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Modelling the influence of regional landscape drivers on spatio-temporal patterns of wildfire activity

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Abstract

Identifying the drivers of fire activity's spatio-temporal variability is challenging in densely populated and fire prone landscapes. Human usage and climate affect the local fire regime in contrasting ways. The identification of these drivers is further complicated due to the stochastic nature of fire activity. Fire regimes in Mediterranean France show contrasted spatial patterns and temporal changes at decadal scales. While overall, the number of fires decreased over the last thirty years, certain zones suffered local increases in fire activity. To describe and understand the drivers of those changes and the spatial variability, we introduced several improvements in the *Firelihood* model - a probabilistic framework capable of prediction fire occurrence of >1ha fires, and exceedance probabilities of 10 and 100 ha thresholds - by incorporating Land-Use Land-Cover (LULC) explanatory variables, as well as by enhancing its spatio-temporal components to account for unexplained variability in models. The novel model - fitted on a 2km-pixel grid, but relying on variables aggregated at various spatial aggregations (2, 4, 8 and 16km) - is used to explain the observed spatial patterns of fire activity during the last 27 years, as well as the regional and local changes observed between two decades with contrasted fire activities by running counterfactual scenarios.

LULC variables, including road density, wildland-urban interface, or expert-based fuel type rating explain a significant part (as much as fire-weather) of the variability in fire occurrence (>1ha), thereby reducing the effect of unexplained spatial variability. The selected occurrence model uses only 2km-resolution variables, as local factors have a high influence on fire ignition and initial spread. The occurrence of larger fire (>10 ha or >100 ha) is largely driven by fire-weather, followed by unexplained spatial variability; selected models for larger fires uses a few LULC variables aggregated at 4, 8 and/or 16 km. This indicates the influence of surrounding factors on fire size extension. The spatial effect for fire occurrence presents contrasted hot and cold-spots throughout the area, while it has a clear east to west decreasing trend for fire size.

Regarding temporal changes in fire activity between the two decades, changes in fire weather induced a strong increase in fire probability in many hot spots throughout the region, but this effect was overcompensated by a negative trend associated with unexplained temporal factors (and of larger magnitude than fire weather). LULC variables had negligible effect on the fire regime's temporal trends. Moreover, an east-to-west gradient appears for the spatial trends of the larger fires, and for the temporal trends in all sizes, highlighting the increase in fire activity in the western side of the region. Those results suggest that observed temporal changes in fire activity are the result of a changing socio-economic or policy frame, probably related to reinforced suppression policies following the year 2003, and the increasing agricultural abandonment.

1. Introduction

In south-eastern France, the Mediterranean climate creates fire-prone fuel moisture conditions and regional winds often trigger large fire events (Ruffault et al. 2017). The climatic and land characteristics of the region (Fréjaville and Curt 2015; Barbero et al. 2019) shape the spatial patterns of fire activity: highest burnt area in fire-prone populated areas, with high exposure of human settlements to fire, and in hinterland and inland mountains lower summer fire activity, despite local "hot-spots" (Figure 1A).

Fire-weather largely drives seasonal and interannual variations in fire activity in south-eastern France (Pimont et al. 2021), and it has increased in the last decades, suggesting a rise of potential fire risk (Fréjaville and Curt 2015; Barbero et al. 2020), yet the translation of this potential to realized fire risk remains unknown. Fire records show a decrease in fire activity in the last 40 years which makes the assessment of the weather effects more difficult. To understand past changes in fire regimes and risk, and anticipate future scenarios, it is necessary to disentangle how climate, landscape and human factors affected spatio-temporal dynamics of fires.

Several studies aimed to explain different aspects of fire activity in south-eastern France and how it varies in time and space (e.g., Ruffault et al. 2017, Pimont et al. 2021). However, there are still many uncertainties about the role of human and biophysical factors in the spatial and temporal trends in this region. Here we improved the *Firelihood* probabilistic fire activity model (Pimont et al. 2021) to quantify how much of the observed changes in fire activities can be attributed to these factors and how these temporal changes are distributed at the regional scale. This second goal is not only important in the context of retrospective analysis of changes in fire activity, but also in the context of anticipation of the near future.

2. Materials and methods

Firelihood (FL) is a Bayesian probabilistic framework accounting for the stochastic nature of fire activities with several statistical components that model daily occurrence and size of wildfires as a marked point process parametrized with several explanatory variables (Pimont et al. 2021). FL models the occurrence of fire larger than 1ha (escaped fires) as a Poisson process and the size of these fires as a combination of exceedance threshold probability and piecewise size distributions. FL includes spatio-temporal effects to account for limitations in explanatory variables. Effects are adjusted with the R-INLA package, which implements the Integrated Nested Laplace Approximation and allows spatial effects with Matérn covariance function represented through the Stochastic Partial Differential Equation (SPDE) approach.

The first developments (in the following FL1) included FWI and Forest Area as explanatory variables and spatio-temporal effects of the occurrence component were seasonal, spatial and annual, with a shift following the 2003 heat wave. The estimation was done in 8-km pixels (Pimont et al. 2021). In FL1, spatio-temporal effects were critical to mitigate the impact of large unexplained effects which can induce confusion between factors and limit the accuracy of estimated effects of explanatory variables. Moreover, they allow a realistic representation of processes involved in fire activities, so that simulations can be used to carry out spatio-temporal analyses, despites of the stochasticity in fire observations.

FL1 was limited for detailed analyses of the evolution of spatio-temporal patterns of fire activity. We develop an extension of FL1, referred as FL2, which includes additional LULC at 2-km resolution and refined spatio-temporal effects. The occurrence component of FL2 includes a yearly effect and a spatial effect for temporal trends (equation 1). Size exceedance models for 10 and 100 ha include a yearly effect and spatial effects for Sylvo-Eco Regions exhibiting similar characteristics (equation 2).

$$\begin{aligned}\log N_{i,d}^{1ha} \sim \beta_0 &+ \underbrace{f_{FWI}(FWI_{i,d}) + f_{WEEK}(WEEK_{i,d})}_{FL1} + \beta(WAp_{i,y}) \\ &+ \sum_{LULC} f_{LULC}(LULC_{i,y}) + f_{X,Y}(X_i, Y_i) \\ &+ \underbrace{f_{YEAR}(y) + f'_{X,Y}(X_i, Y_i)(y-1992)}_{Spatio-temporal\ trends}\end{aligned} \quad (1)$$

$$log \frac{p_{i,d}^u}{1-p_{i,d}^u} = \beta_0^{p,u} + f_{FWI}^{p,u}(FWI_{i,d}) + \sum_{LULC} f_{LULC}^{p,u}(LULC_{i,y}) + f_{YEAR}^{p,u}(y) + f_{BESAG}^{p,u}(SER) \qquad U = [10,100] \quad (2)$$

Simulations with FL2 (Figure 1B) allowed to (i) quantify the relative contributions of the different variables to spatial patterns thanks to a partition of variance; (ii) predict the evolution of fire activities from the 1993-2002 decade, to which would have occurred during the 2009-2018 decade if only climate, LULC or unexplained factors had changed at a time, allowing to attribute observed changes to the different explanatory variables.

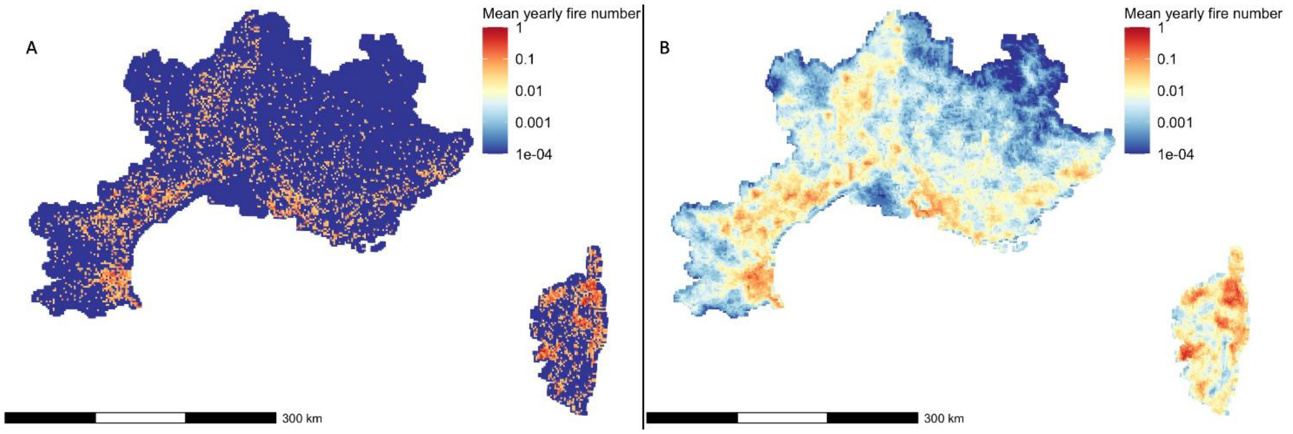

Figure 1. Fire occurrence over the study period expressed as the mean number of fires larger than 1ha per year in each 2km pixel: (A) Observed; (B) Simulated.

3. Results and discussion

3.1. Variable selection and model performance

Variable selection based on DIC and AUC led to FL2, summarized in Table 1. Significant improvements were obtained with the inclusion of LULC. The coarser scales of spatial aggregation (4, 8 and 16km) underperformed to explain occurrence, so that only finer predictors (2km) were retained. This highlights that occurrence patterns were better explained by fine scale landscape factors, contrary to size models for which 4km and even 8 and 16km were sometimes better predictors.

The effects of the occurrence model components were consistent, showing increases associated with FWI (Figure 2B), fuel type rating (Figure 2C), wildland area (Figure 2A), road length and population (not shown). Inverted U-shape responses associated with wildland area, slope, aspect or wildland urban interface were explained by reverse effects of these factors on ignition and initial spread, as already observed for wildland area in Pimont et al. (2021). Road length and population are among the most influential variables, confirming the key role of accessibility to forest areas found in other regions of Europe and the influence of human activities (e.g. Costafreda et al. 2017).

The yearly effect (Figure 2D) confirmed the huge decay in fire activity observed after the 2003 crisis. The negative values of the spatial effect (Figure 3A) corresponds to areas where explanatory factors tend to overestimate the observed activity. The spatial distribution of annual trends (Figure 3B) was contrasted from west to east, with positive trends to the west and negative to the east. In a context where unexplained factors depending on the local conditions are very important, this approach allowed accurate estimations of the effect of explanatory variables and of residual unexplained spatio-temporal random effects.

The partial effects of both size models were similar (100ha in Figure 2), with monotonic responses. Exceedance probabilities increased with FWI (Figure 2F), fuel type rating (Figure 2G), wildland (Figure 2E), shrubland and coniferous areas and slope, and decreased with broadleaved and agricultural areas, and population (not shown). Upper ranges were generally associated with saturations. The yearly effect for the 100ha threshold decreased - except the 2003 peak-, but with a non-significant trend as current trends (blue dashed line) were inside the credible interval of early years (Figure 3H. The spatio-temporal effects here are less sophisticated because the datasets for fires above 100 ha were too small to afford the approach described above for occurrence. The temporal effects allowed potential yearly changes and spatial effects into SylvoEcoRegions and proved to enhance the predictive ability of the model. The spatial effect (Figure 3C) shows a west-east gradient with increased probability in the eastern part and in mountainous regions, possibly explained by operational constraints in suppression policies in remote mountainous regions.

Table 1. Variable selection of the occurrence model (OCCURRENCE) and size models for the 10 ha (SIZE 10) and the 100ha (SIZE100) exceedance thresholds. The distance indicated in parenthesis refers to the spatial aggregation used for a given variable (by default is 2km).

Model	Variables	DIC	AUC (training)	AUC (validation)
OCCURRENCE	Intercept + WAp + Fuel + WA + Aspect + Slp + WUI + Pop + Agri + Roads + SPDE + Sp_temp + Years	50131,24	0,877	0,827
SIZE 10	Intercept + FWI + WA(4km) + Agri (4km) + Con + Brl + Shr + Pop + Slp + Mxf (8km) + Fuel + Besag + Years	5646,03	0,71	0,66
SIZE 100	Intercept + FWI + WA(4km) + Agri (4km) + Con + Brl + Shr (4km) + Pop + Slp (16km) + Fuel + Besag + Years	2002,53	0,79	0,78

Where: : **WAp** – Wildland area presence, **Fuel** – ONF's fuel rating, **WA** – Wildland area, **Aspect** – Aspect of the pixel, **Slp** – Slope, **WUI** – Wildland to Urban interface, **Pop** – Population per pixel, **Agri** – Agricultureal area, **Roads** – Road length, **Con** – Coniferous forest area, **FWI** – Fire Weather Index, **Brl** – Broadleaved forest area, **Shr** – Shrublkand area, **Mxf** – Mixed forest area, **SPDE** – Spatialmodel, **Sp_temp** – spatio-temporal model, **Besag** – Spatial model based on the SER. DIC and AUC are the criterion for the model evaluation," fit" and "pred" Make refference to the training and validation data respectively.

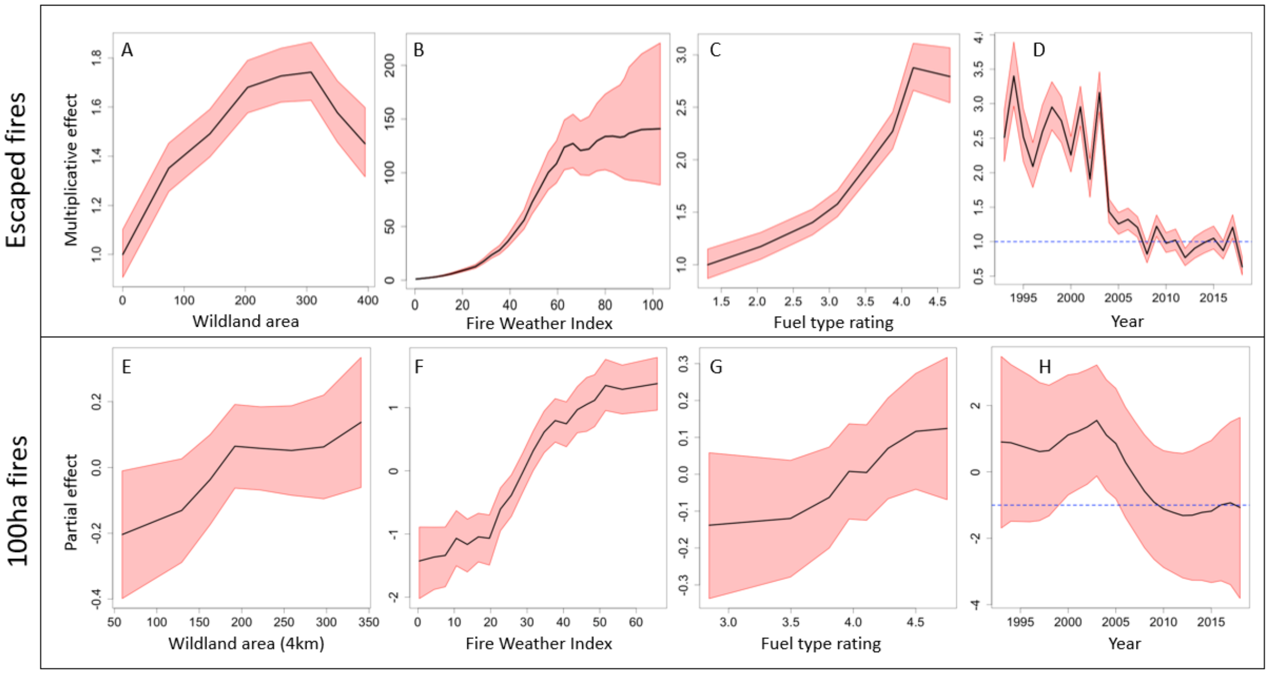

Figure 2. Examples of: (A-D) multiplicative effects for the predictor variables of the occurrence model (escaped fires) with confidence intervals; (E-H) partial effects (E-H) of the predictor variables for the 100ha exceedance probability models.

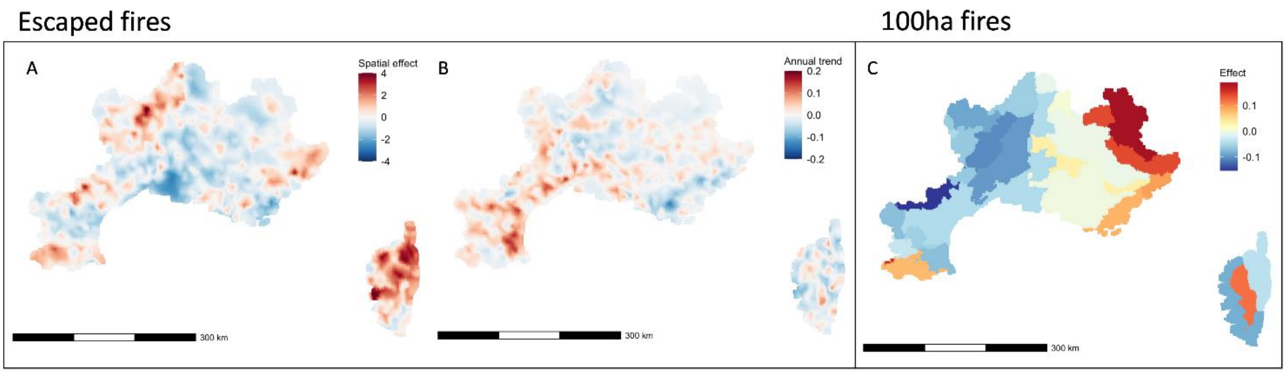

Figure 3. Spatial effect of the occurrence model from SPDE (A); spatial trends of the occurrence model (B); Spatial effect from the "Besag" component of the 100ha exceedance model (C). The effect's magnitude is drawn in a color coding in each pixel, the labels inside each polygon (thin black lines) corresponds to the code of the SylvoEcoRegions.

3.2. Factors explaining spatial distributions and their changes

The partition of fire activity variance allowed to attribute the spatial variability to three types of effects (Fire-weather, LULC and unexplained) over the whole period. The spatial effect had the biggest contribution to 1ha-number simulations (40%), while LULC and fire-weather explained one fourth of the total variance each. The "temporal effect" in spatial patterns - associated with spatial trends- was less important. For larger fire numbers (N10 and N100), the fire weather explained the biggest part of spatial variance (~50%), followed by the spatial effect (~25%), while LULC were around 17-20%. The temporal effect was marginal. Therefore, fire-weather and LULC together explained roughly 50% of spatial distribution of 1ha fires and up to 70% for larger fires (N10 and N100).

The next analysis aimed at determining whether the changes in spatial distribution between 1993-2002 and 2009-2018 could be explained by these variables. The comparison between decades for the actual evolution of variables confirmed a decrease in fire numbers for all sizes, ranging between -50 and -60%. When considering changes in factors one at a time, simulations for the recent decade were more contrasted. The "Fire-weather-change" scenario shows an increase in fire events while the "LULC-change" scenario did not affect the fire number. The "other-temporal-change" scenario showed a decrease in fire number, but with bigger magnitude than the "actual" simulations. The potential increase caused by fire-weather change was overcompensated by temporal changes which were not explained by LULC variables. It is very likely that suppression fire policy strongly reduced the number of escaped fires in part of the region.

We then investigated the spatial distributions of these changes by mapping anomalies between the reference period and recent scenarios (Figure 4). The spatial distributions were similar throughout the three fire sizes. Both the real-present and the other-temporal-changes (Figure 4A,D) scenarios showed a widespread decrease over the eastern regions and sharp local increases in the western regions, revealing that the overall trend was very heterogeneous over the territory. Fire-weather change (Figure 4B) induced scattered increases in a few "hot spots", in locations where the effect on activity should have increased the most, without other changes. Finally, changes in LULC (Figure 4C) produced marginal changes, clearly not explaining any of the recent fire regime change.

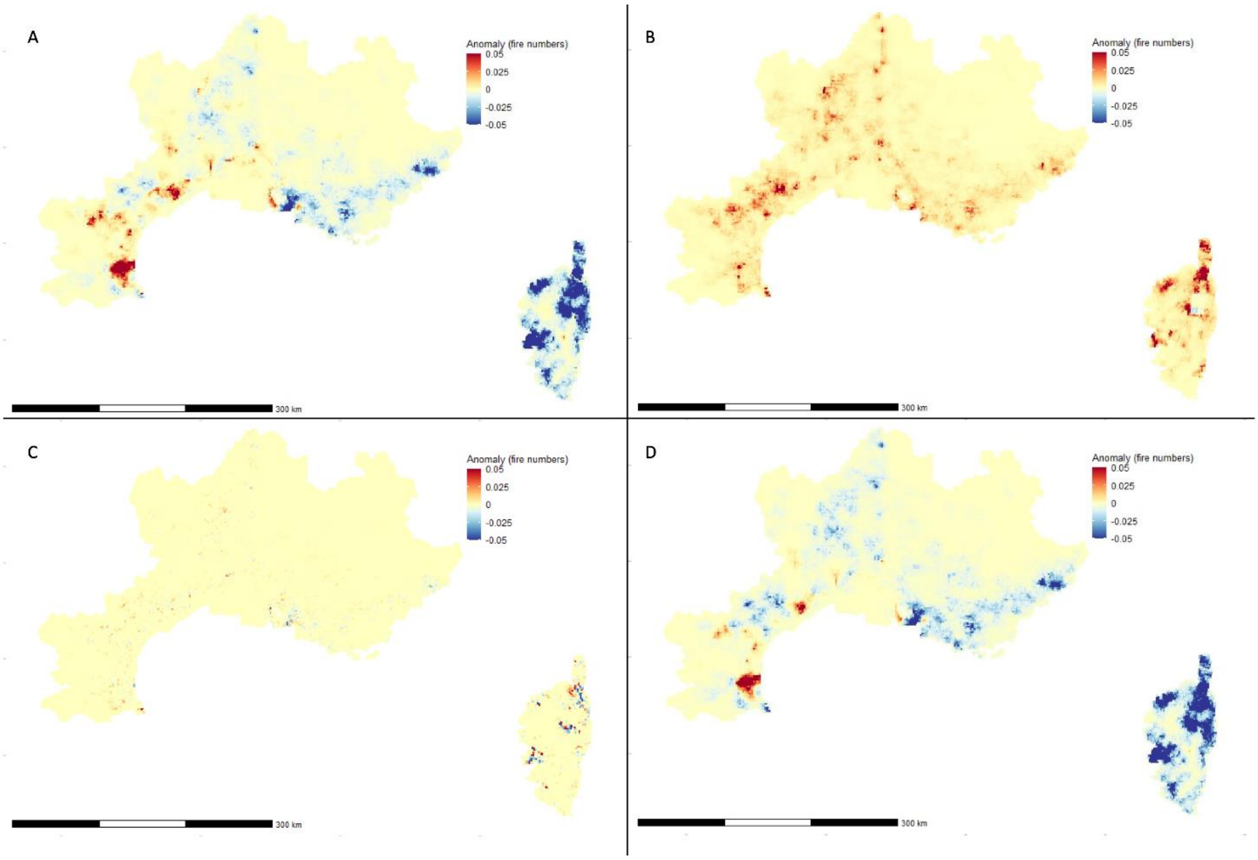

Figure 4. Spatial distribution of anomalies between the 1993-2002 and 2009-2018 decades for 1ha fire numbers. A: Real present. B: Fire-weather. C: LULC. D: Other temporal changes.

4. Conclusion

Analyzing factors of fire activities at regional scales is highly challenging. Our modeling framework and the simulation plan allowed to quantify important changes in fire activity and their drivers. We showed that usual explanatory variables (fire-weather, LULC) failed to explain the main temporal changes observed over recent decades, because of large unexplained factors. Among these unexplained factors, prevention and suppression policies affect the fire regime. Our study reveals that, if very significant reductions occurred after the 2003 heat wave on the number of escaped fires (1ha fires), no significant reduction could be detected over the last decade, neither on the ability of escaped fires to turn into large fires. Finally, spatial patterns of these changes were very contrasted from west to east, suggesting that significant reductions could be reached. Our framework might be extended to future scenarios involving climate, vegetation or human drivers

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