ASSESSING SPATIAL DISTRIBUTION OF FIRE EFFECTS IN FORESTS USING GIS

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Abstract Due to past wildfire suppression in the Northwestern United States, forest fires are increasing in both number and intensity. More frequent and intense forest fires represent an increasing threat to both human and natural resources. Two of the major environmental problems related to forest fires are the increases in surface runoff and water erosion during rain and snowmelt events as a result of increased detachment of the mineral soil exposed after the vegetation is burned. The goal of this study was to determine which environmental attributes of the landscape may influence the distribution of mineral soil exposure following wildfire in forested watersheds. In a field investigation two months after a simulated wildfire we measured the changes in ground cover and a number of environmental variables such as: slope, aspect, distance to streams, solar radiation, elevation, curvature, profile curvature to determine their relationships to postfire mineral soil exposure. The study was conducted within four small watersheds in the Boise Basin Experimental Forest in Idaho, Northwestern United States. We assessed the spatial distribution of fire effects along hillslopes using a Geographic Information System (GIS), and have derived a regressional relationship to estimate the postfire mineral soil exposure from key environmental variables, namely aspect, solar radiation, and profile curvature. Aspect and profile curvature were determined to be the leading variables for predicting mineral soil exposure in the regression model.

INTRODUCTION

More than 90 years of research showed that the severity of forest wildfires depends on the synergy of four factors acting together: weather, fuel load, soil water content, and terrain characteristics (USDA, 2003). The only factor we can control is the fuel load; an understanding of the other factors can help us in managing forests, fire suppression, and postfire mitigation.

Historically, fire has been a dynamic, ecological force in Pacific Northwest forests (van Wagtendonk, 2007; Hamman, 2008). Fire regime was first influenced by the Native Americans by controlling fires near their villages (Anderson, 2006 as cited in van Wagtendonk, 2007). Following the arrival of Europeans, people have tried to suppress fire to protect forest resources and nearby human settlements. This has resulted in a buildup of flammable plant materials on the forest floor, which increased the probability of more severe fires (USDA, 2003). The current practices, in contrast to the fire suppression paradigm, are intended to reintroduce fires as a natural process for land management (Neary et al., 1999).

With the development of the Geographic Information System (GIS) as a spatial analysis tool, researchers are able to better analyze and understand the processes influencing fire spread and its effect on the environment, and to develop models to help minimize the adverse effects of wildfires on the landscape and human resources. Not all the effects are visible immediately post-burn. Flames and smoke are an immediate danger to humans, animals, and plant species. After-effects, such as erosion, landslides, debris flows, and altered water quality, can be equally devastating (USGS, 2006). All these effects are directly linked to the severity of a fire.

Fires not only consume or deeply char the vegetation but also affect the properties of soils, including the structure, porosity and hydraulic conductivity (Neary et al., 1999). When soil structure degrades, macropores (>0.6 mm dia.) and soil infiltration capacity decrease, leading to an increase in runoff (Neary et al., 1999). The fire impact on sediment loss and runoff could be minimal in the absence of significant rainfall; however, if a large storm event occurs after a fire, exposed mineral particles can be easily detached and transported to streams. (Robichaud et al., 2000). Therefore, mineral soil exposure is usually the most important index of fire effect on soil erosion that can be measured (Hudak et al., 2007).

Sediment is the most common pollutant of forest streams (Elliot and Glaza, 2008). The risk of excessive sedimentation increases as the amount of mineral soil exposed after a fire increases. Models to predict post-burn erosion have been developed, but modeling natural phenomena is difficult for several reasons. First, models are simplified analogue of the real world. Missing or inadequate representation of the key physical processes by the model can lead to substantial errors in model prediction. Second, data used to parameterize the models may not accurately reflect the true field conditions due to their spatial variation. Third, data collection and reporting methods are not uniform among researchers and managers, leading to data errors. The structural factors of wildfires that can affect the accuracy of erosion prediction include environmental (vegetation type, topographic characteristics, and climatic condition) and human elements (type and intensity of land use, road accessibility, and fire prevention measures). Together, they determine the background conditions for the fire distribution and variability of severity (Chou and Minnich, 1990).

Forest managers need estimates of runoff and erosion to make decisions about postfire mitigation activities. There are several models that predict runoff and erosion from burned areas (Elliot et al., 2007). Most of these models require topography as an input. Topography has been used to characterize forest soils (Griffiths et al., 2009), for autocorrelation of wildfire distribution (Chou and Minnich, 1990), and reoccurrence of the fires (Vazsques and Moreno, 2001). Topography is also considered to be the most important factor controlling spatial patterns of soil water and vegetation production (Petersen and Stringham, 2008).

The goal of our study was to investigate the correlations between mineral soil exposed after a fire and environmental variables, especially, topographic features and climatic variables. The specific objectives were to evaluate the correlations between fire effects and the type and amount of postfire soil cover, and to develop a model to predict the spatial distribution of mineral soil in burned areas.

MATERIALS AND METHODS

Site description The study site was located in the Boise Basin Experimental Forest managed by the USDA Forest Service Rocky Mountain Research Station (Figure 1). Ten small watersheds were monitored for erosion, with three treatments applied: 1) simulated wildfire (four watersheds), 2) forest thinning (four watersheds), and 3) undisturbed control (two watersheds).

Our study was focused on the four watersheds that received the simulated wildfire treatment. The elevation at the study site was 1381–1485 m, and most of the area had a dominant N–NE aspect.

The slope ranged between 9º and 34º, and soils were generally deep, except on extremely steep slopes and ridges where they were shallow and were mostly coarse to moderately coarse in texture (Elliot and Glaza, 2008). The four watersheds were burned on August 25th, 2008 (Table 1).

Table 1 Characteristics of the four study watersheds.

Watershed	Area (ha)	Elevation (m)	Average Slope (%)
6	2.1	1357	40
7	1.9	1363	46
10	1.2	1424	37
11	1.2	1363	34

Ponderosa pine (*Pinus ponderosa*) was the dominant species, and none of the four watersheds had been disturbed in the past 50 years by fire, thinning or harvesting prior to the prescribed burn in 2008 (Elliot and Glaza, 2008).

The climate is characterized by warm, dry summers and cool, wet winters with annual average precipitation of 635 mm that falls mostly from October through June. The temperature averages between −4º C in the winter and 19º C in the summer.

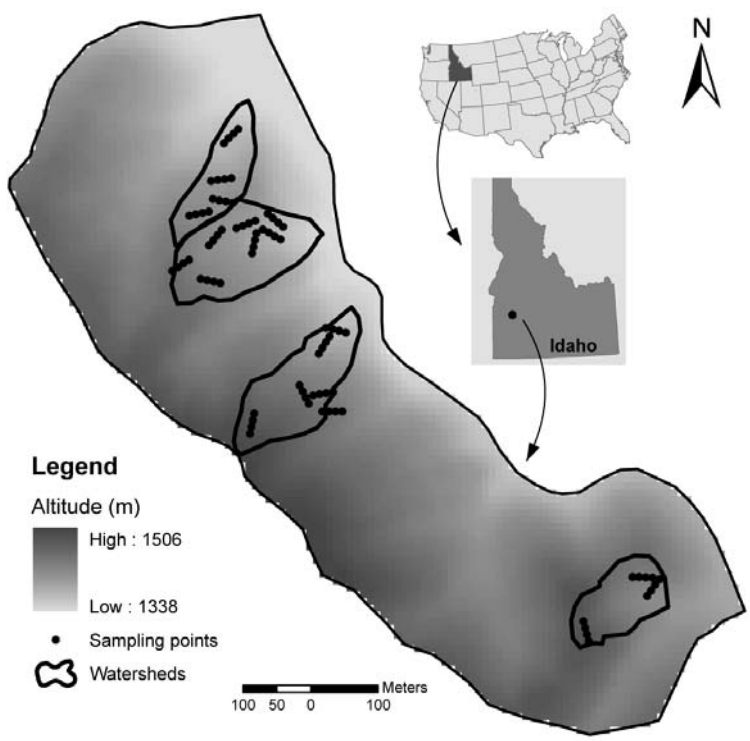


Figure 1 Location of the study watersheds and distribution of the sampling points.

Field sampling We conducted field measurements during September 15th–18th, 2008. Twenty sites were previously selected for measuring vegetation response for multispectral satellite

imagery analysis (Hudak et al., 2007). The sites were marked in the fields by iron stakes at a 50-m spacing.

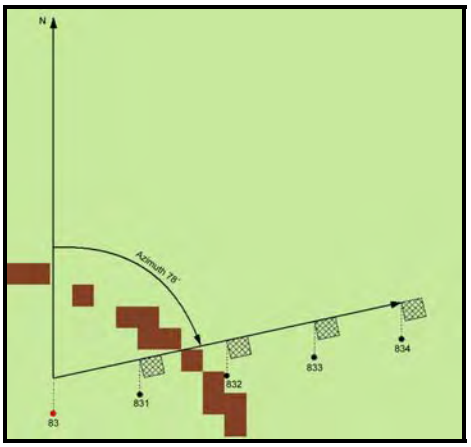


Figure 2 Schematic of a 40-m transect and cover measurement locations.

Figure 3 One-square-meter frame used for cover measurements.

From each of these 20 sites, we randomly selected a 40-m transect to capture the variability of the slopes and the ground cover (Fig. 2). At every 10 m along these transects (Fig. 2) we measured the cover within a 1-m^2 frame placed on the ground (Fig. 3) which yielded a total of 20×4=80 measurement locations. We recorded the cover material for a total of 100 points beneath the frame as mineral soil, ash, rock, woody material, organic matter, or charcoal (Fig. 4). For each transect, we also measured the azimuth angle as degrees from the north. After dropping the four locations on the transects that were outside the watershed boundaries, we were left with 76 measurement locations.

0	1	2	3	4	5	6	7	8	9	10
1	o	o	w	o	o	a	o	o	m	o
2	m	m	c	o	o	m	m	o	o	o
3	m	o	o	a	o	m	o	o	o	o
4	m	o	m	o	o	o	m	a	o	m
5	m	m	m	m	a	o	o	o	o	o
6	r	m	o	m	m	o	o	a	o	o
7	o	o	o	a	a	m	m	o	o	m
8	m	c	o	a	a	o	o	m	o	o
9	m	o	c	o	m	m	m	o	o	a
10	m	o	c	o	m	m	a	o	o	o

	Key	Count	Cover
m =	mineral soil	30	0.30
a =	ash	11	0.11
r =	Rock	1	0.01
w =	woody material	1	0.01
o =	Other Organic Matter	53	0.53
c=	charcoal	4	0.04
		100	

Figure 4 Example of cover percent records with a 1-m^2 frame.

Geographic Information System (GIS) analysis The GIS analysis was conducted in ArcGIS 9.x (ESRI, 2007). Using a 10-m resolution DEM, we derived the environmental variables regarded as related to the percent of mineral soil exposed after fire: elevation, slope, aspect, distance to streams, solar radiation, plan curvature, profile curvature and tangent curvature. We transposed on the map the 76 field measurement locations by locating the transects, and increasing 10-m increments in the direction of observed azimuth, using the Direction/Length

command from the Editing tool. We assumed that the mineral soil exposed after a fire in different watersheds would differ due to changes in topography. For example, a 20 percent slope is considered less dangerous than a 40 percent slope in the fire spread and hazard analysis (Christiansen, 2005).

We generated a solar radiation map with the GIS where each pixel was assigned an insolation value (in WH/m^2). The global radiation was calculated as a sum of direct radiation and diffuse radiation that were obtained by overlaying the viewshed, sunmap, and skymap layers, which were created automatically in computing the Global radiation (ESRI, 2007).

Using the GIS functions, we computed three raster maps of solar radiation: annual, seasonal, and August only. We then obtained the Spearman correlation coefficients to determine which form of radiation best correlated with the ground cover based on our data set. The annual solar radiation showed a slightly stronger correlation with the cover (r=0.23) but the correlation between the cover and each of the other two representations of radiation was also statistically significant, at a significance level of $\alpha = 0.05$.

We hypothesized that the distance to streams may play a role in exposing the mineral soil after fire, that is, soils closer to the stream would have a higher water content thus limiting the soil exposure after fire. This assumption was used in the postfire erosion model developed by Robichaud et al. (2007), but it has not been assessed using field data. Based on the 10-m DEM, we computed two distances to stream: 1) the perpendicular distance from our measurement location to the middle of the corresponding stream cell, and 2) the distance from the measurement location to the middle of the stream cell located perpendicular to the contour lines. The correlation analysis showed that neither method was significantly correlated with the ground cover.

We also generated maps of curvature, plan curvature, profile curvature and tangent curvature. Curvature, representing the derivative of elevation (ESRI, 2007), indicates on a cell-by-cell basis if the topographical surface is concave or convex. The profile curvature is calculated in the direction of the maximum slope, while the plan curvature perpendicular to the direction of the maximum slope.

Statistical analyses All statistical analyses were conducted in SAS 9.1 (SAS, 1999). We used a series of visual methods (histograms, box-and-whisker plots, probability plots, pp plots), descriptive statistics (skewness, Kurtosis, dispersion), and statistical tests (goodness-of-fit, W test) to assess the normality of each variable. Only two variables were close to a normal distribution: solar radiation and curvature. Consequently, we assumed a normal distribution for these two variables, and performed three types of transformations (natural logarithm after adding 1 to the original value to avoid zeros; square root, and power) on others, so that the transformed variables were normally distributed as determined by the Shapiro-Wilk test in SAS. Note that a likely reason for the lack of normality in the variable aspect was the predominantly NE aspects of all watersheds.

We assessed correlations among all 14 variables using the Spearman correlation coefficient. The aspect ranged from 0º to 360º. For our study, we were interested only in the deviation of the

aspect from the south. This is because the more southerly the aspect, the greater the solar radiation, which generally leads to drier soils and duff at the time of the fire, resulting in greater duff consumption and greater exposure of mineral soil. We calculated the aspect value for the statistical analysis from the relationship:

$$\text{Aspect for Analysis} = 180^{o} - |\text{Observed Aspect} - 180^{o}| \quad (1)$$

Hence, a true north value will be 0º, and an observed south aspect will have a maximum value of 180º. The East and West aspects will both be 90º.

To develop an equation to predict the ground cover from the environmental variables, we used the Stepwise regression procedure in SAS. Because aspect and solar radiation were correlated (r=0.8), only one of these two variables, the one that gave a better fit, was used in the Stepwise procedure. Once we identified the best prediction equation from the Stepwise procedure, we applied the General Linear Model (GLM) procedure to determine the detailed statistics of the predictive equation.

RESULTS

Correlation analysis The significant results from the Spearman correlation analysis are presented in Table 2. Twenty four correlations were significant (at p-value<0.05) among all 14 variables and four of them were significant for correlation with mineral soil exposure: solar radiation (0.23), aspect (0.30), profile curvature (−0.24), and ash (0.25). The variable ash cover was discarded from our subsequent analyses because it was not a environmental variable.

Table 2 Correlation among environmental variables and cover percent at a significant level of α = 0.05. The non-significant correlations are denoted by "NS".

Variables	Mineral	Ash	Rock	Wood debris	Organic matter	Charcoal	Aspect	Solar radiation
Aspect	0.3	NS	NS	NS	NS	NS	1	**0.80**
Distance to streams	NS	NS	NS	0.36	0.28	NS	−0.39	NS
Solar radiation	0.23	−0.26	NS	−0.22	−0.22	NS	**0.80**	1
Elevation	NS	NS	NS	0.29	NS	NS	NS	NS
Profile Curvature	−0.24	NS	NS	NS	NS	−0.34	NS	NS
Slope	NS	−0.39	NS	NS	NS	NS	NS	−0.39
Mineral	1	0.25	NS	NS	NS	NS	0.3	0.23
Ash	0.25	1	NS	NS	NS	**0.62**	NS	−0.26
Wood	NS	NS	NS	1	**0.47**	NS	NS	−0.22

Among all the variables, solar radiation and distance to streams were most strongly correlated with the other variables. While solar radiation was correlated with the mineral soil exposure after a fire, the distance to streams was not.

A regression equation for the postfire mineral soil exposure The Stepwise procedure in SAS yielded two independent variables as being significant in a multiple linear regression for predicting postfire mineral soil exposure: aspect and profile curvature. The regression equation for mineral soil is given by:

$$\text{mineral soil exposure} = 0.48 + 0.17\times\text{aspect} - 2.60\times\text{profile curvature} \quad (2)$$

The model showed a relatively poor fit (R^2=0.26, Figure 5). Hence, there may be other important variables that were not measured and included in our model or our sample size was not large enough. We only considered topographic variables, and variables related to fire behavior, but prefire vegetation and soil properties likely contribute to postfire conditions. (Petersen and Stringham, 2008).

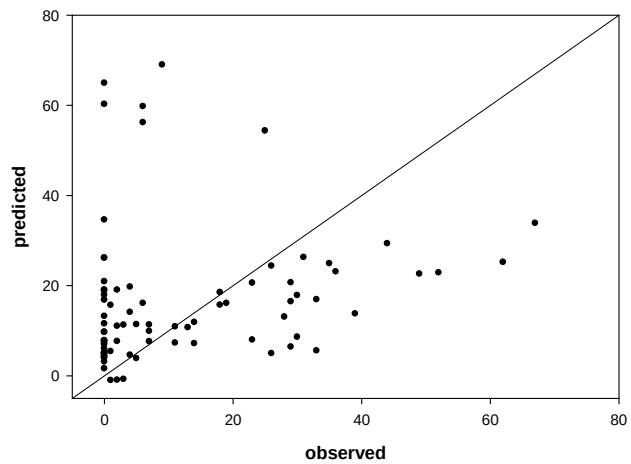


Figure 5 Observed vs. predicted mineral soil exposed.

DISCUSSION

Considering the correlations with radiation in Table 2, we found that, on slopes with less solar radiation there was more ash, and on slopes with more solar radiation, there was more mineral soil. There was a positive correlation between ash and mineral soil, suggesting that where there was more ash, there was more mineral soil exposed. This, however, is not consistent with the observations, and is likely due to the interactions between mineral soil and the materials that cover the mineral soil. Since the two always add up to 100% and the non-mineral components except ash, all decrease as cover increases. As the correlation among these materials is generally weak, such anomalies would happen. Another observation is that ash appeared to increase both down- and upslope. One reason could be that there was more material at the bottom of the hill before the fire, which would potentially turn to ash, and less wood and charcoal, leaving only ash for cover at the top of the hill. For these reasons we chose to focus on the direct correlations only, i.e., slopes receiving less solar radiation are north-facing, slopes receiving less solar radiation have less mineral soil exposed so there is less mineral soil exposed on north-facing slopes.

The total number of significant correlations was 24 and 7 correlations were statistically significant (at $p<.0001$). These correlations were between ash and charcoal (0.62); aspect and solar radiation (0.80); wood and organic matter (0.47); distance to stream and elevation (0.50), distance to stream and curvature (0.54), distance to stream and plan curvature (0.59), distance to stream and tangent curvature (0.54).

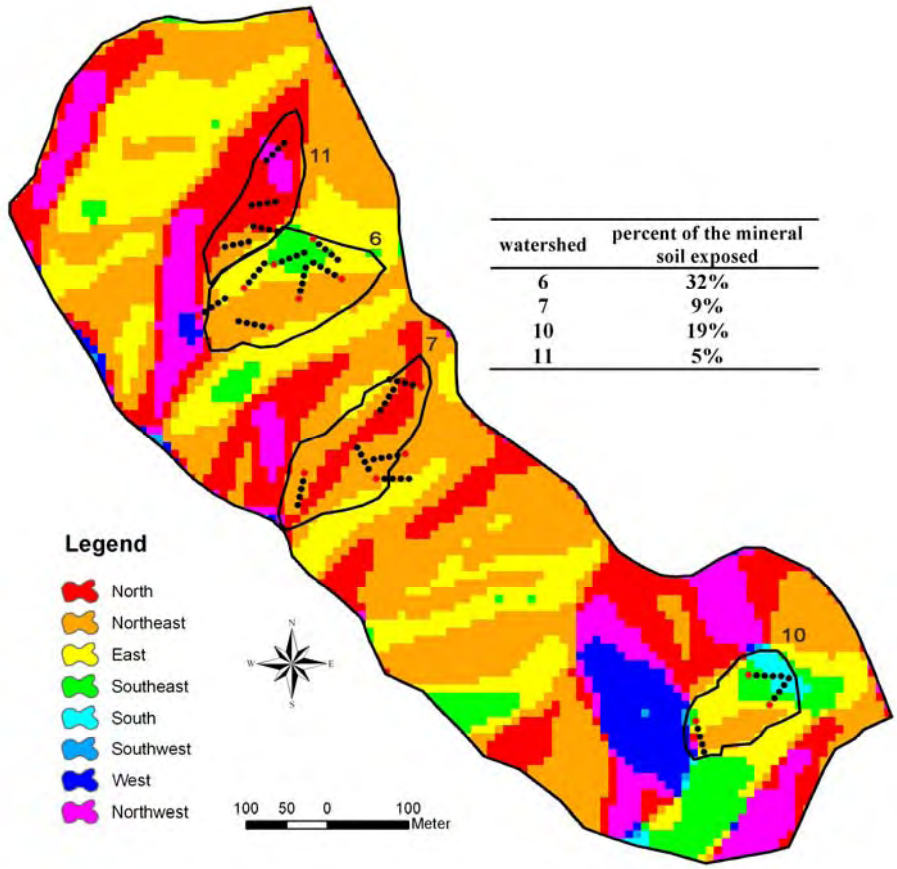
Correlation among variables There was a positive relation between mineral soil exposed with solar radiation and aspect: the amount mineral soil exposed after a fire was greater on surfaces that received more solar radiation and on south-facing slopes. There was less solar radiation and less mineral soil exposed after a fire on north-facing slopes than on south-facing slopes. There were more charcoal, mineral soil exposed and organic matter, on gentler slopes further away from stream channels. The negative correlation between mineral soil and profile curvature indicates that there was more mineral soil where profile curvature was negative, on the shoulders of the hills, and less mineral soil exposed where the curvature was positive, near the bottoms of the slopes near the channels.

We also discovered the following relationships among the cover and environmental variables: the amount of charcoal decreases on concave surfaces so does the ash; as solar radiation increases, the amount of wood debris and ash decreases; there is more organic matter further from streams and more wood debris closer to the streams; there is less organic matter and less wood on slopes with more solar radiation; at higher elevations, there is more wood debris. All this information could be useful in targeting management practices after wildfire to prevent soil erosion.

We have also found other correlations useful in characterizing the study area: slope increases closer to the streams and is steeper on concave surfaces; there is more solar radiation on south facing slopes but less solar radiation on steeper slopes; the surfaces became more convex at higher elevations and the further they were from the streams; the distance to stream increases with elevation and aspect is more southerly closer to the streams on the study watersheds.

It should be noted that these correlations between mineral soil and environmental variables may differ from site to site. As shown in a previous study (Lewis, 2006) in Hayman Fire, CO, the authors found that mineral soil was more correlated with ash (−0.33). Additionally, they found a correlation between mineral soil with rock (0.23) and wood debris (−0.23). In our study, we considered wood debris as a broad category whereas in their study this category was further divided into small woody debris, live trees, and dead trees.

As aspect was an important variable that correlates with mineral soil, we compared the percent of mineral soil measured in the fields with the aspect map (Figure 6) for any potential additional information that could be gained. Evidently, the least amount of mineral soil exposed after fire was in Watershed 11 (5%), which has mostly north-facing slopes, and the greatest amount of mineral soil exposed was in Watershed 6 (32%), which has mostly southeast- or east-facing slopes. Another observation is that the relatively long, narrow Watersheds 7 and 11 had less mineral soil exposure than the wider Watersheds 6 and 10. Therefore, the configuration of watersheds likely contributed to the importance of the profile curvature in the predictive model.



watershed	percent of the mineral soil exposed
6	32%
7	9%
10	19%
11	5%

Figure 6 The aspect map and the percent of mineral soil measured for each watershed.

CONCLUSIONS

Aspect, solar radiation, and profile curvature were strongly correlated with mineral soil exposure after a fire in the four small watersheds within Boise Basin Experimental Forest, Idaho, USA. Generally, there was more mineral soil exposed after a fire on convex surfaces, uphill, and on the south-facing slopes. The linear regression equation had a poor fit, yet it yielded useful information about the variables that are most important to consider in fire management in the Pacific Northwestern forests.

Accurate prediction of the mineral soil exposed is difficult due to the complex interactions among structural and spatial factors in forested watersheds. These kind of analyses are often weak due to the complexity of natural ecological systems in which the ecological responses of interest is influenced by many correlated variables.

As this study was focused on the environmental variables and their relation with burned ground cover, the results revealed only a portion of the total relations that may occur in a pre-fire landscape. Additionally, our study was conducted on a relatively small area (~ 64 ha), which did not allow us to use climatic variables to model exposure of mineral soil. For broader scale modeling, climate along with other variables, such as parent material, soil depth, water

repellency, roads, and management regime may play an important role in estimating the mineral soil, and ultimately accurately predict erosion in areas affected by wildfires.

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