of EM values; grid cells with more than 35% bare soil were assumed to have burned at high severity, and grid cells with ≤35% bare soil were assumed to have burned at low severity (Robichaud 2000). The combination of four soil texture classes and two burn severities yielded a total of eight soil classes.

Erosion rates in WEPP are affected by the percentage of rock fragments (>2 mm) until the proportion exceeds 50% (Elliot *et al.* 2000). According to the STATSGO data, the soils in the study area had from 0 to 85% rock fragments. We therefore divided the soils into 27 rock-fragment classes using 2% increments; soils with more than 50% rock fragments were included in the 50% class. The combination of four soil texture classes, two burn severity classes, and 27 rock fragment classes necessitated the generation of 216 soil input files.

Topographic data, watershed delineation, and processing

The LANDFIRE project provided a seamless 30-m DEM of the study area derived from the National Map (USGS 2002) (Table 1). GeoWEPP uses a topographic analysis software, TOPAZ: Topographic Parameterisation (Garbrecht and Martz 1999), to delineate watersheds and create the slope files needed to run WEPP. Required input parameters for TOPAZ include the critical source area (CSA) and minimum source channel length (MSCL). To be consistent with our modelling philosophy and available data, we used the default values in GeoWEPP of 5 ha for CSA and 100 m for MSCL, and these values resulted in a mean hillslope size of ~6 ha.

To more efficiently model the study area, GeoWEPP was modified to run batch files (C. Renschler, State University of New York at Buffalo, pers. comm., 2005). These batch files were created in ESRI's *ArcInfo GIS* (ESRI Inc., Redlands, CA) software by first delineating watersheds based on the DEM data, and then clipping the surface cover and soil layers to match this initial delineation. The predominant soil and surface cover values for each hillslope determined which soil and plant–management files were used in GeoWEPP. This processing created some gaps in the output layer, and these were primarily caused by the failure of TOPAZ to delineate watersheds in flat regions. There also were some gaps near UTM boundaries due to an inadequate buffer when reprojecting the data. Taken together, these data gaps comprised from 10 to 30% of each LANDFIRE zone.

To the extent possible, these gaps were filled by dividing the unmodelled watersheds into smaller units and rerunning GeoWEPP. The finer-scale delineation isolated the flattest areas, which allowed the remaining watersheds to be successfully modelled. Because the second pass divided the area into smaller units, approximately 1 h of processing time per 80 km^2 was required using a personal computer in 2005 compared with 280 $km^2 h^{-1}$ for the first pass. This generally reduced the gaps in the output data to only 5–10% of the modelled area; however, to save time, this was only done for areas with forest or dense shrub cover. Modelling was completed for the 12 most heavily forested LANDFIRE zones in the western USA over an 8-month study period (Fig. 2).

Sensitivity analysis

The sensitivity analysis evaluated the changes in predicted erosion as a result of variations in climate, surface cover, slope steepness, slope length, soil rock content, soil texture and length of the simulated climate. The baseline scenario for these analyses assumed a 60 m-long hillslope with a 30% slope, a loam soil with 25% rock fragments, and 50% surface cover. The relative effects of climate and surface cover were evaluated by systematically varying the surface cover from 20 to 100% for six climate stations with widely varying mean annual precipitation (MAP). The other sensitivity analyses were run for both a dry and a wet climate. The dry climate was represented by the Cheesman station in the Colorado Front Range, where the predicted 5-year MAP is 406 mm. The wet climate was represented by Strawberry Valley on the west slope of the Sierra Nevada in California, where the predicted 5-year MAP is 2235 mm. Each sensitivity analysis used a 5-year simulated climate except for assessing the effect of the length of the simulated climate on predicted erosion rates. The combined effect of changing the CSA and MSCL parameters was evaluated by rerunning GeoWEPP for an 800-ha watershed in the Sierra Nevada of California with exceptionally high predicted erosion rates.

Validation

Validation of the predicted erosion rates was severely limited by the paucity of directly comparable field measurements. At the time of this study, the two most extensive and readily available datasets were: (1) hillslope-scale measurements from the Colorado Front Range, and (2) small-watershed sediment yields from four western states.

The hillslope-scale erosion data from the Colorado Front Range were collected from 50 different hillslopes immediately after four wildfires that occurred in late spring or early summer and two prescribed fires (Benavides-Solorio and MacDonald 2005; Pietraszek 2006). The mean contributing area for each hillslope was ~0.1 ha, and sediment production was measured with sediment fences similar to those of Robichaud and Brown (2002). The measured sediment production from each hillslope was averaged over the first 2 years after burning for two reasons. First, vegetative recovery in Colorado is slow given the coarse-textured soils and cool, dry climate, so post-fire erosion rates are nearly identical for the first and second summers after burning when normalised by rainfall erosivity (Benavides-Solorio and MacDonald 2005; Larsen *et al.* 2009). Second, over 90% of the post-fire erosion is generated by summer convective storms, and in the Colorado Front Range, summer precipitation in the year of burning is typically below average (Benavides-Solorio and MacDonald 2005; Pietraszek 2006). Erosion is usually higher in the second summer after burning than the first summer (Pietraszek 2006). As it is not known if precipitation is generally below normal in the first year after burning in other areas, the bias in the field data due to the below-normal precipitation relative to the predicted values was reduced by averaging the measured erosion in the first 2 years after burning. Erosion rates were also averaged for the hillslopes within each fire that burned at high and moderate severity, as the measured hillslopes had relatively consistent soils, slopes and ground cover, they were in close proximity, and the hillslope areas were typically much smaller than the modelled hillslopes. The measured mean annual erosion values for each fire were compared with the mean predicted erosion for the two or three hillslopes that encompassed the field data from each fire.

The second dataset consisted of erosion data from six high-severity-burned 1–13-ha watersheds in California, Colorado, Montana and Washington (Robichaud *et al.* 2008). The sediment captured in large weirs at each watershed outlet was periodically cleaned out, weighed and summed to yield annual amounts. The outlet coordinates and characteristics of each watershed were used to identify the nearest comparable modelled hillslope. As with the first dataset, the mean erosion rate for the first 2 years of data from each watershed was compared with the mean predicted value for the corresponding hillslopes.

Results

Predicted exposed soil and erosion rates

The predicted amount of EM ranged from 0 to 81% (Fig. 3). The intermountain west and southern Rocky Mountains generally had the highest amounts of EM and the lowest amounts of surface cover after burning (Table 2*a*). In these areas, the mean predicted EM after burning was ~55–65%, and this decreased to 45–50% for the northern Rocky Mountains, eastern Oregon and eastern Washington. Wetter areas along the northern Pacific Coast had the lowest predicted EM and highest surface cover values (Fig. 3; Table 2*a*). The lower EM values in Fig. 3 can be attributed to the higher NFDR-TH fuel moisture values in areas with more precipitation. The predicted post-fire surface cover values within each LANDFIRE zone were relatively consistent, as the coefficient of variation (CV) for the 1-km^2 pixels ranged only from 13 to 21% (Table 2*a*). More variability could be expected with a finer-scale map of fuel types.

Predicted first-year erosion rates spanned a broad range within and among the 12 LANDFIRE zones modelled in this project (Table 2*b*; Fig. 4). Predicted erosion rates were typically less than 5 $Mg\,ha^{-1}\,year^{-1}$ (5 $t\,ha^{-1}\,year^{-1}$) for the Rocky Mountains and interior west where mean annual precipitation is often low and much of the precipitation falls as snow. The lowest predicted mean erosion rate was 0.9 $Mg\,ha^{-1}\,year^{-1}$ for zone 23, which is split between Colorado and Utah (Table 2*b*; Fig. 4).

Mean predicted erosion rates were at least an order of magnitude higher along the Pacific Coast, with values ranging from 52 $Mg\,ha^{-1}\,year^{-1}$ in western Washington to 155 $Mg\,ha^{-1}\,year^{-1}$ for north-western California (LANDFIRE zones 1 and 3 respectively) (Table 2*b*; Fig. 4). The mean predicted erosion rate for eastern Oregon (zone 7) was 28 $Mg\,ha^{-1}\,year^{-1}$, which effectively split the difference between the low values in the

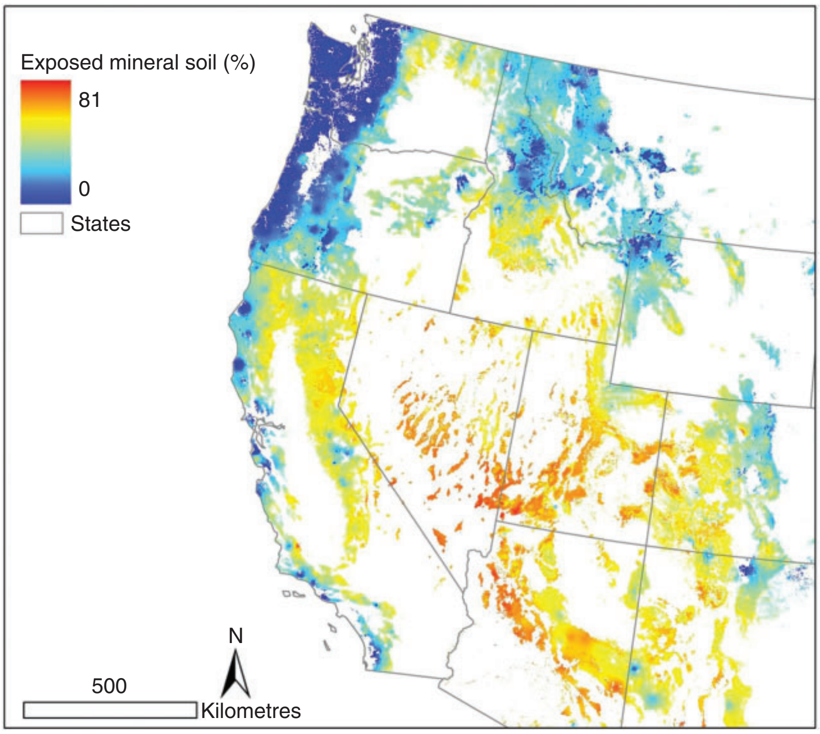

Fig. 3. Predicted percentage of exposed mineral soil after burning.

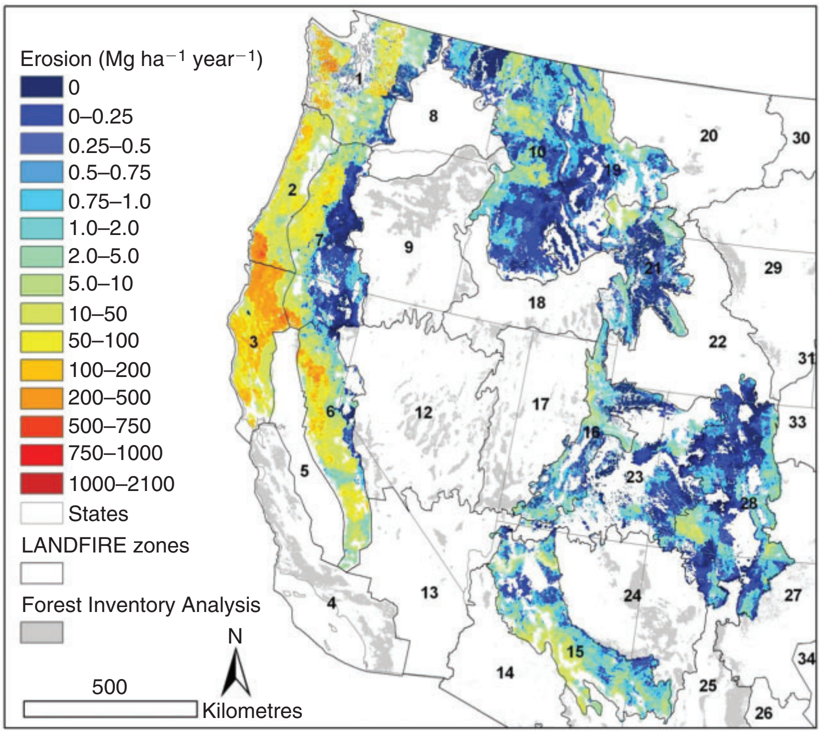

Fig. 4. Predicted post-fire erosion rates for the first year after burning for the 12 LANDFIRE zones where the modelling was completed. The grey colour in the background indicates forests and shrublands according to the Forest Inventory Analysis (Zhu and Evans 1994).

Table 2. (*a*) Mean, standard deviation, minimum, maximum and coefficient of variation (CV) for the predicted amount of post-fire surface cover (100% – EM) based on 1-km^2 pixels assuming 98–100% ERC. (*b*) Predicted hillslope erosion rates for each LANDFIRE zone where the modelling was completed

EM, percentage exposed mineral soil; ERC, Energy Released Component (see text for details). See Fig. 2 for the location of the LANDFIRE zones; values are rounded to reflect the likely uncertainty

(*a*) Post-fire cover (%)												
LANDFIRE zones	1	2	3	6	7	10	15	16	19	21	23	28
Mean	70	69	49	41	53	52	36	36	57	54	37	45
Standard deviation	15	11	9	5	10	9	6	6	9	9	6	8
Minimum	33	38	30	25	28	28	20	20	33	33	20	23
Maximum	98	98	93	75	98	98	68	68	98	95	73	83
CV (%)	21	16	19	13	19	18	17	18	17	16	16	18
(*b*) Post-fire erosion (Mg ha^{-1} year^{-1})												
LANDFIRE zones	1	2	3	6	7	10	15	16	19	21	23	28
Mean	52	88	155	47	28	2.1	5.3	2.4	2.3	1.6	0.9	1.3
Median	10	38	115	15	1.9	0.4	1.8	0.8	0.5	0.2	0.1	0.3
Standard deviation	96	134	141	84	64	4.1	8.6	4.8	4.3	3.6	1.8	2.7
Minimum	0	0	0	0	0	0	0	0	0	0	0	0
Maximum	1500	1400	1200	2100	1200	330	120	220	38	45	62	100
CV (%)	190	150	91	180	230	200	160	200	190	230	200	210

intermountain west and the much higher values along the Pacific Coast. The forests and shrublands in the Sierra Nevada of California (LANDFIRE zone 6) also had a relatively high predicted mean erosion rate of 47 Mg ha^{-1} year^{-1}, and this zone also had the highest hillslope-scale erosion rate of 2100 Mg ha^{-1} year^{-1} (Table 2*b*).

The distribution of predicted erosion rates within each LANDFIRE zone was highly skewed as maximum values were 8 to 160 times the mean (Table 2*b*). LANDFIRE zones with lower mean annual erosion rates (under 6 Mg ha^{-1} year^{-1}) were all from drier interior zones where the mean was typically 3–9 times the median (Table 2*b*). The remaining wetter zones on or near the coast (1, 2, 3, 6 and 7) all had mean annual erosion rates over 28 Mg ha^{-1} year^{-1} and the mean was 1–15 times the median.

Some sharp spatial changes in the predicted post-fire erosion rates that are not due to topography can be attributed to a sudden change in the climate stations selected by GeoWEPP (Fig. 4). These discontinuities were most pronounced in mountainous areas, as these areas have fewer climate stations and there can be large changes in the amount and type of precipitation between adjacent stations.

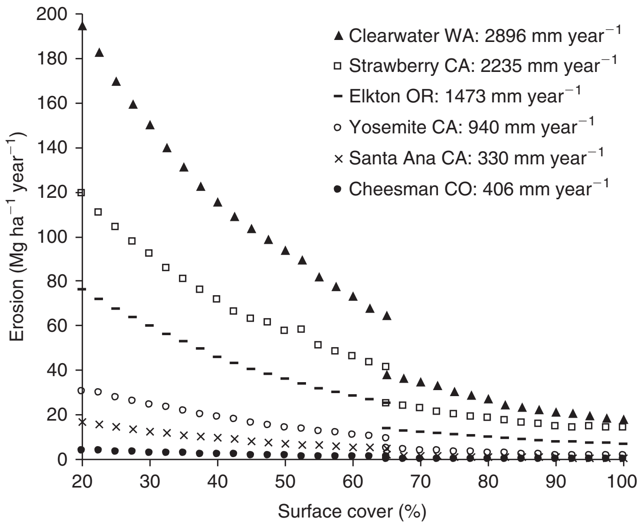

Fig. 5. Predicted erosion rates *v.* surface cover percentage for six climate stations with mean annual precipitation values ranging from 330 to 2896 mm year^{-1}.

Sensitivity analysis

Climate and surface cover

The first sensitivity analysis evaluated the effect of climate and surface cover percentage on predicted erosion rates. There was a very steep, non-linear decline in predicted erosion rates for the three wetter climates as surface cover percentage increased from 20 to 65%, and a much smaller decline as surface cover increased from 65 to 100% (Fig. 5). For the three drier climates, the relative decline in predicted erosion rates with increasing cover was similar to the three wetter climates, though the absolute range was smaller (Fig. 5). For each station, the sudden decline at 65% surface cover was due to the shift from high to low burn severity and the resulting changes in soil properties and other input parameters. The non-linear decline in predicted erosion with increasing ground cover is consistent with field studies (e.g. Walsh and Voight 1977; Larsen *et al.* 2009).

A quantitative analysis of the climate stations with varying MAP indicates climate has a greater effect on the predicted erosion rates than surface cover percentage (Fig. 5). It is important, however, to note that the predicted erosion rates depend on the precipitation intensity and duration of individually modelled storms, not annual precipitation amounts. At 20% surface cover (corresponding to the maximum predicted EM of 80% in Table 2*a*), the predicted erosion rate for Cheesman is just

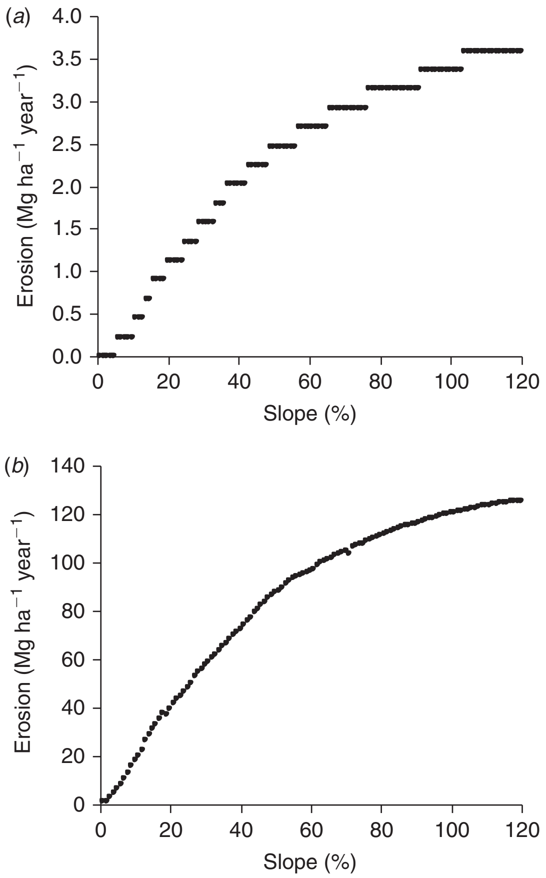

Fig. 6. Predicted erosion rates *v.* slope percentage for: (*a*) a dry climate (Cheesman, CO); and (*b*) a wet climate (Strawberry Valley, CA). Note the different scales for the *y* axes.

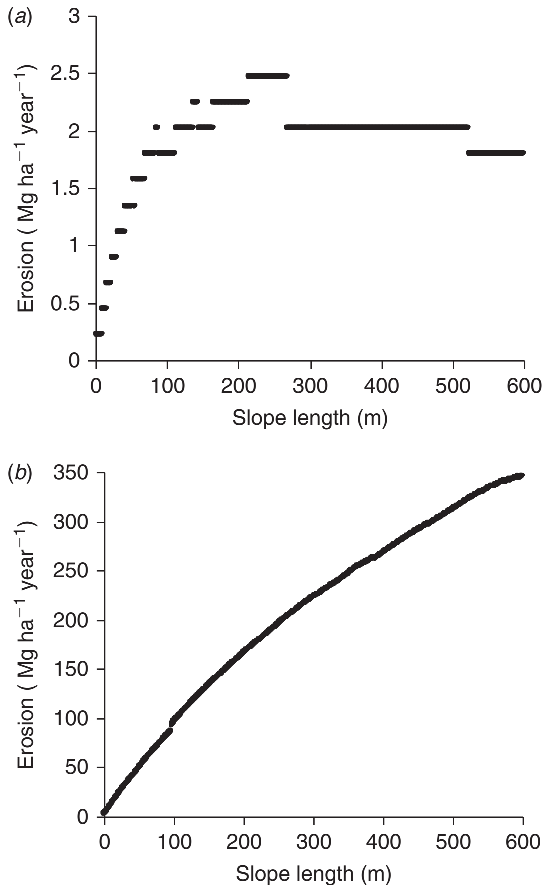

Fig. 7. Predicted erosion rates *v.* slope length for: (*a*) a dry climate (Cheesman, CO); and (*b*) a wet climate (Strawberry Valley, CA). Note the different scales for the *y* axes.

under 4 Mg ha^{-1} year^{-1} as compared with nearly 200 Mg ha^{-1} year^{-1} for the wettest climate. Effective rainfall intensities for these two stations were similar; which indicates that a seven-fold increase in MAP resulted in a 50-fold increase in erosion (Fig. 5). The type of precipitation also affects predicted erosion rates, as the Santa Ana climate in southern California yielded slightly higher erosion rates than the Cheesman climate, even though the MAP for Santa Ana is 19% less than for Cheesman (Fig. 5). The lower erosion rates for the Cheesman climate can be attributed to the fact that at least one-third of the annual precipitation at Cheesman falls as snow (Libohova 2004), and snowmelt causes very little post-fire erosion (Benavides-Solorio and MacDonald 2005; Pietraszek 2006). These results confirm the relatively dominant effect of precipitation on the predicted erosion rates, even when two of the stations in Fig. 5 include substantial amounts of snow.

Slope steepness and slope length

An increase in slope percentage caused a nearly linear increase in predicted post-fire erosion rates for slopes from nearly zero to 30–40% for both the dry (Cheesman) and the wet (Strawberry) climates (Fig. 6). The increase in predicted erosion was progressively smaller as slopes increased beyond 40%. The overall pattern was similar for both climates, but for the wet climate the absolute erosion rates were ~35 times greater than for the dry climate (Fig. 6).

An increase in slope length had a very different effect on the predicted erosion rates for the dry climate than the wet climate (Fig. 7). For the dry climate, the predicted unit area erosion rates increased sharply as slope length increased up to ~100 m, increased more slowly as slope length increased to ~260 m, and then declined slightly as slope length increased from 260 to 600 m (Fig. 7*a*). Plots of the predicted runoff against slope length showed the decline in erosion is due to a decrease in unit area runoff and sediment transport capacity with increasing slope length.

Under the wet climate, the predicted erosion rate initially increased nearly linearly with slope length up to ~150 m, and then increased more slowly as the slope length increased from ~150 to 600 m (Fig. 7*b*). The continued increase in erosion in the wet climate can be attributed to the continuing increase in runoff and sediment transport capacity as the contributing area increased with slope length.

Rock fragment percentage and soil texture

Both the percentage of rock fragments in the soil profile and soil texture class affected the predicted erosion rates (Fig. 8). For the dry climate, the predicted soil loss always increased with soil

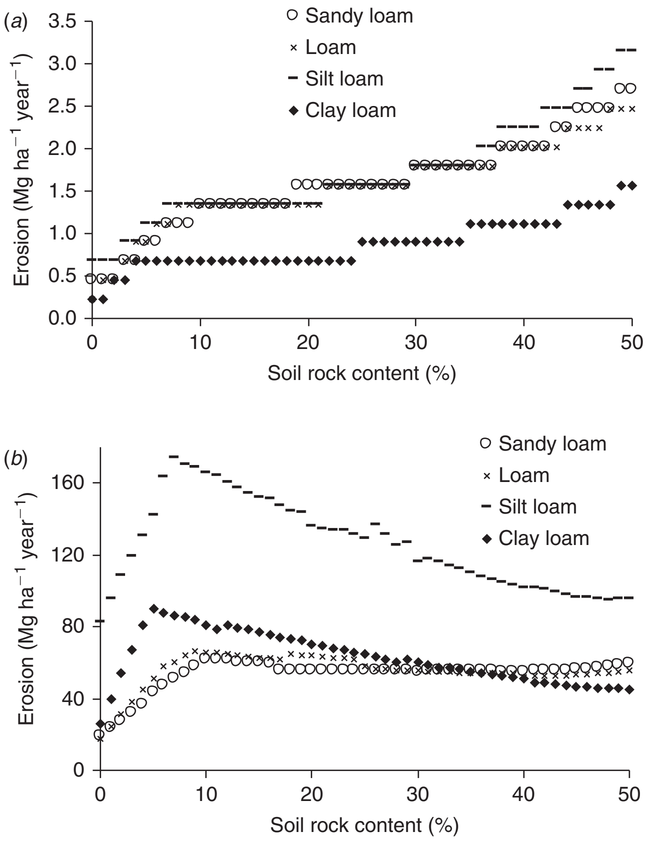

Fig. 8. Predicted erosion rates *v.* soil rock content for each of the four soil types in: (*a*) a dry climate (Cheesman, CO); and (*b*) a wet climate (Strawberry, CA). Note the different scales for the *y* axes.

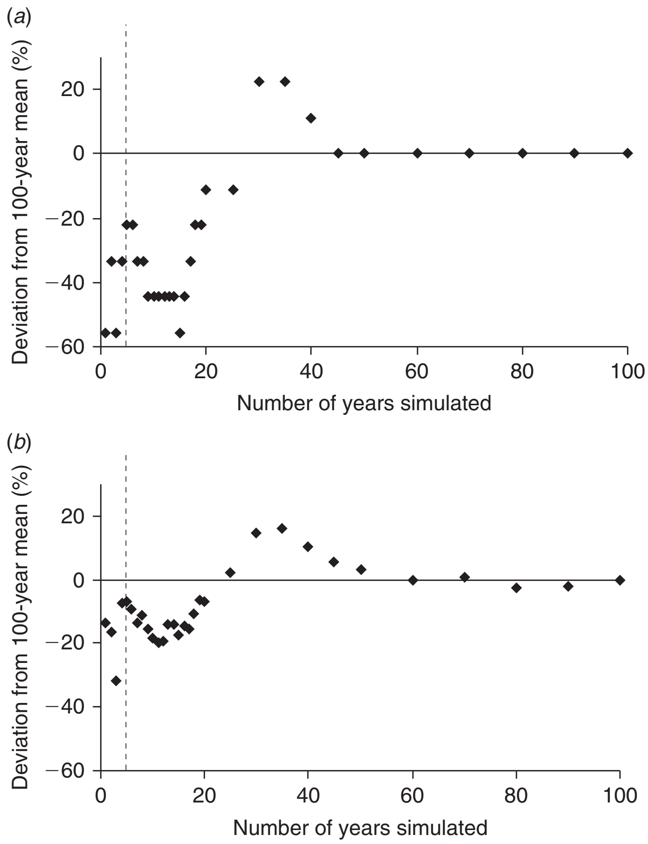

Fig. 9. Deviation of the predicted average annual erosion from the 100-year mean *v.* the length of the simulated climate for: (*a*) a dry climate (Cheesman, CO); and (*b*) a wet climate (Strawberry, CA). The dashed vertical line indicates the 5-year simulation used in this project.

rock content, and this increase was most rapid as the rock content increased from 0 to 10% and from 40 to 50% (Fig. 8*a*). The overall pattern was similar for all four soil textures, although the increase in erosion with increasing soil rock content was much smaller for the clay loam than the other three soil types because the clay loam has a low infiltration rate and low rill erodibility.

For the wet climate, the predicted erosion rate increased rapidly as rock content increased from zero to either 5 or 10% (Fig. 8*b*). Increasing the rock content to 50% reduced the predicted erosion rates by ~50% for the silt loam and clay loam, but had almost no effect on the predicted erosion rates for the two coarser-textured soils. The rapid initial increase in erosion with increasing rock content is attributed to a decrease in infiltration due to a decrease in pore volume. Beyond 5 or 10% rock content, the lower hydraulic conductivity for the finer-textured soils causes WEPP to predict lower soil moisture contents at the end of each day during wet periods, and the resulting increase in soil moisture storage capacity reduces surface runoff and erosion. The effect of increasing the amount of rock fragments on the soil surface was not evaluated, but an increase in rock cover should have a similar effect on erosion rates to an increase in ground cover, as this will reduce rain-splash, sheetwash and rill erosion (Bunte and Poesen 1994).

In the dry climate, the predicted erosion rates were very similar for the silt loam, loam and sandy loam soils, but the predicted erosion rates for the clay loam soil were almost 50% lower (Fig. 8*a*). The lower erosion rates for the clay loam can be attributed to its higher cohesion (Singer and Munns 2002). For the wet climate, the predicted soil loss was two to four times higher for the silt loam than the other three soil types (Fig. 8*b*), and this can be attributed to the relative ease with which silt particles can be detached and transported when there is more rainfall and overland flow (Singer and Munns 2002).

Length of the simulated climate

Increasing the length of the stochastically generated climate caused a similar pattern in the predicted erosion rates for both the dry and wet climates (Fig. 9). At first, there were considerable fluctuations in the mean annual erosion rates as the length of the simulation period increased from 1 to 20 years, and the predicted mean erosion rate peaked at ~30–35 years. Mean erosion rates then declined, and after ~45–50 years the length of the simulation had little or no effect on the predicted soil loss (Fig. 9). For both climates, there was a local maximum in the predicted erosion rates at approximately 5 years, and this local maximum was 78% of the long-term mean for the dry climate and 93% of the long-term mean for the wet climate (Fig. 9). The larger difference between the 5-year and long-term mean erosion in the dry climate is due to the greater skew in the

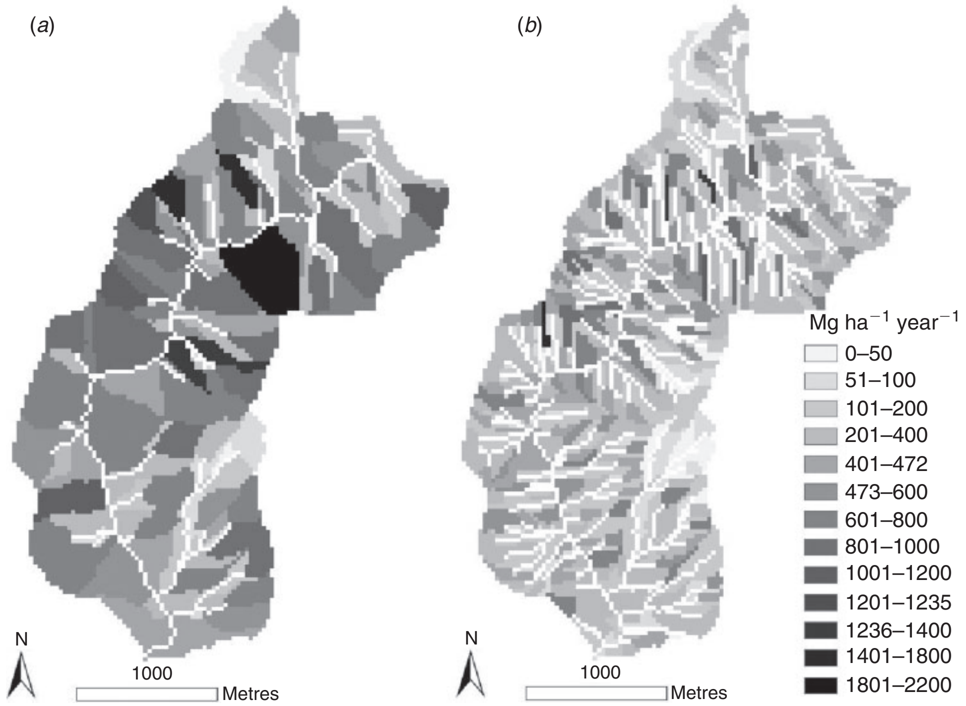

Fig. 10. Effect of reducing the critical source area (CSA) and the minimum source channel length (MSCL) on hillslope size and the predicted erosion rate for a watershed in California's Sierra Nevada. In (*a*) CSA is 5 ha and MSCL is 100 m, and in (*b*) CSA is 1 ha and MSCL is 60 m. The outlet is at −121.05268°W and 39.523284°N.

distribution of annual erosion rates, as the biggest storms in dry climates generate proportionally more erosion than in wetter climates (Haan *et al.* 1994).

These results demonstrate that the mean annual erosion predicted using a 5-year simulated climate is a reasonable compromise between computational time and accuracy. In practice, the mean erosion from a 5-year climate record is more likely to occur than the mean value calculated from a longer climate record because the very wet years have such a low probability of occurrence. Some studies also suggest that the year of burning will have below-normal precipitation and hence potentially lower erosion rates than the second season after burning (Shakesby *et al.* 1996; Larsen *et al.* 2009).

Critical source area and minimum source channel length

The effect of decreasing the critical source area (CSA) and minimum source channel length (MSCL) was evaluated for an 800-ha watershed in the Sierra Nevada of California with a relatively high mean erosion rate of 677 Mg ha^{-1} year^{-1}. Decreasing the default CSA from 5 to 1 ha and the default MSCL from 100 to 60 m reduced the predicted mean erosion rate by 53% to 319 Mg ha^{-1} year^{-1} (Fig. 10). This decrease is partly due to a reduction in hillslope size and hence hillslope length. The lower CSA and MSCL values also increased stream channel density, and the proportion of the watershed designated as channels increased from 5.7% to nearly 16% (Fig. 10). These results are consistent with a study showing that increasing the CSA from 5 to 50 ha increased both hillslope length and predicted erosion rates (Conroy 2005).

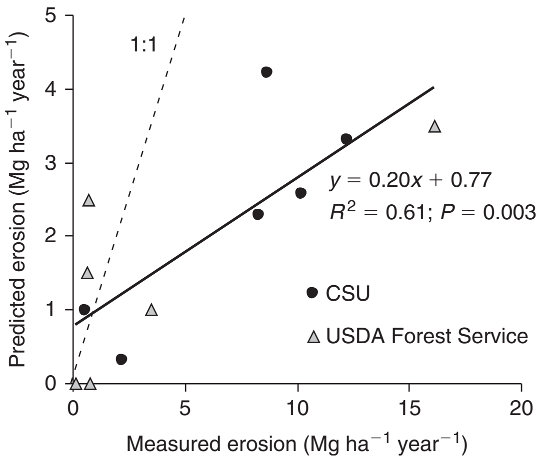

Fig. 11. Measured *v.* predicted post-fire erosion rates. The Colorado State University (CSU) data are mean hillslope erosion rates from different fires in Colorado, and the USDA Forest Service data are from small watershed studies at different locations in the western USA.

Model validation

The comparison of measured and predicted erosion rates yielded a strong positive correlation ($R^2 = 0.61$, $P = 0.003$), but the predicted values were generally much lower than the measured values (Fig. 11). The range of the predicted values also was quite limited, as the highest predicted value for the validation sites was only 4 Mg ha^{-1} year^{-1}. Although this value is larger than the median predicted value for eight of the twelve LANDFIRE zones modelled in this project, it is much less than the median predicted values for the four wetter zones (Table 2, Fig. 4) where there are almost no post-fire hillslope-scale erosion data that can be directly compared with our predicted values (Moody and Martin 2009).

Discussion

Concerns and potential improvements

The underlying modelling philosophy was to use existing models and a consistent approach to demonstrate the feasibility of predicting post-fire erosion at a large scale and to maximise the comparability of the results. Several important concerns were identified when assessing the results, and these included: (1) higher than expected erosion rates in wetter areas, particularly for areas burned at low severity (i.e. less than 35% bare soil); (2) uncertainties in predicting the conditions under which a given area will burn and the associated reliability of predicted exposed mineral soil after burning; (3) spatial discontinuities in the predicted erosion rates, particularly in mountainous areas; (4) difficulties in validating the predicted erosion rates; and (5) incorporating the frequency of burning to estimate long-term post-fire erosion risks rather than short-term post-fire erosion rates.

High erosion rates in wet areas

The predicted hillslope-scale erosion rates appear to be excessively high in the wetter areas along the Pacific Coast, particularly LANDFIRE zones 1, 2 and 3. In LANDFIRE zone 3 in north-western California, for example, the mean predicted post-fire surface cover was 49%, and the predicted median erosion rate was 115 Mg ha^{-1} year^{-1}. These values are high relative to the mean maximum hillslope plot values of 12 Mg ha^{-1} year^{-1} measured in the northernmost portion of zone 5 (Sampson 1944) and <1 Mg ha^{-1} year^{-1} for the Oakland fire just south of zone 3 (Booker *et al.* 1993, 1995, cited in Moody and Martin 2009). The predicted values also are much higher than suggested by qualitative field observations, such as the limited amount of rilling and sediment deposition after the 2002 Biscuit fire in south-western Oregon and north-western California (Bormann *et al.* 2005).

The high predicted erosion rates in wet areas relative to field data and qualitative observations, plus the results of our sensitivity analysis, have triggered additional evaluations of, and improvements to, the WEPP model. More specifically, WEPP was overpredicting surface runoff in wet areas, in part because percolation below 200 mm and lateral flow were being routed as a single output at the end of each daily simulation. If the top 200 mm of soil became saturated, the infiltration rate dropped to zero during the storm rather than to the saturated hydraulic conductivity, and the resultant infiltration-excess overland flow helped generate the very high predicted erosion rates. The Disturbed WEPP Fortran code has been since modified to resolve this problem, reducing the high predicted erosion rates in wet areas. Other changes are being made to the plant–management files in both the online versions of WEPP and the Windows interface for WEPP.

To evaluate the effect of these changes, the models were rerun for the 800-ha watershed (Fig. 10) using the March 2008 version of GeoWEPP, the October 2008 version of WEPP, and new plant–management and soil input files designed to reduce the frequency of saturation. These changes reduced the predicted mean erosion rate from 677 to 190 Mg ha^{-1} year^{-1}, or 72% (Fig. 12); similar reductions can be expected in other high-rainfall areas.

There are at least two other ways to reduce the high predicted erosion rates in wet areas. First, the CSA and MSCL could be reduced, and this would reduce the predicted hillslope erosion rates (Fig. 10) (Renard *et al.* 1997; Cochrane and Flanagan 2005). Both of these parameters should be lower in wet areas owing to the greater amounts of runoff and higher drainage densities. Field studies have shown that the contributing area needed to generate surface runoff can drop dramatically after a high-severity wildfire (Libohova 2004; Moody and Kinner 2006). The problem is that there are no simple, physically based methods for determining the appropriate CSA and MSCL values in response to the variations in climate, soils, vegetation and burn severity across the entire study area (Moody and Kinner 2006). This is a key research need that could greatly improve the relative and absolute accuracy of the predicted erosion rates.

A second possibility for reducing high erosion rates in wet areas is to improve parameter accuracy in the plant–management files. The modified plant–management files used in this project yielded erosion rates that were consistent with measured values from the Hayman wildfire in Colorado. Under the Cheesman climate, there was no difference in the predicted erosion rates between simulations using the plant–management files modified to maintain 100% cover and the standard plant–management file in Disturbed WEPP for a 20-year-old forest. Subsequent analyses have shown that in a wet climate, the predicted erosion rate for a fixed cover of 100% was several times higher than the predicted erosion from the standard plant–management file for a 20-year-old forest. More detailed sensitivity studies are needed to determine the relative importance of the different parameters in the plant–management files, and these results should stimulate field studies to better determine key parameter values for WEPP under different conditions. In the meantime, the erosion values predicted here are believed to be more valid on a relative rather than an absolute scale and more valid within climatic regions, which is consistent with other erosion models (e.g. Wischmeier 1976; Renard *et al.* 1997).

Predicting the conditions for burning and exposed mineral soil

A key assumption was that areas would burn at the 98–100th percentile of ERC. This assumption is important because the assumed ERC level affects the NFDR-TH fuel moisture values, which then control the predicted EM after burning (Eqn 1). The midpoint of the assumed ERC range is the 99th percentile, and on average, these weather conditions should occur for slightly less than 2 days in a 6-month fire season. In reality, wildfires can occur under less extreme conditions because they also depend on an ignition source, fuel loadings and topography, as well as weather and fuel moistures (Sugihara *et al.* 2006).

The effect of assuming a more extreme ERC class of 99–100% on the predicted EM values was evaluated for 14 fire

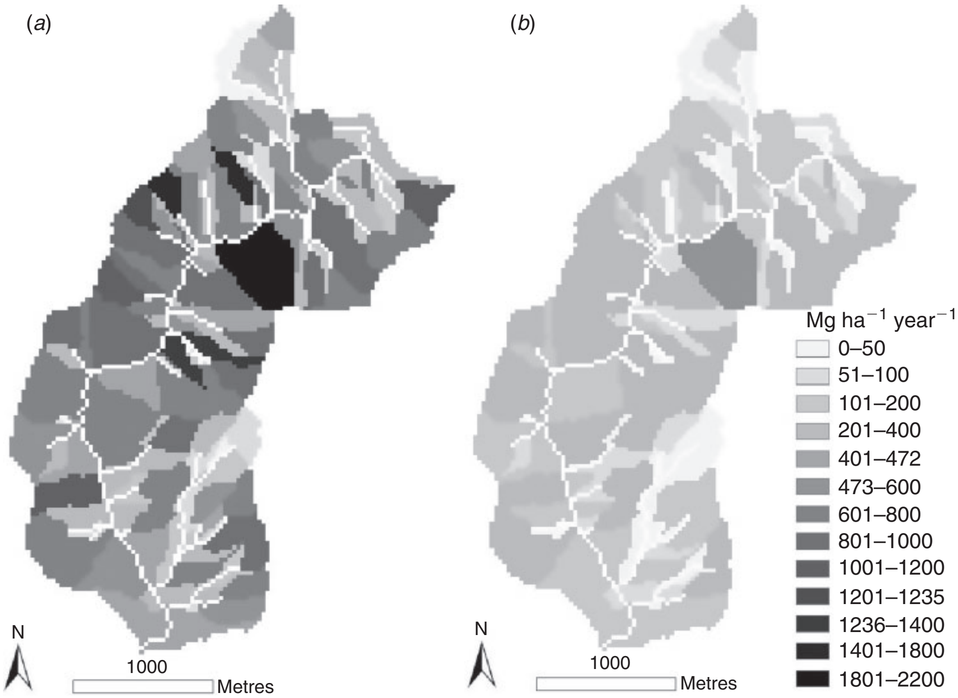

Fig. 12. Predicted erosion rates for a watershed in the Sierra Nevada of California: (*a*) as originally modelled in this study; and (*b*) using the March 2008 version of GeoWEPP, the October 2008 version of WEPP, and updated soil and plant–management files.

weather stations using FireFamilyPlus version 3.0.5. The mean increase in predicted EM was only 2%, and this would increase the predicted erosion rate by 5–10% (Fig. 5). This increase in erosion would yield a better validation in drier areas (Fig. 11), but further increase the predicted erosion rates in wet areas (Fig. 5).

A critical research need is to develop a better procedure for predicting EM values after burning. Field data show the highest predicted EM of 81% is substantially less than the values of 90% or more that have been measured after high-severity fires in the Colorado Front Range (e.g. Libohova 2004; Larsen *et al.* 2009) and other parts of the Rocky Mountains (e.g. Robichaud *et al.* 2008). An increase in the bare soil percentage from 80 to 95% would increase the predicted erosion rate by nearly 50% for the Cheesman climate, which again would improve the validation results (Fig. 11).

Efforts to validate the predicted EM values were hampered by differences in the resolution of the predicted values (1 km^2) relative to the measured values (<5 ha). The extreme patchiness of EM, particularly after low- and moderate-severity fires (Robichaud *et al.* 2007*b*), makes it difficult to validate the predicted EM values and accurately predict post-fire erosion. An improved procedure for predicting EM after wildfires could lead to higher EM values and more accurate erosion predictions in dry areas, and possibly lower EM values and lower predicted erosion rates in wet areas.

Spatial discontinuities in the predicted erosion rates

The sharp spatial changes in predicted erosion rates due to shifts in the climate stations selected by GeoWEPP have been addressed by the incorporation of PRISM and Rock:Clime into GeoWEPP (Minkowski and Renschler 2008). PRISM (Parameter-elevation Regressions on Independent Slopes Model) uses a DEM, point sources of climatic data and other spatial datasets to generate grids of climate data at a resolution of 4 km^2 or finer (Daly *et al.* 1997). Rock:Clime (Elliot *et al.* 1999; Scheele *et al.* 2001) uses elevation to adjust precipitation and temperature values in mountainous areas, which would help determine whether precipitation falls as rain or snow. A change from rain to snow will greatly reduce post-fire erosion rates (e.g. Benavides-Solorio and MacDonald 2005), and this could help reduce the predicted erosion rates in some of the higher-elevation areas in California, Oregon and Washington. PRISM and Rock:Clime also could be used to improve the accuracy of the NFDR-TH values, but this would have a much smaller effect on the predicted erosion rates.

Difficulties in validating the predicted erosion rates

Model validation is a critical step in the development and use of any model (Oreskes *et al.* 1994; Beven 2001), but the inherent problems in validating hillslope-scale predictions of post-fire erosion rates should not be underestimated. These include the extent to which the simulated climate matches the weather conditions at each site during the measurement period, the differences in spatial scale between the predicted and measured erosion rates, the resolution of the underlying GIS layers, the matching of field measurements to a specific modelled hillslope, and the logistical difficulties in measuring post-fire erosion.

The measured erosion rates after a fire are highly dependent on the weather experienced in the first 1–3 years after burning

(Benavides-Solorio and MacDonald 2005; Moody and Martin 2009). The erosion rates predicted in the current study are the annual means for a 5-year stochastic climate record, and these values can differ from field measurements simply because the weather during the field measurement period is unlikely to match the stochastically simulated values. Differences in weather can account for many of the random differences between predicted and observed erosion rates, but there are at least two possible sources of systematic bias. First, the predicted erosion rates were based on the nearest climate station in the WEPP database, but these stations are typically in towns at lower elevations than the field sites. Hence, these stations are likely to underestimate the amount of precipitation and the predicted post-fire erosion rates. The second potential bias is the tendency for precipitation to be below normal in the year of burning (Shakesby *et al.* 1996; Pietraszek 2006). This second bias would reduce the measured erosion rates relative to the values predicted using mean climate data or a stochastic weather sequence, and an adjustment for this bias would help reduce the gap between the measured and predicted erosion rates shown in Fig. 11.

Differences in spatial scale between the predicted and measured values were a potential concern for validating the hillslope plots in the Colorado Front Range. However, field data from convergent hillslopes and small watersheds in the Hayman and Bobcat fires in Colorado show that erosion rates are relatively constant for plots ranging in size from a few hundred square metres up to 4 ha (Larsen and MacDonald 2007). This observation is consistent with the precept that most post-fire sediment is derived from rill and channel erosion (e.g. Moody and Martin 2001; Pietraszek 2006), as there is often a tremendous headward extension of the channel network after a high-severity fire (Libohova 2004; Moody and Kinner 2006). These results indicate erosion rates after high-severity fires may not follow the standard assumption of decreasing sediment yields with increasing area as evidenced by most sediment delivery ratios (Walling 1983) and predicted by WEPP for drier areas (Fig. 7*a*). Additional work is needed to determine the relationships between spatial scale and post-fire erosion rates for different climatic regimes and fire severities, and incorporate this knowledge into post-fire erosion models.

The USDA Forest Service watersheds and the modelled hillslopes were similar in size, but it was difficult to precisely match the measured watersheds to one or more modelled hillslopes. The predicted erosion rates were relatively consistent among neighbouring hillslopes adjacent to the field sites, so the effect of any errors in spatially matching the modelled and measured values should have little effect on the validation results shown in Fig. 11.

DEM resolution can affect the predicted values and validation results because this can affect both slope length and slope steepness, and these parameters directly affect predicted erosion rates (Figs 6, 7). A 30-m DEM, as used in this project, underpredicted hillslope steepness by 34% relative to a mean measured value of 23.8%, and a finer resolution 10-m DEM underpredicted slope steepness by 21% (Yao 2009). For the Cheesman climate, an underestimate of slope steepness by 34% could result in a 30% underprediction of erosion. However, a higher-resolution DEM will generally decrease slope length (Cochrane and Flanagan 2005; Zhang *et al.* 2009), and this would counteract the associated underestimate of slope steepness.

The final and largest difficulty for validating the results is the lack of field data, particularly in wetter areas. This problem will not be easily resolved, as wildfires are inherently less common in wetter environments. The paucity of post-fire hillslope-scale erosion rate data in wet areas is immediately apparent in any compilation of post-fire erosion data (e.g. fig. 1 in Moody and Martin 2009). At the hillslope scale, rill erosion is the largest sediment source in severely burned areas (Moody and Martin 2001; Pietraszek 2006); therefore, our validation only used measurements that included erosion due to rilling. Thus, we used weir and sediment fence data, but excluded point measurements from erosion pins and small-scale measurements from Gerlach troughs because these measurements typically do not cover a large enough scale to capture rill erosion. We also were not able to use the extensive post-fire erosion data from southern California as the modelling for this zone was not completed (Fig. 2).

The logistical issues of measuring post-fire erosion rates also must be recognised. The gap between a fire and the first storm(s) is often only a few days or weeks, and it is difficult to obtain the necessary funding and personnel to establish study sites immediately after a fire (Lentile *et al.* 2007). The spatial variability in post-fire erosion rates means that replicated sites are needed to obtain an accurate mean value, but replication at scales larger than a hillslope is costly and difficult owing to problems of accurately measuring sediment yields at larger scales (Bunte and MacDonald 1999; Edwards and Glysson 1999). These limitations mean that large-scale, spatially explicit modelling efforts will be difficult to validate, and that the results will necessarily be more valid on a relative than an absolute scale.

Frequency of burning

The erosion rates predicted under this project are for the first year after burning using a 5-year simulated climate, but there is no consideration of the frequency of burning. Hence, the predicted erosion rates are largely a function of the amount of precipitation and EM, even though the frequency of burning can vary by an order of magnitude or more between climatic regions and vegetation types. If the objective is to predict longer-term risk to aquatic resources – such as domestic water supplies, habitat for an endangered fish species or reservoir sedimentation – the frequency of burning also must be considered, as this will greatly lower the predicted erosion rates in wet areas.

To predict long-term post-fire erosion rates (R_{lt}, Mg ha^{-1} year^{-1}), one must sum the probability of each different fire severity (P_{fs}) over the period of interest times the associated cumulative post-fire erosion for each fire severity (E_{fs}, Mg ha^{-1}) divided by the period interval (T, years) (Eqn 2):

$$R_{lt} = \frac{\sum(P_{fs} \cdot E_{fs})}{T} \tag{2}$$

To calculate R_{lt}, the frequency and severity of burning need to be determined, which is problematic owing to changes in forest structure and density, increased frequency of anthropogenic ignition sources and climate change (Elliott and Parker 2001; Schmidt *et al.* 2002; Guyette and Dey 2004; Westerling *et al.* 2006). Then the cumulative erosion for each fire severity has to be predicted.

Since the initial modelling was completed, the LANDFIRE project has developed a spatially explicit fire frequency map for the entire US (Rollins 2009). As a first step, the erosion rates shown in Fig. 1 could be multiplied by these fire frequencies to estimate the long-term mean erosion rate from burning without having to estimate P_{fs} and E_{fs} for all locations. The problem with this approach is that fire severity varies with fire frequency.

An alternative would use the relative probabilities of low-, mixed- and high-severity fires developed by the LANDFIRE project (Rollins 2009). Multiplying these relative probabilities times fire frequency would yield a recurrence interval for each fire severity. The modelling process followed in the present project could then be completed for each fire severity using different assumed ERC values. Entering these probabilities and erosion rates into Eqn 2 would yield a mean long-term predicted erosion rate. The frequency of burning can also better guide the allocation of resources for forest thinning among geographic regions and forest types. Additionally, post-fire erosion could be predicted by simply selecting the appropriate predicted erosion rates using a map of fire severity.

Model applications

An important benefit of the work reported here is the suite of logic and procedures developed for predicting post-fire erosion over large geographic areas. The high cost of fuel treatments and fire suppression is forcing government agencies in the US and elsewhere to develop procedures for allocating funds in the most cost-effective manner. Portions of this work have already been used to assess the risk to domestic water supplies in the Colorado Front Range (D. Martin, US Geological Survey, pers. comm., 2009) and reservoir sedimentation in Lake Hemet, CA. The erosion predictions developed in this project also are being incorporated into pilot efforts to quantify watershed risk in the Pacific Northwest (D. Calkin, USDA Forest Service, pers. comm., 2010). Finally, the predicted EM values were incorporated into large-scale efforts to predict post-fire debris flows (S. Cannon, US Geological Survey, pers. comm., 2006).

The results from this study already have led to improvements in the underlying WEPP model and identified key information needs. Similar modelling efforts in other areas can help confirm the results presented here and identify other research needs. Over time, the absolute predictions should become more accurate as additional information becomes available and the underlying models are improved.

Conclusions

This project developed and applied procedures to predict first-year post-fire erosion rates for forests and dense shrublands in the continental western USA to help prioritise fuel reduction treatments. The modelling process first predicted exposed mineral soil from historical fire weather data, a spatially explicit map of fuel moistures at 98–100% ERC for the different fuel types in the study area, and an empirical equation from the First Order Fire Effects Model. The maximum predicted EM value of 81% is less than the values of 90–95% observed after some high-severity wildfires. Validation of the predicted EM values was hampered by the coarse spatial scale of the predicted values relative to field measurements, and the high spatial variability of observed values. Percentage EM was combined with a 5-year simulated climate, local soil information and a DEM to model over 650 000 km^2.

Mean predicted erosion rates ranged from less than 5 Mg ha^{-1} year^{-1} in the Rocky Mountains and intermountain west to 50–155 Mg ha^{-1} year^{-1} for north-western California, western Oregon and western Washington. The limited field data indicate a reasonable correlation between the predicted and observed values for the Rocky Mountain region ($R^2 = 0.61$), but the predicted values in drier climates were generally too low in absolute terms. In wetter climates, the limited qualitative and quantitative data indicate that the predicted erosion rates are too high.

The predicted erosion rates were more sensitive to mean annual precipitation than bare soil percentage, and this helps explain why the predicted erosion rates in wetter areas were much higher than expected. These and other results have led to a series of improvements in the underlying WEPP model and changes to the plant–management files used in Disturbed WEPP.

The present study was successful in demonstrating that post-fire erosion predictions can be done relatively rapidly over large spatial scales, and in identifying key limitations and research needs. Like most erosion models, the results are most useful in relative terms and on a local scale rather than predicting absolute values across different climatic zones. The procedures developed here can serve as a model for other areas, and the results already are being used to determine which areas should have the highest priority for fuel treatments, and to quantify risks to water resources at the watershed scale. Additional studies and field data are needed to: better understand and predict the amount of exposed mineral soil after burning; improve predictions of post-fire erosion, particularly in wetter areas; and account for the frequency of burning to estimate longer-term post-fire erosion rates.

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References

Agee JK (1993) 'Fire Ecology of Pacific Northwest Forests.' (Island Press: Washington, DC)

Benavides-Solorio J, MacDonald LH (2005) Measurement and prediction of post-fire erosion at the hillslope scale, Colorado Front Range. *International Journal of Wildland Fire* **14**, 457–474. doi:10.1071/WF05042

Beven KJ (2001) 'Rainfall-runoff Modelling: the Primer.' (Wiley: Chichester, UK)

Booker FA, Dietrich WE, Collins LM (1993) Runoff and erosion after the Oakland Firestorm – expectations and observations. *California Geology* **46**(6), 159–173.

Booker FA, Dietrich WE, Collins LM (1995) The Oakland Hills Fire of 20 October 20 [sic, 1991]: an evaluation of post-fire response. In 'Brushfires in CaliforniaWildlands: Ecology and Resource Management'. (Eds JE Keeley, T Scott) pp. 163–170. (International Association of Wildland Fire: Fairfield, WA)

Bormann B, Homann P, Cromack K Jr., Darbyshire R, Grant G, Molina, R (2005) Ecosystem effects and propagation of the Biscuit Fire across the large-scale plots of the long-term ecosystem productivity experiment. Report to the Joint Fire Science Program from project AFP3-2003. (Boise, ID)

Brough D, Lawrence P, Fraser G, Rayner D, Le Grand J (2004) Improved inputs for prediction of regional-scale soil erosion potential for Queensland. In 'Proceedings ISCO 2004', 4–8 July 2004, Brisbane, QLD. (International Soil Conservation Organisation: Brisbane, QLD)

Brown JK, Marsden MA, Ryan KC, Reinhardt ED (1985) Predicting duff and woody fuel consumed by prescribed fire in Northern Rocky Mountains. USDA Forest Service, Intermountain Forest and Range Experiment Station Research Paper INT-337. (Ogden, UT)

Bunte K, MacDonald LH (1999) Scale considerations and the detection of sedimentary cumulative watershed effects. National Council of Air and Stream Improvement, Technical Bulletin 776. (Research Triangle Park, NC)

Bunte K, Poesen J (1994) Effects of rock fragment size and cover on overland flow hydraulics, local turbulence and sediment yield on an erodible soil surface. *Earth Surface Processes and Landforms* **19**, 115–135. doi:10.1002/ESP.3290190204

Burgan RE, Klaver RW, Klaver JM (1998) Fuel models and fire potential for satellite and surface observations. *International Journal of Wildland Fire* **8**, 159–170. doi:10.1071/WF9980159

Cannon SH (2001) Debris-flow generation from recently burned watersheds. *Environmental & Engineering Geoscience* **7**(4), 321–341.

Cochrane TJ, Flanagan DC (2005) Effect of DEM resolutions in the runoff and soil loss predictions of the WEPP watershed model. *Transactions of the ASAE* **48**(1), 109–120.

Conroy WJ (2005) A coupled upland-erosion and hydrodynamic-sediment transport model for evaluating management-related sediment erosion in forested watersheds. PhD dissertation, Washington State University, Pullman, WA.

Daly C, Taylor GH, Gibson WP (1997) The PRISM approach to mapping precipitation and temperature. In 'Proceedings 10th Conference on Applied Climatology', 20–24 October 1997, Reno, NV. pp. 10–12. (American Meteorological Society: Boston, MA)

Dissmeyer GE, Foster GR (1981) Estimating the cover-management factor (C) in the Universal Soil Loss Equation for forest conditions. *Journal of Soil and Water Conservation* **36**, 235–240.

Edwards TK, Glysson GD (1999) Field methods for measurement of fluvial sediment. US Geological Survey, Open-File Report 86–531. (Washington, DC)

Elliot WJ (2004) WEPP internet interfaces for forest erosion prediction. *Journal of the American Water Resources Association* **40**, 299–309. doi:10.1111/J.1752-1688.2004.TB01030.X

Elliot WJ, Hall DE, Scheele DL (1999) Rock:Clime Rocky Mountain Research Station Stochastic Weather Generator Technical Documentation. USDA Forest Service, Rocky Mountain Research Station. (Moscow, ID) Available at http://forest.moscowfsl.wsu.edu/fswepp/docs/rockclimdoc.html [Verified 5 October 2009]

Elliot WJ, Hall DE, Scheele DL (2000) Disturbed WEPP (Draft 02/2000) WEPP interface for disturbed forest and range runoff, erosion and sediment delivery. USDA Forest Service, Rocky Mountain Research Station (Moscow, ID) Available at http://forest.moscowfsl.wsu.edu/fswepp/docs/distweppdoc.html [Verified 23 October 2009]

Elliott JG, Parker RS (2001) Developing a post-fire flood chronology and recurrence probability from alluvial stratigraphy in the Buffalo Creek watershed, Colorado, USA. *Hydrological Processes* **15**, 3039–3051. doi:10.1002/HYP.390

Flanagan DC, Nearing MA (1995) USDA – Water Erosion Prediction Project: hillslope profile and watershed model documentation. USDA-ARS National Soil Erosion Research Laboratory, NSERL Report 10. (West Lafayette, IN)

Flannigan MD, Stocks BJ, Wotton BM (2000) Climate change and forest fires. *The Science of the Total Environment* **262**, 221–229. doi:10.1016/S0048-9697(00)00524-6

Forrest CL, Harding MV (1994) Erosion and sediment control: preventing additional disasters after the southern California fires. *Journal of Soil and Water Conservation* **49**(6), 535–541

Fosberg MA, Rothermal RC, Andrews PL (1981) Moisture content calculations for the 100-hour timelag fuels. *Forest Science* **27**(1), 19–26.

Fox D, Berolo W, Carrega P, Darboux F (2006) Mapping erosion risk and selecting sites for simple erosion control measures after a forest fire in Mediterranean France. *Earth Surface Processes and Landforms* **31**, 606–621. doi:10.1002/ESP.1346

Gabet EJ (2003) Sediment transport by dry ravel. *Journal of Geophysical Research* **108**(B1), 2049. doi:10.1029/2001JB001686

GAO (1999) Western national forests: a cohesive strategy is needed to address catastrophic wildland fire threats. US General Accounting Office, Report GAO/RCED-99-65. (Washington, DC)

GAO (2007) Wildland fire management: better information and a systematic process could improve agencies' approach to allocating fuel reduction funds and selecting projects. US General Accounting Office, Report GAO-07-1168. (Washington, DC)

Garbrecht J, Martz LW (1999) TOPAZ: an automated digital landscape analysis tool for topographic evaluation, drainage identification, watershed segmentation and subcatchment parameterization. USDA Agricultural Research Service, Publication GRL 99–1. (El Reno, OK)

Guyette RP, Dey D (2004) The effects of humans and topography on wildland fire, forests, and species abundance. USDA Forest Service, Southern Research Station General Technical Report SRS-73. (Asheville, NC)

Haan CT, Barfield BJ, Hayes JC (1994) 'Design Hydrology and Sedimentology for Small Catchments.' (Academic Press: San Diego, CA)

Hall BL, Brown TJ, Bradshaw LS, Jolly WM, Nemani R (2003) National standardized energy release component forecasts. In 'Proceedings Second International Wildland Fire Ecology and Fire Management Congress and Fifth Symposium of Fire and Forest Meteorology', 16–20 November 2003, Orlando, FL. J11.10. (American Meteorological Society: Boston, MA) Available at http://ams.confex.com/ams/pdfpapers/66258.pdf [Verified 17 August 2011]

Istanbulluoglu E, Tarboton DG, Pack RT, Luce C (2002) A probabilistic approach for channel initiation. *Water Resources Research* **38**(12), 1325–1338. doi:10.1029/2001WR000782

Keane RE, Ryan KC, Veblen TT, Allen CD, Logan J, Hawkes B (2002) Cascading effects of fire exclusion in Rocky Mountain ecosystems: a literature review. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-91. (Fort Collins, CO)

Krammes JL (1960) Erosion from mountain side slopes after fire in southern California. USDA Forest Service, Pacific Southwest Forest and Range Experiment Station, Research Note 171. (Berkeley, CA)

Laflen JM, Elliot WJ, Flanagan DC, Meyer CR, Nearing MA (1997) WEPP – predicting water erosion using a process-based model. *Journal of Soil and Water Conservation* **52**(2), 96–102.

Larsen IJ, MacDonald LH (2007) Predicting post-fire sediment yields at the hillslope scale: testing RUSLE and Disturbed WEPP. *Water Resources Research* **43**, W11412. doi:10.1029/2006WR005560

Larsen IJ, MacDonald LH, Brown E, Rough D, Welsh MJ, Pietraszek JH, Libohova Z, Benavides-Solorio JD, Schaffrath K (2009) Causes of post-fire runoff and erosion: water repellency, cover, or soil sealing? *Soil Science Society of America Journal* **73**, 1393–1407. doi:10.2136/SSSAJ2007.0432

Lentile L, Morgan P, Hardy C, Hudak A, Means R, Ottmar R, Robichaud P, Kennedy Sutherland E, Szymoniak J, Way F, Fites-Kaufman J, Lewis S, Mathews E, Shovik H, Ryan K (2007) Value and challenges of conducting rapid-response research on wildland fires. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-193. (Fort Collins, CO)

Libohova Z (2004) Effects of thinning and a wildfire on sediment production rates, channel morphology, and water quality in the upper South Platte River watershed. MSc thesis, Colorado State University, Fort Collins, CO.

MacDonald LH, Sampson RW, Brady D, Juarros L, Martin D (2000) Predicting post-fire erosion and sedimentation risk on a landscape scale: a case study from Western Colorado. *Journal of Sustainable Forestry* **11**, 57–87. doi:10.1300/J091V11N01_04

Miller JD, Nyhan JW, Yool SR (2003) Modeling potential erosion due to the Cerro Grande Fire with a GIS-based implementation of the Revised Universal Soil Loss Equation. *International Journal of Wildland Fire* **12**, 85–100. doi:10.1071/WF02017

Minkowski M, Renschler CS (2008) GeoWEPP for ArcGIS 9.x full version manual. (Department of Geography, The State University of New York at Buffalo, NY) Available at http://www.geog.buffalo.edu/∼rensch/geowepp/arc_index.html [Verified 25 October 2009]

Montgomery DR, Dietrich WE (1989) Source areas, drainage density and channel initiation. *Water Resources Research* **25**, 1907–1918. doi:10.1029/WR025I008P01907

Moody JA, Kinner DA (2006) Spatial structures of stream and hillslope drainage networks following gully erosion after wildfire. *Earth Surface Processes and Landforms* **31**, 319–337. [Published online ahead of print 27 September 2005] doi:10.1002/ESP.1246

Moody JA, Martin DA (2001) Hydrologic and sedimentation response of two burned watersheds in Colorado. US Geological Survey, Water Resources Investigative Report 01–4122. (Denver, CO)

Moody JA, Martin DA (2009) Synthesis of sediment yields after wildland fire in different rainfall regimes in the western United States. *International Journal of Wildland Fire* **18**, 96–115. doi:10.1071/WF07162

National Fire and Aviation Management (2005) Fire and weather data. Available at http://fam.nwcg.gov/fam-web/weatherfirecd/ [Verified 25 October 2009]

Neary DG, Ryan KC, DeBano LF (2005) Wildland fire in ecosystems: effects of fire on soils and water. USDA Forest Service, Rocky Mountain Research Station, General Technical Report 42, vol. 4. (Ogden, UT)

Nicks AD, Lane LJ, Gander GA (1995) Weather generator. In 'USDA – Water Erosion Prediction Project Hillslope Profile and Watershed Model Documentation'. (Eds DC Flanagan and MA Nearing) pp. 2.1–2.22. (USDA Agricultural Research Service: West Lafayette, IN)

Oreskes N, Shrader-Frechette K, Belitz K (1994) Verification, validation and confirmation of numerical models in the earth-sciences. *Science* **263**, 641–646. doi:10.1126/SCIENCE.263.5147.641

Ottmar RD, Sandberg DV (1985) Calculating moisture content for 1000-hour timelag fuels in western Washington and western Oregon. USDA Forest Service, Pacific Northwest Forest and Range Experiment Station, Research Paper PNW-336. (Portland, OR)

Pietraszek J (2006) Controls on post-fire erosion at the hillslope scale, Colorado Front Range. MSc thesis, Colorado State University, Fort Collins, CO.

Reinhardt ED (2003) Using FOFEM 5.0 to estimate tree mortality, fuel consumption, smoke production and soil heating from wildland fire. In 'Proceedings Second International Wildland Fire Ecology and Fire Management Congress and Fifth Symposium of Fire and Forest Meteorology', 16–20 November 2003, Orlando, FL. 5.2. (American Meteorological Society: Boston, MA) Available at http://ams.confex.com/ams/pdfpapers/65232.pdf [Verified 17 August 2011]

Reinhardt ED, Keane RE, Brown JK (1997) First Order Fire Effects Model: FOFEM 4.0, user's guide. USDA Forest Service, Intermountain Research Station, General Technical Report INT-GTR-344. (Ogden, UT)

Renard KG, Foster GR, Weesies GA, McCool DK, Yoder DC (1997) Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agriculture Handbook 703. (Washington, DC)

Renschler CS (2003) Designing geo-spatial interfaces to scale process models: the GeoWEPP approach. *Hydrological Processes* **17**, 1005–1017. doi:10.1002/HYP.1177

Robichaud PR (2000) Fire effects on infiltration rates after prescribed fire in northern Rocky Mountain forests, USA. *Journal of Hydrology* **231–232**, 220–229. doi:10.1016/S0022-1694(00)00196-7

Robichaud PR, Brown RE (1999) What happened after the smoke cleared: onsite erosion rates after a wildfire in eastern Oregon. In 'Proceedings Annual Summer Specialty Conference (Track 2: Wildland hydrology)', 30 June–2 July 1999, Bozeman, MT. (Eds DS Olsen, JP Potyondy) pp. 419–426. (American Water Resources Association: Middleburg, VA) [Revised 2000]

Robichaud PR, Brown RE (2002) Silt fences: an economical technique for measuring hillslope soil erosion. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-94. (Fort Collins, CO)

Robichaud PR, Elliot WJ, Pierson FB, Hall DE, Moffet CA (2007*a*). Predicting post-fire erosion and mitigation effectiveness with a web-based probabilistic model. *Catena* **71**, 229–241. doi:10.1016/J.CATENA.2007.03.003

Robichaud PR, Lewis SA, Laes DYM, Hudak AT, Kokaly RF, Zamudio JA (2007*b*). Post-fire soil burn severity mapping with hyperspectral image unmixing. *Remote Sensing of Environment* **108**, 467–480. doi:10.1016/J.RSE.2006.11.027

Robichaud PR, Wagenbrenner JW, Brown RE, Wohlgemuth PM, Beyers JL (2008) Evaluating the effectiveness of contour-felled log erosion barriers as a post-fire runoff and erosion mitigation treatment in the western United States. *International Journal of Wildland Fire* **17**, 255–273. doi:10.1071/WF07032

Rollins MG (2009) LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire* **18**, 235–249. doi:10.1071/WF08088

Sampson AW (1944) Effect of chaparral burning on soil erosion and on soil-moisture relations. *Ecology* **25**(2), 171–191. doi:10.2307/1930690

Sampson RN, Atkinson RD, Lewis JW (2000) Indexing resource data for forest health decision making. *Journal of Sustainable Forestry* **11**, 1–14. doi:10.1300/J091V11N01_01

Scheele DL, Elliot WJ, Hall DE (2001) Enhancements to the CLIGEN weather generator for mountainous or custom applications. In 'Soil Erosion Research for the 21st Century'. (Eds JC Ascough II and DC

Flanagan) pp. 392–395. (American Society of Agricultural Engineers: Saint Joseph, MI)

Schmidt KM, Menakis JP, Hardy CC, Hann WJ, Bunnell DL (2002) Development of coarse-scale spatial data for wildland fire and fuel management. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-87. (Fort Collins, CA)

Shakesby RA, Boakes DJ, Coelho C de OA, Goncalves AJB, Walsh RPD (1996) Limiting the soil degradational impacts of wildfire in pine and eucalyptus forests in Portugal: a comparison of alternative post-fire management practices. *Applied Geography* **16**(4), 337–355. doi:10.1016/0143-6228(96)00022-7

Singer MJ, Munns DN (2002) 'Soils: an Introduction.' (Prentice Hall Publishers: Upper Saddle River, NJ)

Soto B, Diaz-Fierros F (1998) Runoff and soil erosion from areas of burnt scrub: comparison of experimental results with those predicted by the WEPP model. *Catena* **31**, 257–270. doi:10.1016/S0341-8162(97)00047-7

Spigel KM, Robichaud PR (2007) First-year post-fire erosion rates in Bitterroot National Forest, Montana. *Hydrological Processes* **21**, 998–1005. doi:10.1002/HYP.6295

Sugihara NG, van Wagtendonk JW, Shaffer KE, Fites-Kaufman J, Thode AE (Eds) (2006) 'Fire in California's Ecosystems.' (University of California Press: Berkeley, CA)

The National Map LANDFIRE (2005) LANDFIRE Rapid Assessment Fire Regimes layer. US Geological Survey. Available at http://gisdata.usgs.net/website/landfire/ [Verified 25 October 2009]

The Nature Conservancy, USDA Forest Service, US Department of the Interior (2005) 'LANDFIRE Rapid Assessment Modeling Manual, Version 2.1.' (Boulder, CO)

Tiedemann AR, Conrad CE, Dieterich JH, Hornbeck JW, Megahan WF (1979) Effects of fire on water. A state-of-knowledge review. USDA Forest Service, General Technical Report WO-10. (Washington, DC)

USDA (1991) State soil geographic (STATSGO) data base data use information. USDA Miscellaneous Publication 1492. (Washington, DC)

USDA Forest Service (2002) FireFamily Plus version 3.0, software and user's guide. USDA Forest Service, Rocky Mountain Research Station. Available at http://www.fs.fed.us/fire/planning/nist/distribu.htm [Verified May 2005]

USGS (2002) The national map – elevation. USGS Fact Sheet 106–02. Available at http://nationalmap.gov/ [Verified 25 October 2009]

Walling DE (1983) The sediment delivery problem. *Journal of Hydrology* **65**, 209–237. doi:10.1016/0022-1694(83)90217-2

Walsh RPD, Voight PJ (1977) Vegetation litter; an underestimated variable in hdyrology and geomorphology. *Journal of Biogeography* **4**, 253–274. doi:10.2307/3038060

Westerling AL, Hidalgo HG, Cayan DR, Swetnam TW (2006) Warming and earlier spring increase western US forest wildfire activity. *Science* **313**, 940–943. doi:10.1126/SCIENCE.1128834

Wischmeier WH (1976) Use and misuse of the Universal Soil Loss Equation. *Journal of Soil and Water Conservation* **31**, 5–9.

Wohlgemuth PM (2003) Hillslope erosion following the Williams Fire on the San Dimas Experimental Forest, Southern California. In 'Proceedings Second International Wildland Fire Ecology and Fire Management Congress and Fifth Symposium of Fire and Forest Meteorology', 16–20 November 2003, Orlando, FL. 1B.8. (American Meteorological Society: Boston, MA) Available at http://ams.confex.com/ams/pdfpapers/67248.pdf [Verified 17 August 2011]

Yao C (2009) Rill erosion initiation and effect of DEM resolution. PhD dissertation, Washington State University, Pullman, WA.

Yu B (2002) Using CLIGEN to generate RUSLE climate inputs. *Transactions of the ASAE* **45**(4), 993–1001.

Zhang JX, Wu JQ, Chang K, Elliot WJ, Dun S (2009) Effects of DEM source and resolution on WEPP hydrologic and erosion simulation: a case study of two forest watersheds in northern Idaho. *Transactions of the ASAE* **52**(2), 447–457.

Zhu Z, Evans DL (1994) US forest types and predicted percent forest cover from AVHRR data. *Photogrammetric Engineering and Remote Sensing* **60**(5), 525–531.