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Modelling post-fire soil erosion hazard using ordinal logistic regression: A case study in South-eastern Spain

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ABSTRACT

Treatments that minimize soil erosion after large wildfires depend, among other factors, on fire severity and landscape configuration so that, in practice, most of them are applied according to emergency criteria. Therefore, simple tools to predict soil erosion risk help to decide where the available resources should be used first. In this study, a predictive model for soil erosion degree, based on ordinal logistic regression, has been developed and evaluated using data from three large forest fires in South-eastern Spain. The field data were successfully fit to the model in 60% of cases after 50 runs (i.e., agreement between observed and predicted soil erosion degrees), using slope steepness, slope aspect, and fire severity as predictors. North-facing slopes were shown to be less prone to soil erosion than the rest.

1. Introduction

The role of wildfires in shaping the landscapes and ruling the dynamics of ecosystems all over the European Mediterranean Basin during thousands of years has been widely reported or reviewed (Pausas, 2004; García-Ruiz, 2010; Keeley et al., 2012). Plant communities in the area are adapted to fire, so they usually recover to a pre-fire state, through successive stages that may take a long time, depending on the structure of plant communities (Margalef, 1974). One basic condition for this is a relatively low fire frequency (Pausas, 1999a, 2004). Otherwise, entire landscapes are threatened by degradation processes affecting plants, soils and water, all of which would mean serious environmental degradation.

Fire frequency, either high or low, depends on the ecosystem, and the different species living in it. For example, we could assume a high fire frequency for *Pinus halepensis* if the return interval between consecutive fires is lower than that required to regenerate the seed bank (from soil, canopy and/or serotinous cones). *P. halepensis* blooms at a relatively early age (less than 10 years), but the production of serotine cones starts some years later, depending on the environmental conditions (15–20 years, Pausas, 1999b; Arianoutsou et al., 2002). Therefore this time could be considered as a threshold between high and moderate fire frequency for *P. halepensis* stands. Conversely, a very low fire frequency would correspond to a time exceeding that of the entire life of the plant.

Regarding soils, wildfires are known to change soil organic matter quantity and quality (Knicker, 2007; Pérez-Cabello et al., 2010; Aznar et al., 2013); deplete soil nutrients directly by volatilization (Johnson et al., 2009) or indirectly by enhanced post-fire erosion (Soto et al., 1997); modify microbial populations (Villar et al., 2004; Dangi et al., 2010); and induce or increase soil water repellency depending on the temperatures and residence time of fire (Doerr et al., 2006; Doerr and Shakesby, 2009), thus lowering water infiltration and increasing water overland flow and runoff (Imeson et al., 1998; Robichaud et al., 2000; Martin and Moody, 2001; Rulli and Rosso, 2007). Estimates of post-fire soil erosion rates have been shown to correlate negatively with the scale of measurement (i.e., plot, hillslope or catchment; Shakesby and Doerr, 2006; Boix-Fayos et al., 2007; Cantón et al., 2011), because the ruling erosion mechanisms vary across different spatial scales (Cameraat, 2002).

Like other regions that undergo periodical wildfires, the main factors related to high post-fire soil erosion rates along the Mediterranean basin are, according to the literature, fire severity (Inbar et al., 1997; Pierson et al., 2002; Varela et al., 2010), plant cover density (Cerdá, 1999; Gimeno-García et al., 2007) and slope (García-Fayos et al., 1995, 2000; García-Fayos and Cerdà, 1997) in terms of both steepness and aspect (Cerdà et al., 1995; Herranz et al., 1991a). The former two factors can be linked, as fire severity, as an expression of fuel consumption and damages to soil (Lentile et al., 2006), is usually higher over dense, continuously distributed fuels (Ruiz Gallardo et al., 2004; Lentile et al., 2006). On the other hand, north-facing slopes have been attributed high soil moisture contents and plant cover densities, which lead to lower erosion rates (Cerdà et al., 1995; Andreu et al., 2001; Pérez-Cabello

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et al., 2006). Other factors include fire frequency (Campo et al., 2006) and soil type (Cerdà et al., 2009). In the Spanish Mediterranean regions, soil types are relatively uniform, because they have mostly developed over limestones or lime-rich parent materials, so that water erosion rates are more dependent on other factors such as climate, topography and land use (Imeson et al., 1998), whose influence may vary from local to regional scales.

The Universal Soil Loss Equation model (Wischmeier and Smith, 1978), or its improved version (Revised USLE or RUSLE; Renard et al., 1991) are among the models most commonly used to predict the mass of eroded soil in different situations. The Water Erosion Prediction Project (WEPP; Nearing et al., 1989) has found acceptance in assessments of soil losses after intense rains over burned areas (Robichaud, 2005; Moffet et al., 2007; Dun et al., 2009). These models provide numerical estimations of the sediment mass eroded after rainfall, and therefore constitute a useful tool for stakeholders to prioritize preventive management at locations under high risk (Mallinis et al., 2009). However, they require a high number of inputs, which may not be always available to researchers and/or managers. In addition, these models are intended to work under a wide range of situations, but under certain particular conditions, they may require some modifications. For example, many years after the release of the first version of the WEPP model, some adaptations in it were found necessary to predict soil erosion in forested areas (Dun et al., 2009), where water dynamics is not comparable to that in agricultural lands.

Other kinds of predictive models (usually based upon geographical or remotely sensed data) classify the erosion risk along an ordinal scale (Shrimali et al., 2001; Fox et al., 2006; Rahman et al., 2009; Mutekanga et al., 2010; Zhang et al., 2010), in categories from "no erosion" to "extreme erosion" risk or degree. This is usually achieved by overlying different thematic layers in GIS and applying different classification criteria and/or indexes to the resulting map. Their advantages lie on their simplicity, flexibility and fewer input requirements to foresee how intense post-fire soil water erosion can be. Whenever the available input data are insufficient to obtain quantitative results (Mutekanga et al., 2010), these models constitute quite a reasonable choice (Ruiz-Gallardo et al., 2004; Zhang et al., 2010) and may be as useful for decision taking as the WEPP or RUSLE models (Shrimali et al., 2001).

Regression analysis and, more precisely, ordinal logistic regression (see below for theoretical basis), can be another way to obtain this kind of results over an ordinal scale when no quantitative data (e.g., eroded sediment mass) are available. This situation is common in field surveys carried out long after a wildfire and/or in areas where no previous erosion studies such as rainfall simulations and experiments in erosion plots have been made. This also applies to fire severity, often qualitatively estimated in the field (Shakesby et al., 2007; Chafer, 2008). As compared to other semi-quantitative estimations of soil erosion, the advantages of a model based on ordinal logistic regression would consist of: (i) deciding which variables to use as predictors, (ii) using as many variables as desired, and (iii) determining the global reliability of the model upon a numerical, objective basis.

The use of remote sensed imagery has become increasingly widespread to measure fire effects over burnt areas, usually calculating pre- and post-fire vegetation indices (e.g., Chuvieco, 2007; Chafer, 2008; De Santis and Mallinis et al., 2009). However, when the facilities needed for this kind of analysis such as soft/hardware, remotely sensed data and/or adequately trained staff are not available, visual field estimations or measurements of fire severity are often the only way left for the assessment.

Several cases of logistic regression applications in soil or forest science can be found in the literature. Pérez-Cabello et al. (2006) used binary logistic regression to predict high water erosion risk in burned areas of the Pyrenees (Northern Spain), using a wide set of predictors (fire severity, soil parent material, vegetation parameters, topographic and climatic data) resulting from satellite imagery and field surveys. Stephens and Finney (2002) used logistic regression to predict conifer tree mortality after prescribed fires in the USA, whereas Dimitrakopoulos et al. (2010) did so to estimate ignition probability and moisture of extinction under Mediterranean grassy fuels. Other recent examples include Badía et al. (2011) to determine the probability of ignition at the forest–urban interface, and Vega et al. (2011) to predict the post-fire probability of delayed tree mortality.

As compared with binary logistic regression, ordinal logistic regression models allow the researcher including multiple levels for the dependent variable, as explained above. Thus, Pérez-Cabello et al. (2006) applied a binary logistic regression to discriminate only high vs. non-high erosion risk levels in the Pyrenees. As long as areas under high erosion risks are the primary concern of environmental managers, we agree with this approach. However, it might be useful to identify moderately burnt areas from those just slightly burned or unburned, in the case of applying suitable, specific soil rehabilitation tasks. Thus, field assessments for soil degradation and rehabilitation after wildfires in the Western U.S. by the Burned Area Emergency Rehabilitation (BAER) team consider three categories of soil erosion risk (low, moderate and high; Robichaud et al., 2000, 2007). The inclusion of more than two erosion risk levels was related to soil water repellency and soil burn severity degrees, also divided into three classes/categories (Robichaud et al., 2000; Miller et al., 2003).

This paper aims to predict fire-induced soil water erosion by means of ordinal logistic regression, taking fire severity and topographic parameters as predictors. The model we present here was developed from individual wildfire events that happened in Albacete (SE Spain).

2. Material and methods

2.1. Ordinal logistic regression

Logistic regression allows building predictive models on a probabilistic basis. Like in any other regression analysis, it predicts a response (dependent) variable, in this case categorical, from one or several predictor (independent) variables. Categorical predictors can also be included in the calculations, once turned into binary (or *dummy*) variables, with as many of them as classes in the original variable minus one. Logistic regression applies to a binary dependent variable (e.g., fire occurrence vs. non-occurrence), with a regression equation like this:

$$\mathrm{Logit}(p) = \mathrm{a} + \mathrm{b}_1 x_1 + \mathrm{b}_2 x_2 + \mathrm{b}_3 x_3 + \ldots + \mathrm{b}_n x_n \tag{1}$$

where p is the probability of occurrence of an event, a is the intercept, b_1, b_2, …, b_n are the regression coefficients and $x_1, x_2, \ldots, x_n$ are the independent (predictor) variables. Finally, Logit (p), commonly referred to as the odds ratio, is defined as:

$$\mathrm{Logit}(p) = \mathrm{Ln}\ [(p/(1-p)]. \tag{2}$$

Logistic regression can also be applied to dependent variables with more than two classes, either nominal or ordinal. In the case of an ordinal dependent variable, we calculate the probability of a given event and all others ordered before it. Thus, if the dependent variable Y takes the values 2, 1 and 0, meaningful in terms of order or preference, we first calculate $p(Y \leq 2)$, $p(Y \leq 1)$ and $p(Y = 0)$, and then $p(Y = 2) = p(Y \leq 2) - p(Y \leq 1)$, and $p(Y = 1) = p(Y \leq 1) - p(Y = 0)$. If the values of the dependent variable denote a difference but not necessarily an order or preference, then the regression model is multinomial instead of ordinal. An ordinal logistic regression model with multiple (X_1, …, X_n) predictors can be written as:

$$\mathrm{Ln}\left(\theta_j\right) = \alpha_j – \beta_1 X_1 - \ldots - \beta_n X_n \tag{3}$$

where θ_j = prob(score $\leq j$)/prob(score $> j$), α_j is the intercept for the logit j, and β_n is the regression coefficient for the independent variable