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Why not use niche modelling for computing risk of wildfires ignition and spreading?

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Abstract
A forest fire can be a true ecological calamity, regardless of whether it is caused by natural forces or human actions. Although it is impossible to control nature, it is possible to map wildfire risk zones, and thence minimize the frequency of wildfires and prevent damages. Wildfire risk zones are locations where a fire is likely to start, and from where it can spread to other areas. Predictions of wildfires ignitions are critical aspects of biodiversity conservation and management, and they are only possible when a reliable fire risk zone map is available. I suggest in this paper that wildfire ignition risk computed from points of past wildfires obeys the same conceptual and mathematical rules of niche models commonly applied to points of sampled plants or animals. Therefore, niche modeling can also be an inductive approach for an effective and inexpensive computation of wildfires ignition and spreading likelihood.

Keywords biodiversity preservation; ignition likelihood; Maxent; niche modeling; wildfires.

1 Introduction

Frequent occurrence of fires is one of the reasons for the degradation of forests worldwide. Fire is the biggest enemy of standing vegetation and wild animals. Small trees and regeneration are often impacted very adversely. Annual fires decrease the growth of grasses, herbs and shrubs, which may in turn result in increased soil erosion. Even big trees are not spared if the wildfire is severe. Ground fire destroys the organic matter, which is needed to maintain an optimum level of humus in the soil (Verma et al., 2012).

The causes of the forest fires can be classified into three categories (a) natural causes, (b) intentionally/deliberately caused by man and (c) unintentionally/accidentally caused by man. Around 95% of the forest fires in Italy are anthropogenic in nature (Italian Ministry of the Environment, unpublished data), while this percentage reaches 99% for the Emilia-Romagna region (Ferrarini, 2010). Zone mapping of the wildfire risk is the first step to preventing disastrous and damaging incidents of forest fires. Fire risk is defined as the chance that a fire might start, hence it expresses an ignition probability index. There is general agreement on this definition among numerous international organizations, including the National Wildfire Coordinating Group (NWCG, 2003), the Society of American Foresters (1990) and the Food and Agriculture Organization (FAO, 1986).

The fire proneness depends on many factors such as vegetation type/density/wetness, proximity to settlements and distances from roads. Human, animal and vehicular movements and activities on roads provide opportunities for accidental/man-made fires. Forests located near roads are therefore much more fire-prone.

Topography is related to wind behavior and, hence, affects the fire proneness of the area. Fire travels most rapidly up-slopes and least rapidly down-slopes. The climatic regime determines the vegetation in a region and hence, plays a dominant role in creating fire-prone areas. The drier the climate is in a particular region, the more fire prone the site will be.

Many attempts to compute fire ignition risk from GIS commonly adopt the following approach (e.g. González-Olabarria et al., 2011): a) build GIS layers of wildfires predictors, b) weight previous layers after determining the influence of each factor on wildfire risk, c) the considered factors are then integrated for calculating the forest fire risk index.

While there’s also a variety of approaches for wildfire risk computation based on remote sensing models (e.g. Knorr et al., 2011; Roy et al., 1991), in this paper I suggest that fire risk assessment from points of past wildfires obeys the same conceptual and mathematical rules of niche models commonly applied to points of sampled plants or animals. Therefore, niche modeling can be an effective and inexpensive approach to wildfires ignition and spreading likelihood as well. In addition it would represent an inductive modeling approach able to take into account past events of wildfires occurrences, and to integrate them with their plausible driving forces. In addition I suggest here that one risk map is not enough for proactive wildfire prevention. Due to the prevalently anthropogenic nature of wildfires, I suggest here that for each study area 24 maps based on niche modeling of wildfires ignition risk would be much more predictive.

2 Biodiversity Niche Modeling (BNM)

Niche modeling, also known as species or habitat potential distribution modeling (Guisan et al., 2005), is commonly used to interpolate or extrapolate fundamental niche outside the locations where a species is present (i.e. realized niche), by relating species presence to environmental predictors. BNM is important for a range of land management activities. Examples include predicting the distribution of rare and threatened species and plant communities (Engler et al., 2004; Parolo et al., 2008), risk assessment of invasive species (Peterson, 2003) and the appraisal of the likely intensity of biological responses to climate change (Thuiller, 2004).

Various methods have been developed for BNM. Generalized linear models (GLM; McCullagh & Nelder, 1989) and generalized additive models (GAM; Hastie & Tibshirani, 1986) require presence/absence data in order to generate discriminant functions rules. However, there is a growing interest in making use of just presence-only data. In fact, the large majority of available data consist of presence-only data sets, with no reliable data on where the species is truly absent. Hence, a second group of methods, including genetic algorithms (GARP; Stockwell and Peters, 1999) and Bioclim (Busby, 1991), is gaining more and more consideration. The recently proposed Maximum Entropy (Maxent) algorithm (Phillips et al., 2006) allows the use of presence-only data and categorical predictors.

Maxent is a machine-learning technique based on the principle of maximum entropy (Jaynes, 1957). When approximating an unknown probability distribution. Maxent seeks the approximation that satisfies a set of constraints on the unknown distribution and that, subject to those restraints, maximizes the entropy of the resulting distribution. Given m sample points $x_1 ... x_m$ (occurrence data), a study area composed of k pixels and a set of features $f_1 ... f_n$ (environmental predictors), each feature f_i assigns a real value $f_i(x_j)$ to each point x_j (e.g. the altitude of sample point x_j). The empirical average of each feature f_i is thus defined as:

$$\pi(f_i) = \frac{\sum_{j=1}^{m} f_i(x_j)}{m} \qquad (1)$$

Maxent searches for the probability distribution that maximizes

$$H = \max\left(-\sum_{k} p_k * \ln(p_k)\right) \tag{2}$$

under the constraints that for each feature f_i

$$\pi(f_i) - \sum_{j=1}^{m} p_k(x_j) * f_i(x_j) \leq \beta_i \tag{3}$$

for some constants β_i (known as regularization value) and

$$\sum_{k} p_k = 1 \tag{4}$$

where $p_k(x_j)$ is the unknown quantity (i.e. the probability to be assigned to each pixel). Without the regularization value (an empirically tuned value depending on the sample size), the computed distribution is likely to undergo overfitting. In the regularized case, it is used as a relaxed constraint where feature expectations are only close to empirical average over sample locations rather than exactly equal to them. Because these probabilities must sum to 1, each probability is extremely small. Hence, Maxent presents the probability distribution in a cumulative representation, where the value assigned to a pixel is the sum of the probabilities of that pixel and all other pixels with equal or lower probability, multiplied by 100 to give a percentage. Pixels with values close to 100 are the most suitable, while cells close to 0 are the least suitable within the study area.

3 The Newly Poposed Wildfires Niche Modeling (WNM)

Like the occurrences of plants and animals, points of past wildfires happen prevalently at locations where this physical process is more probable regardless of its natural or anthropogenic reason.

Like the occurrences of plants and animals, locations of past wildfires can be compared with those driving forces that determine such probability (e.g., distance from roads, distance from settlements, slope, vegetation type; Fig. 1).

Like the occurrences of plants and animals, likelihood of wildfires ignition can be computed using a niche model that relates past wildfires points with the selected driving forces (Fig. 1). Among niche models, Maxent has been shown to perform better than other algorithms. Elith et al. (2006) demonstrated that Maxent performed very well when compared to more established methods such as Bioclim, GARP, GAM and GLM. Hernandez et al. (2006) tested four modelling methods and showed that Maxent had the strongest performance among the tested methods, since it remained stable in prediction accuracy across all sample size categories.

But unlike biodiversity niche modeling, risk of wildfires ignition strongly depends on the temporal interval as well (Ferrarini, 2010). Since almost 100% of wildfires are caused by man (intentionally/deliberately or unintentionally/accidentally), the period with higher probability usually corresponds to weekends (Sunday in particular, but also Saturday), when tourists accidentally give rise to wildfires ignitions, and pyromaniacs more frequently set dry grasses and bushes on fire. For wildfires, vegetation dryness, that mainly depends on climatic conditions (rainfalls and temperature), is fundamental. Since climatic conditions usually depend on months, WNM must consider both weekly and monthly aspects of wildfires ignition risk. This can be achieved by producing not one, but 2*12 risk maps where 2 is due to the two periods of the week (weekdays and weekend) while 12 corresponds to the months of the year. As a result, 24 maps based on Maxent modeling of

past wildfires could be very predictive of wildfires risk. To do this, wildfires ignition risk should be divided into 24 categories:
January – weekdays,
January – weekend (Saturday and Sunday),
February – weekdays,
February – weekend,
etc., and of course each risk map must rely just on the wildfires points of that category. Then, depending on the day of the week and on the month, just one of the 24 risk maps should be used.

Once areas with highest (or higher) Maxent ignition scores are calculated, spread simulations of wildfires can be initiated from those points using mean T° and rainfalls values of that month. Maxent scores of each risk map can also be classified into classes of risk, for instance:

0-25%	low risk
25-50%	moderate risk
50-75%	high risk
75-100%	extreme risk

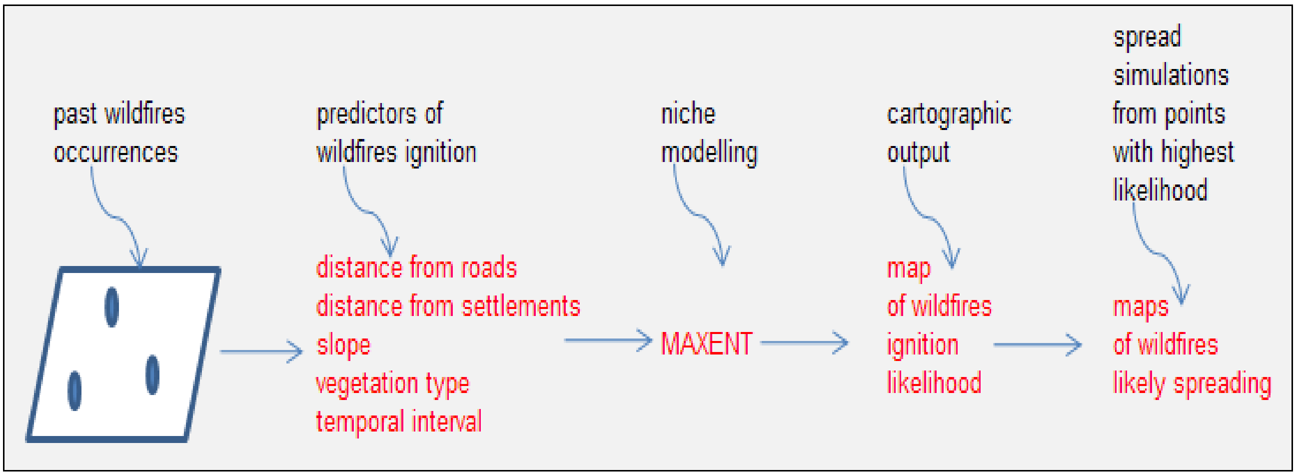

Fig. 1 The proposed framework for the computation of wildfires ignition and spreading risk.

4 Conclusions

Occurrences of wildfire is one of the reasons for the degradation of forests worldwide, and zone mapping of the wildfire risk is the first step to preventing disastrous and damaging incidents of wildfires. Besides the environmental damages, their economic cost is extremely elevated as well.

I proposed here wildfire niche modelling (WNM) as an effective solution based on the syncretical use of niche modelling, commonly used for plants and animals, applied to occurences of past fires. It's much more inexpensive than methods based on remote sensing, furthermore it is not prone to the subjectivity of methods based on weighted summation (or similar functions) of GIS layers, where the computation of weights is very ticklish. In WNM, weights are inductively achieved by past wildfires occurrences using the optimization procedure of Maxent modeling. In addition, WNM requires that wildfires ignition likelihood for each study area is computed taking also into account the temporal interval, due to the prevalently anthropogenic nature of wildfires. Once areas of higher wildfire risk are depicted, fire spread simulations can be initiated from those points, thus producing also reliable maps of wildfires spreading risk.

References

Busby J.R. 1991. Bioclim– a bioclimatic analysis and prediction system. In: Nature Conservation: Cost Effective Biological Surveys and Data Analysis (Margules CR, Austin MP, eds). 64-68, CSIRO, Melbourne, Australia

Elith J, Graham CH, Anderson RP, et al. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography, 29: 129-151

Engler R, Guisan A, Rechsteiner L. 2004. An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudo-absence data. Journal of Applied Ecology, 41: 263-274

Ferrarini A. 2010. Analisi del rischio di incendi e simulazione della loro diffusione in Emilia-Romagna. Technical report, Italy

Food and Agriculture Organization (FAO). 1986. Wildland fire management terminology. FAO Forestry Paper 70, Food and Agriculture Organization of the United Nations, Rome, Italy

Hastie T, Tibshirani R. 1986. Generalized additive models. Statistical Science, 3: 297-318

Hernandez PA, Graham CH, Master LL, et al. 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. Ecography, 29: 773-785

González-Olabarria JR, Pukkala T. 2011. Integrating fire risk considerations in landscape-level forest planning. Forest Ecology and Management 261: 278-287

Guisan A, Thuiller W. 2005. Predicting species distribution: offering more than simple habitat models. Ecology Letters, 8: 993-1009

Jaynes ET. 1957. Information theory and statistical mechanics. Physical Review, 106: 620-630

Knorr W, Pytharoulis I, Petropoulos GP, et al. 2011. Combined use of weather forecasting and satellite remote sensing information for fire risk, fire and fire impact monitoring. Computational Ecology and Software, 1(2):112-120

McCullagh P, Nelder JA. 1989. Generalized Linear Models. Chapman & Hall, London, UK

National Wildfire Coordinating Group (NWCG). 2003. Glossary of Wildland Fire Terminology. http:// www.nwcg.gov/teams/pmo/products/wfglossary/content.htm.

Phillips SJ, Anderson RP, Schapire RE. 2006. Maximum entropy modelling of species geographic distributions. Ecological Modelling, 190: 231-259

Parolo G, Rossi G, Ferrarini A. 2008. Toward improved species niche modelling. *Arnica montana* in the Alps as a case study. Journal of Applied Ecology, 45: 1410-1418

Peterson A.T. 2003. Predicting the geography of species' invasions via ecological niche modeling. Quarterly Review of Biology, 78: 419-433

Roy PS, Ranganath BK, Diwakar PG, et al. 1991. Tropical forest type mapping and monitoring using remote sensing. International Journal of Remote Sensing, 12: 2205-2228

Society of American Foresters. 1990. Glossary of Wildland Fire Management Terms Used in the United States. University of Arizona Press, Tuscon, Arizona, USA

Stockwell D, Peters D. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. International Journal of Geographical Information Science, 13: 143-158

Thuiller W. 2004. Patterns and uncertainties of species' range shifts under climate change. Global Change Biology, 10: 2020-2027

Verma S, Jayakumar S. 2012. Impact of forest fire on physical, chemical and biological properties of soil: A Review. Proceedings of the International Academy of Ecology and Environmental Sciences, 2(3): 168-176