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ABSTRACT

Background. Identifying if and how climatic and non-climatic factors drive local changes in fire regimes is, as in many other human-dominated landscapes, challenging in south-eastern France where both heterogeneous spatial patterns and complex fire trends are observed. **Aim.** We sought to identify the factors driving the spatial-temporal patterns of fire activity in southeastern France. **Methods.** We incorporated several non-climatic variables into the probabilistic *Firelihood* model of fire activity and implemented an enhanced spatio-temporal component to quantitatively assess remaining unexplained variations in fire activity. **Key results.** Several non-climatic drivers (i.e. orography, land cover and human activities) contributed as much as fire-weather to the distribution of fire occurrence (>1 ha) but less to larger fires (>10, 100 and 1000 ha). Over the past decades, increased fire-weather induced a strong increase in wildfire probabilities, which was actually observed on the western part of the region but not so in the east and Corsican Island, most likely due to reinforced suppression policies. **Conclusions.** While spatial patterns in fire activity are driven by land-use and land-cover factors, temporal patterns were mostly driven by changes in fire-weather and unexplained effects potentially related to suppression policies but with large differences between regions.

Keywords: Bayesian, Firelihood, forest fires, Mediterranean France, modelling, risk management, spatial changes, temporal changes.

Introduction

It is well established that wildfire activity has changed in a number of regions of the world during the past decades (Jones *et al.* 2022). Wildfires result from the combination of many factors including fuel configuration, fire-weather conditions, human- or naturally-triggered ignition source and the fire suppression and mitigation policies (Costafreda-Aumedes *et al.* 2017). As climate, vegetation and human settlement patterns are spatially diverse and evolving over time, the spatial and temporal trends of fire activity result from complex interactions between these factors that may sometimes act in opposite directions. Thus, while increased fire-weather has been observed in most areas of the world (Jolly *et al.* 2015), fire activity has shown a wide range of regional trends due to the influence of non-climatic drivers, including land-use land-cover (LULC) and fire suppression (Vilar *et al.* 2016; Park *et al.* 2021). Yet, identifying the drivers of these changes, and quantifying their relative contribution, often proves to be challenging (Pezzatti *et al.* 2013; Fernandes *et al.* 2014; Moreno *et al.* 2014).

In regions such as the Euro-Mediterranean area (EU-Med) where landscapes have a long history of human activities and practices, the spatial patterns of fire activity are strongly driven by human settlement patterns (Moreira *et al.* 2011). Humans dominate the wildfire regime supplying the vast majority of ignitions (Ganteaume and Jappiot 2013), but also alter land cover and perform suppression activities, both influencing burnt areas. The study of human-caused fire occurrence has therefore received much attention (Martínez *et al.* 2009; Ganteaume and Jappiot 2013) and modelling efforts (e.g. Oliveira *et al.* 2012; Rodriguez y Silva *et al.* 2014; Costafreda-Aumedes *et al.* 2017; Ruffault and Mouillot 2017). Results have shown that the 'wildland–urban interface' (WUI) and the 'wildland–agricultural interface' (WAI), as well as the density of human settlements (such as road density or building density), are among the most important drivers of fire occurrence in the EU-Med (Galiana-Martin *et al.* 2011; Martín *et al.* 2019), although the importance of each of these factors varies from one region to another (Moreira *et al.* 2011; Rodrigues *et al.* 2014). In comparison, models for fire sizes (or for exceedance probabilities of size thresholds) incorporating LULC factors are less abundant in Europe (e.g. Moreira *et al.* 2010; Ager *et al.* 2014; Ruffault and Mouillot 2017). Results suggest that types and continuity of fuel play a major role in fire-spread probabilities but that differences in fire selectivity among flammable vegetation types decrease under severe fire-weather (Barros and Pereira 2014; Fernandes *et al.* 2016).

Like spatial fire patterns, historical trends in fire activity were largely driven by non-climatic drivers during the past decades in the EU-Med. While fire-weather increased over much of the area (Giannaros *et al.* 2020), fire activity, including fire numbers and burnt areas, significantly decreased in most regions (Turco *et al.* 2017; Silva *et al.* 2019) because of co-evolving human factors that overwhelmed the impact of climate change. Negative trends can be explained, at least in part, by an increased effort in fire management and prevention in several countries, in response to the large and destructive fires that occurred during the 1980s and 1990s (Moreno *et al.* 2014; Ruffault and Mouillot 2015), albeit this effect remains difficult to quantify at the local scale.

Stochasticity in the wildfire activity, showing rare and sparse events since fire occurrence probabilities at a specific location and time remain low even if conditions are favourable, limits the possibility of conducting simple correlative analyses directly on the observations at the local scale. Handling fire stochasticity requires robust statistical frameworks that account for the different factors – fire-weather, LULC, fire prevention and fighting – affecting the probabilities of ignition, initial spread and spread to larger sizes at various spatial and temporal scales, from hourly and daily to yearly (e.g. Pimont *et al.* 2021). Many factors, as fire suppression, culture, social awareness among others, are not easy to incorporate with measurable metrics. High correlation in time and space between such factors can lead to underestimation of credible intervals and to increased risk of confusion between effects (i.e. of wrong attribution of wildfire activities to their causes). Such spatial or temporal effects have been accounted for in a few studies (e.g. Preisler and Benoit 2004; Woolford *et al.* 2021); they are likely not spatially uniform in magnitude and even direction, as recently suggested by a thorough analysis of spatio-temporal trends in fire numbers and sizes (Koh *et al.* 2021). The interaction between spatial and temporal has recently been addressed by Joseph *et al.* (2019) and Rodrigues *et al.* (2018).

The French Mediterranean area is a particularly challenging place to disentangle the drivers of spatio-temporal wildfire activity. The coupling of hot and dry summers with strong northly winds, known as 'Mistral' and 'Tramontane', promote the occurrence of large fire events in the region (Ruffault *et al.* 2016, 2018). However, the climate conditions and human settlement locations are highly influential, with drier climate in the lowlands near the coast where human population and activities are dense, thereby increasing the probability of fire ignitions (Curt *et al.* 2016; Pimont *et al.* 2021). By contrast, lower fire activity (despite local 'hot-spots') is observed in hinterland and inland mountains, where climate is less dry. Previous studies provided significant insights into local fire drivers (e.g. Curt *et al.* 2013, 2016; Fox *et al.* 2015; Ruffault *et al*. 2017; Ganteaume and Guerra 2018; Ganteaume and Barbero 2019) but, to date, a systematic assessment at the regional scale is still missing. In addition, as in other Mediterranean regions, fire-weather has increased in Mediterranean France during the past decades (Fréjaville and Curt 2015; Ruffault *et al.* 2016; Barbero *et al.* 2020), but the fire number and, above all, burnt areas have decreased by two folds or more (Curt and Frejaville 2018). Earlier reductions in fire activity have been attributed to the effect of fire control policies (Fox *et al.* 2015; Ruffault and Mouillot 2015; Pimont *et al.* 2021), but the magnitude of this effect is difficult to estimate because of the potential confusion with changes in climate, landscape factors or other socio-economic drivers.

Here, we provide a comprehensive assessment of the spatial and temporal trends of wildfire drivers in southern France. We used counterfactual analyses based on spatio-temporal scenarios constructed thanks to the probabilistic *Firelihood* model (Pimont *et al.* 2021) to address two objectives. First, we determine which landscape-related and human factors drive the spatial patterns of fire activity in southern France, assess their effect on fire probability, and quantify their relative contribution in comparison to fire-weather. Second, for each of these factors, we question whether it contributes to the historical trend in fire activity, and if so, we aim to quantify this contribution as well as its local variability across the region.

Methods

Overview

Firelihood (FL) is a Bayesian probabilistic framework that models daily occurrence and size of wildfires as a marked point process (points describing occurrences and marks describing sizes) from explanatory variables (Pimont *et al.* 2021). FL accounts for the stochasticity of fire activity and models the occurrence of fires larger than 1 ha (escaped fires) as a Poisson process and the size of these fires as a combination of threshold exceedance probability and piecewise size distributions. FL includes spatio-temporal effects to account for limitations in explanatory variables. Effects are estimated with the R-INLA package, which implements the integrated nested Laplace approximation (Rue *et al.* 2017) and allows spatially structured Gaussian random effects with Matérn covariance function represented through the stochastic partial differential equation (SPDE) approach (Lindgren and Rue 2015). The Matérn covariance is a flexible and widely used covariance model in spatial statistics that includes the exponential covariance function as a special case, and it offers the advantage of manageable numerical representations even with more than 1000 pixels as here (Krainski *et al.* 2018).

The first instances of FL (later referred as FL1) included the Fire Weather Index (FWI) and forest area as explanatory variables. Spatio-temporal effects were implemented for the occurrence component and included a seasonal, spatial and annual effect, the latter representing a shift in fire numbers after the 2003 heatwave. Estimations of fire activity were carried out in 8-km pixels. Details on FL1 are provided in Supplementary Material S2, and the model has been thoroughly evaluated in Pimont *et al.* (2021). In FL1, the impact of unaccounted factors – corresponding to all unknown explanatory factors – on the estimation of known effects is mitigated by spatio-temporal effects, which additional stochasticity into the model to appropriately capture variability due to unknown factors and statistical uncertainty. Moreover, those spatio-temporal effects allow a realistic representation of fire activities, so that spatio-temporal analyses are possible despite the stochasticity at play in fire observations (e.g. pixels without observed fires during the observation period).

To further study the evolution of spatio-temporal patterns of fire activity in a more detailed manner, we developed an extension of FL, referred to 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 local temporal tendencies. Size exceedance models for 10 and 100 ha include a yearly effect as well as spatial effects for SylvoEcoRegions (SERs).

The simulations performed with FL2 allowed us to: (1) quantify the relative contributions of the different variables to spatial patterns thanks to a partition of variance; and (2) predict the evolution of those fire activities from 1993–2002 that would have occurred during 2009–2018 if only climate, LULC or unexplained factors had changed at a time; hence, allowing us to attribute observed changes to the different explanatory variables.

Study area and fire activity

The study area consists of 15 NUTS3-level French administrative units located in south-eastern France (Fig. 1, 75.560 km^2), which concentrate the majority of burned area during the summer season in France. It is dominated by a Mediterranean climate and a few alpine stages. This area exhibits contrasted patterns of orography, vegetation, population and climate (Supplementary Material S1). Non-urban land covers include crop, coniferous and deciduous forests and shrublands. Fire records between 1993 and 2018 were extracted from the Prométhée database at a 2-km resolution, which was also used as the reference grid for our analyses. Observed fires are scattered over the territory with a few hotspots (Fig. 1). Here, we considered fire activity during the warm fire season (from 25 May to 31 October).

Explanatory variables

The main explanatory variable was the daily FWI, which represents temporal and spatial variations in meteorological fire danger. FWI was computed over the 2-km reference grid from meteorological variables extracted from the SAFRAN

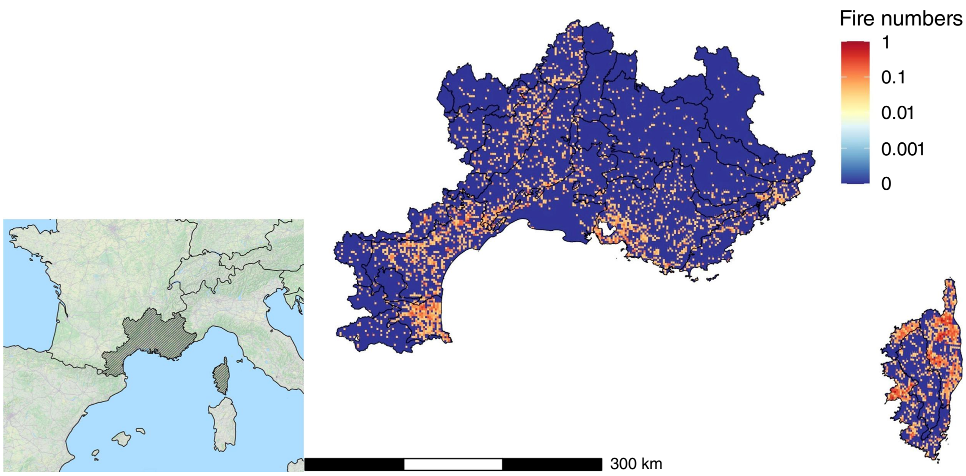

Fig. 1. Patterns of fire occurrence over the study period (1993–2018) expressed as the mean number of fires strictly larger than 1 ha per year in each 2 km pixel of the reference grid (left), with a geographical context map in the right. Note that the scale bar corresponds to the left map.

reanalysis at 8-km pixel size (Vidal et al. 2010), using the cffdrs R package (Wang et al. 2017). For each 2-km pixel, we used the SAFRAN data corresponding to the 8-km pixel containing the centre of the 2-km pixel of interest; i.e. we did not downscale the climatic data.

LULC data, listed in Table 1, was derived from Copernicus land cover data (https://land.copernicus.eu) and French Forest Service databases (Office National des Forêts, ONF). For some variables that are not available on a yearly basis (Table 1), we filled the missing values by linear interpolation between available sources. Although LULC changes (Supplementary Material S4) may not occur gradually we considered this smoothed approach better to avoid noise introduced in the specific years when data is released, which may accumulate the sudden changes having taken place during the previous period. Yearly data was extracted for the 2-km reference grid as either the sum of area per pixel, the mean in the pixel or the value at the pixel centroid, depending on the variable.

Smoothed values of LULC at coarser scales (4–16 km) were also tested as explanatory variables as an alternative to the default 2-km resolution. We hypothesised that the size threshold exceedance probability could be better explained at coarser scales than at ignition location. The variable 'Fuel rating ONF' corresponds to a discrete vegetation sensitivity mapping ranging from 1 to 5, developed by the French National Forest Service; although it is a static variable it creates no negative impacts on the model, since LULC changes are small over time, and this variable will give the same score to a forested area regardless of its area. Here, each index was weighted according to its corresponding area in the pixel, leading to a score ranging from 0 to 5. In order to improve spatial prediction of exceedance thresholds, we used 28 SERs as explanatory variables (Supplementary Fig. A1) corresponding to homogeneous forest productivity or forest habitats (IGN 2019).

FL2 development

The occurrence component assumed a Poisson distribution for fire numbers and explains the spatio-temporal variation of expected fire numbers:

$$\log N_{i,d}^{1\text{ha}} \sim \beta_0 + \underbrace{f_{\text{FWI}}(\text{FWI}_{i,d}) + f_{\text{WEEK}}(\text{WEEK}_{i,d})}_{\text{FL1}} + \beta(\text{WAp}_{i,y}) + \sum_{\text{LULC}} f_{\text{LULC}}(\text{LULC}_{i,y}) + f_{X,Y}(X_i, Y_i) + \underbrace{f_{\text{YEAR}}(y) + f'_{X,Y}(X_i, Y_i)(y-1992)}_{\text{Spatio-temporal trends}} \tag{1}$$

where $N_{i,d}^{1\text{ha}}$ is the expected number of fires larger than 1 ha in pixel i and day d, and the f-terms are the various non-linear effects. Subscript 'y' indicates explanatory variable evolving on a yearly basis.

The effects of daily FWI and week-of-year (seasonal) were the same as in FL1. The wildland area presence ($\text{WAp}_{i,y}$) was

Table 1. List of explanatory variables and their characteristics.

Variable	Extraction	Units	Time step	Source
Wildland area	Pixel area sum	ha	Yearly[A]	CLC 311–131, 322–324
Wildland area presence	Absence/presence	–	Yearly[A]	CLC 311–131, 322–324
Shrubland area	Pixel area sum	ha	Yearly[A]	CLC 322–324
Mix forest area	Pixel area sum	ha	Yearly[A]	CLC 313
Broadleaved forest area	Pixel area sum	ha	Yearly[A]	CLC 311
Coniferous forest area	Pixel area sum	ha	Yearly[A]	CLC 312
Fuel rating ONF	Pixel area weighted sum	Score (0–5)	Static	ONF
Aspect	Mean value/pixel	Azimuth (°)	Static	Copernicus
Slope	Mean value/pixel	Degrees (°)	Static	Copernicus
Wildland–urban interface	Pixel area sum	ha	Yearly[A]	ONF
Agriculture	Pixel area sum	ha	Yearly[A]	CLC 211, 221–223, 241–244
Urban area	Pixel area sum	ha	Yearly[A]	CLC 111, 112, 121–124, 132, 133
Population density	Centroid value/urban area	Num/pixel	Yearly	Insee
Road length	Sum distance/pixel	m/pixel	Static	IGN
Year	–	–	Yearly	–
Fire weather index	Centroid value	Non-dimensional	Daily	SAFRAN, cffdrs

The 'Extraction' field describes how the information was compiled within each grid cell. The 'Units' field expresses the represented dimension. Field 'Time-step' is the period of temporal variation of each variable ('static' is for data that remains constant, either because of the lag of data or because its static nature). The 'Source' is the database that provided the data for the variable (for Corine Land Cover (CLC), the class numbers considered are specified).
[A]Interpolation for missing years.

a binary variable used to differentiate pixels with negligible wildland area from the other pixels. Spatial ($f_{X,Y}$) and spatio-temporal trend components capture the variability in wildfire activity that was not explained by other covariates. Both the spatial effects and the spatially varying change rate $f'_{X,Y}(X_i, Y_i)$ were represented with SPDE. The effect f_{YEAR} accounted for unexplained annual change in fire occurrence for the whole region, whereas $f'_{X,Y}(X_i, Y_i)$ allowed to disentangle regions where the occurrence increases over time ($f'_{X,Y} > 0$) from those where it decreased ($f'_{X,Y} < 0$) – with respect to other covariates.

The size component of FL1 has been improved towards refined exceedance-threshold-probability models for two thresholds u of 10 and 100 ha. The probability $p^u_{i,d}$ of a fire occurring in pixel i and during day d to exceed u is modelled through a logistic regression model:

$$\log\frac{p^u_{i,d}}{1-p^u_{i,d}} = \beta_0^{p,u} + f^{p,u}_{\text{FWI}}(\text{FWI}_{i,d}) + \sum_{\text{LULCM}} f^{p,u}_{\text{LULC}}(\text{LULC}_{i,y}) + f^{p,u}_{\text{YEAR}}(y) + f^{p,u}_{\text{BESAG}}(\text{SER}) \quad (2)$$

These models, referred to as the size models for simplicity, also include a spatio-temporal component, which was not present in FL1. It consists of a yearly random effect and the spatial effect modelled with the spatially-conditionally autoregressive 'Besag' model, allowing dependent effects between adjacent SERs. The approach was used instead of SPDE because the fire size data is too small to estimate a random effect with Matérn covariance function at relatively high spatial resolution.

For both the occurrence and size models, LULC variables were sequentially included according to the parsimony criterions known as Deviance Information Criterion (DIC; Sutanto *et al.* 2021), a non-dimensional indicator which decreses with model quality for a given set of data, and the Area Under the Curve (AUC), scaling from 0.5 to 1, where 0.5 indicates a complete random prediction and 1 a perfect prediction of observation.

FL2 simulations and applications

For a given set of explanatory variables, the occurrence model was used to simulate multiple realisations (here, 100) of $N^{1\text{ha}}_{i,d}$ for the full study region and period. These potential fire activities were averaged over time to draw a probabilistic occurrence map (Fig. 2), which compares well with observations (Fig. 1). It shows that the probability to get a fire is not 0 even if no fires have been recorded over the past 30 years.

The occurrence of fires larger than 10 and 100 ha was obtained by combining simulated occurrence with size models ($N^{10\text{ha}}_{i,d} = N^{1\text{ha}}_{i,d}p^{10\text{ha}}_{i,d}$ and $N^{100\text{ha}}_{i,d} = N^{1\text{ha}}_{i,d}p^{100\text{ha}}_{i,d}$).

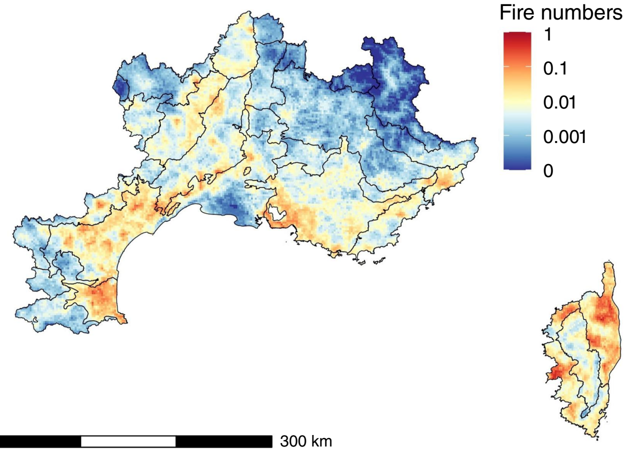

Fig. 2. Simulation of 1 ha fire numbers for the full study period (1993–2018) expressed as the mean number of fires strictly larger than 1 ha per year in each 2 km pixel of the reference grid.

In order to disentangle the role of the different types of effects (fire-weather, LULC and other spatio-temporal effects) in spatial patterns of fire activities, we computed the yearly Poisson intensities related to each type in each pixel, by aggregating daily effects of fire-weather. We then compute the relative contributions (RC) of the different effects as a partition of spatial variance for each year, which was then averaged for years of the study period. Details of this method, and how it applies to $N^{1\text{ha}}$, $N^{10\text{ha}}$ and $N^{100\text{ha}}$ are provided in Supplementary Material S3.

In order to disentangle the role of the different types of effects in the evolution of spatial patterns, we simulated the fire activities during the recent decade (2009–2018) according to four counterfactual scenarios: (1) a scenario 'Fire-weather change' where only climate changed (as observed on the recent period) by reproducing the LULC of the early 1993–2002 decade and ignoring spatio-temporal trends (i.e. ignoring $f_{\text{YEAR}}(\text{YEAR}_i) + f'_{X,Y}(X_i, Y_i)(\text{YEAR}_i - 1992)$ in Eqn 1); (2) a scenario 'LULC change' where only LULC changed over time, using the same FWI time series for the recent decade that the one observed during the earlier period and ignoring the spatio-temporal trends; (3) a scenario 'Other temporal changes' where only the modelled spatio-temporal trends were considered for changes between the two decades, assuming no change in fire-weather and LULC since the 1993–2002 decade; and (4) a scenario where the three types of variables evolved as observed, corresponding to the simulated actual recent decade (2009–2018). These scenarios were compared with activities simulated in 1993–2002 as a reference. Anomalies between the scenarios to the reference allowed us to attribute the changes, observed between the two decades (scenario 4), to the different types of explanatory variables, each type corresponding to one of the three first scenarios. For example, if 'Fire-weather change' scenario matches scenario (4), it would mean that fire-weather change is responsible for most of the observed changes; this process is supported by the spatial representation of anomalies.

Results

Variable selection and model performance

Variable selection based on DIC and AUC is summarised in Table 2, leading to final models. Significant improvements were obtained when including LULC variables. Fire occurrence patterns were better explained by fine-scale landscape factors, contrary to size models for which 4 km and even 8 and 16 km led sometimes to better predictions. We recall that the partial effects of a variable reflect the effect of this variable with all other variables being fixed. The partial effects of the occurrence model were consistent, with intensity increases associated with fuel type rating, FWI, population and road length (Fig. 3*b, c, h, i*). Inverted U-shape responses associated with wildland area, aspect, slope and wildland–urban interface (Fig. 3*a, d, e, g*) were explained by reverse effects of these factors on ignition and initial spread, as already observed for wildland area in Pimont *et al.* (2021). These covariates have a maximum near respectively 250, 80 ha/pixel, 7.5°–17.5°, and south and south-east expositions.

The yearly effect (Fig. 3*j*) confirmed the decay in fire activity observed after the 2003 crisis. The positive spatial effect (Fig. 3*k*) reveals that unexplained factors led to higher occurrence than expected from FWI and LULC predictors in some sub-regions; e.g. in the island of Corsica, or the inner mountain regions. The spatial distribution of annual trends (Fig. 3*l*) was contrasted from west to east: positive trends to the west and negative to the east.

The partial effects of both size models were similar (100 ha in Fig. 3 and 10 ha in Supplementary Fig. A2), with monotonic responses. Exceedance probabilities increased with wildland area, fuel type rating, FWI, coniferous and shrubland areas and slope (Fig. 4*a–e, h*), and decreased with broadleaved and agricultural areas, and population (Fig. 4*f–i*). Upper ranges of the drivers were generally associated with saturations. The yearly effect for the 100 ha threshold decreased – except the 2003 peak – but this change was not significant as current trends (blue dashed line) were inside the credible interval of

Table 2. Variable selection of the occurrence model (OCCURRENCE) and size models for the 10 ha (SIZE 10) and the 100 ha (SIZE 100) exceedance thresholds.

Variables included in the model	DIC	AUC (training)	AUC (validation)
OCCURRENCE			
Intercept + WAp + Fuel + WA	58 876	0.731	0.736
Intercept + WAp + Fuel + WA + Aspect + Slp	58 390	0.743	0.736
Intercept + WAp + Fuel + WA + Aspect + Slp + WUI + Pop + Agri + Roads	57 922	0.754	0.751
Intercept + WAp + Fuel + WA + Aspect + Slp + WUI + Pop + Agri + Roads + SPDE + Sp_temp + Years	50 131	0.877	0.827
SIZE 10			
Intercept + FWI	5948	0.642	0.571
Intercept + FWI + WA(4 km) + Agri (4 km) + Con + Brl + Shr	5719	0.684	0.651
Intercept + FWI + WA(4 km) + Agri (4 km) + Con + Brl + Shr + Pop + Slp + Mxf (8 km)	5673	0.694	0.669
Intercept + FWI + WA(4 km) + Agri (4 km) + Con + Brl + Shr + Pop + Slp + Mxf (8 km) + Fuel + Besag + Years	5646	0.706	0.662
SIZE 100			
Intercept + FWI	2139	0.727	0.692
Intercept + FWI + WA(4 km) + Agri (4 km) + Con + Brl + Shr (4 km)	2035	0.767	0.759
Intercept + FWI + WA(4 km) + Agri (4 km) + Con + Brl + Shr (4 km) + Pop + Slp (16 km)	2019	0.776	0.776
Intercept + FWI + WA(4 km) + Agri (4 km) + Con + Brl + Shr (4 km) + Pop + Slp (16 km) + Fuel + Besag + Years	2002	0.789	0.776

The distance indicated in the parenthesis refers to the spatial aggregation used for a given variable; when there is no written distance, the variable has been used in the original 2 km resolution.

Variables have been added and tested individually. For the sake of brevity, the results for all spatial aggregations have not been presented in the table (only the best one).

WAp, wildland area presence; Fuel, ONF's fuel rating; WA, wildland area; Aspect, aspect of the pixel; Slp, slope; WUI, wildland–urban interface; Pop, population per pixel; Agri, agricultural area; Roads, road length; Con, coniferous forest area; FWI, Fire Weather Index; BRL, broadleaved forest area; Shr, shrubland area; Mxf, mixed forest area; SPDE, spatial model; Sp_temp, Spatio-temporal model; Besag, spatial model based on SERs.

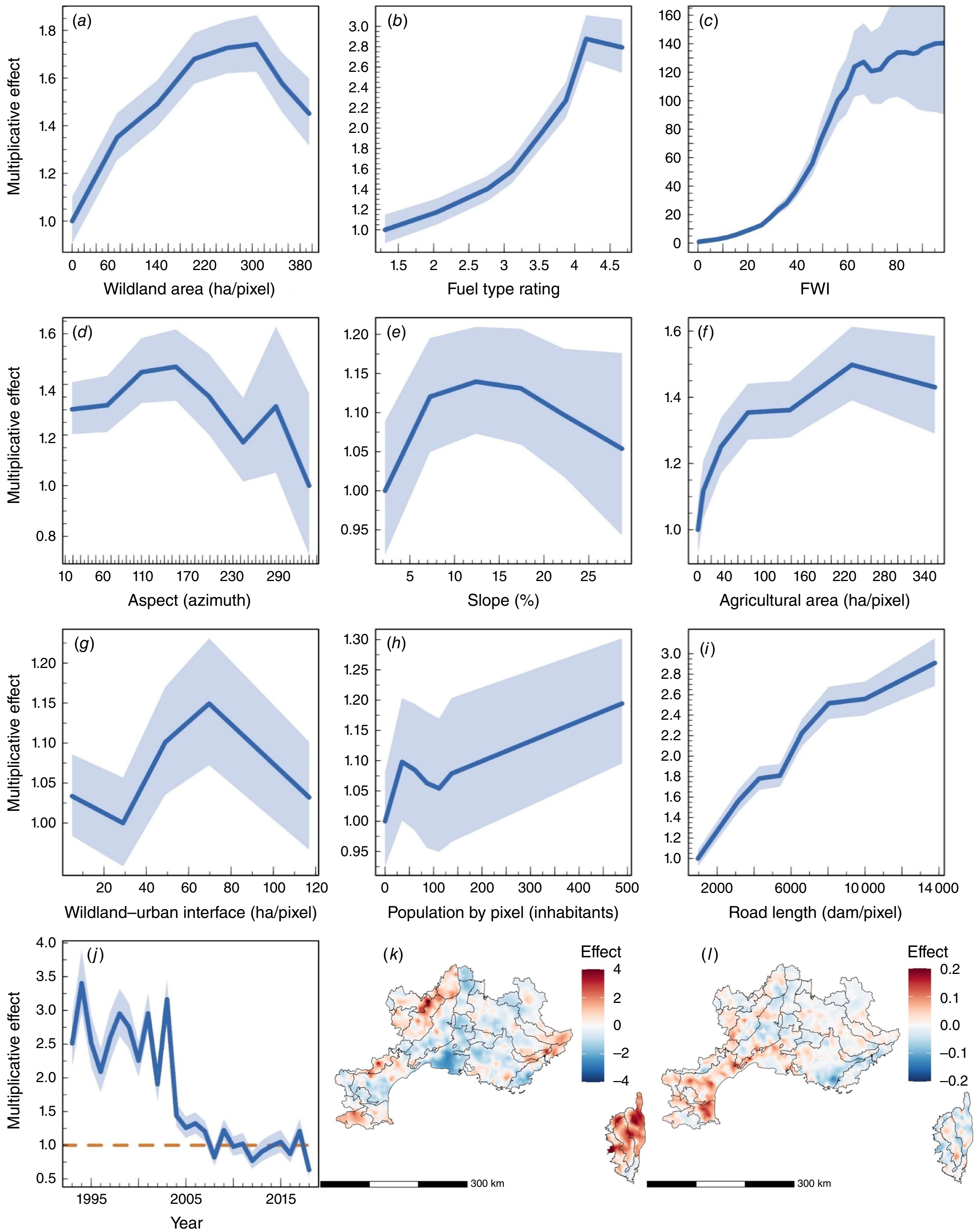

Fig. 3. (*Caption on next page*)

Fig. 3. Multiplicative effects (*a–j*) of the predictor variables in the occurrence model, represented as a graphic line with confidence intervals; the *x*-axis shows the value in each of the variable-specific bins; the *y*-axis is the value of the multiplicative effect; that is, the factor by which the expected number of fires changes with respect to the case of a multiplicative effect of one. Spatial effect ($f_{X,Y}$) for the occurrence model from the SPDE model (*k*); and spatially-dependent annual trend ($f'_{X,Y}$) for the occurrence model (*l*). Note that FWI's effect (*c*) has a larger amplitude compared to the other effects due to it's daily scale inherited from the precedent model, *Firelihood 1.0* from Pimont *et al.* (2021).

early years (Fig. 4*j*). For the 10 ha threshold (Supplementary Fig. S2*k*), after a significant decrease until 2003, no clear trend was observed during the recent years. The spatial effect (Fig. 4*k*) shows a west–east gradient with increased probability in the eastern part and in mountainous regions, which could be explained by operational constraints in suppression policies in remote mountainous regions.

Factors explaining spatial distributions and their changes

The partition of variance of fire activity allowed us to decompose the spatial variability between four types of effects (fire-weather, LULC, spatial and temporal) with quite different importance for relative wildfire risk over the full period (Fig. 5). We found that the spatial effect had the biggest contribution to 1 ha-number simulations, while LULC and fire-weather explained each one-fourth of the total variance. The 'temporal effect' in spatial patterns – associated with spatial trends – was less important. For larger fire numbers (10 and 100 ha), the fire-weather explained the largest fraction of spatial variance, followed by the spatial effect, while LULC were important (17–20%). The temporal effect – associated with temporal trends of occurrence – was marginal. These results show that fire-weather and LULC together explained roughly 50% of spatial distribution of 1 ha fires and up to 70% for larger fires (10 and 100 ha).

The comparison between the earlier and the recent decade for the actual evolution of variables confirmed a decrease in fire numbers for all sizes, ranging between −30 and −45% (Fig. 6). 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 have a notable effect. The 'Other temporal change' scenario showed a decrease in fire numbers, larger than the 'actual' simulations. Hence, the potential increase caused by fire-weather change for the three different fire sizes (1, 10 and 100 ha) was over-compensated by temporal changes that were not explained by LULC variables. We investigated the spatial distributions of these changes by mapping anomalies between past (reference period) and recent scenarios (Fig. 7, Supplementary Figs A3, A4), showing that the spatial distributions were similar throughout fire sizes, with the north-eastern alpine region showing no noticeable changes. Both the real present and the other temporal changes scenarios (Fig. 7*a, d*) showed a widespread decrease over the eastern regions and local increases in the western regions, revealing very heterogeneous trend over the territory. Fire-weather change induced scattered increases by 'hot-spots', even where reductions are observed (Fig. 7*b*). Finally, changes in LULC produced marginal changes (Fig. 7*c*), not explaining the recent fire regime changes.

Discussion

Spatio-temporal modelling and analysis

The goal of this work was to understand the underlying drivers of spatial and temporal patterns of fire activities in south-eastern France, with a focus on the differences between past and recent fire regimes. For this purpose, we implemented spatio-temporal random effects in the Firelihood probabilistic framework (Pimont *et al.* 2021). This approach offers at least two important advantages for the modelling of fire activity. First, we found that these random effects provided realistic fire activity scenarios throughout south-eastern France, despite fire data sparseness. Second, in a context where unexplained factors depending on the local conditions are very important (Díaz-Avalos *et al.* 2016), this approach allowed for accurate estimations of the explanatory variables' effects and of residual unexplained spatio-temporal random effects.

Regarding the occurrence model's components, the spatio-temporal effects implemented in FL2 were very sophisticated, as they account for spatial factors, overall temporal changes – seasonal and yearly – and trends in spatial patterns, the latter effect allowing spatial patterns to change over time linked to processes not directly related with the included explanatory factors. The spatio-temporal effects of the size models (exceedance probability) were simpler because of the reduced size of the dataset for 10 and 100 ha fires. However, the temporal effects allowed for potential yearly changes and spatial effects structured by SERs and proved to enhance the predictive ability of the model.

LULC factors of fire activities

Overall, the LULC factors retained in our model of fire occurrence (>1 ha) were consistent with the findings of previous modelling studies in southern Europe. Indeed, we found that most prevalent factors in human-caused fire occurrence models were human-related, including population density, dwellings and access networks to forest and natural land areas (Costafreda-Aumedes *et al.* 2017). However, vegetation cover of different fuel types was not

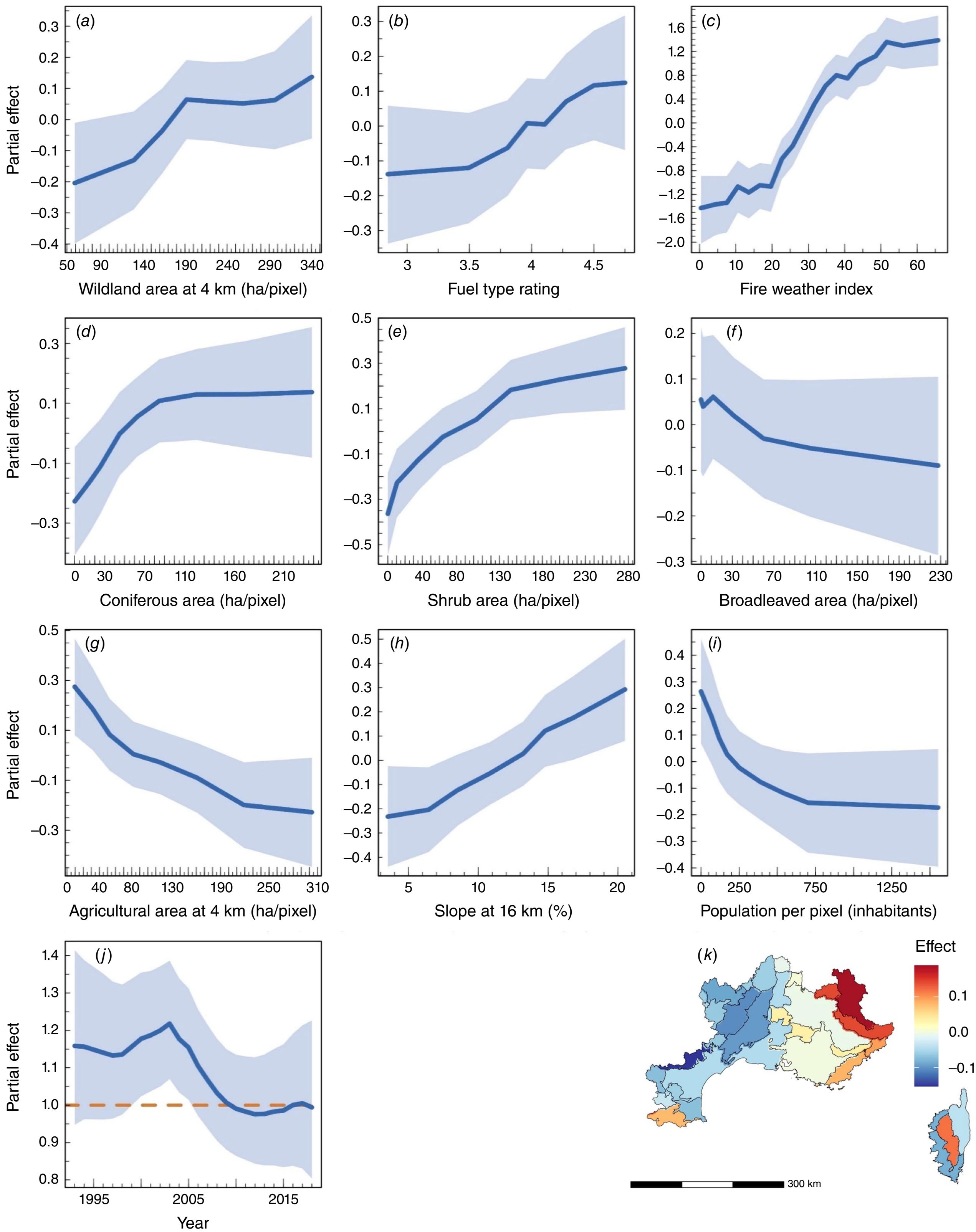

Fig. 4. Partial effects (*a*–*j*) of the predictor variables for the 100 ha exceedance probability model intervals; the *x*-xis shows the value in each bin; the *y*-axis is the contribution of the predictor variable's value to the logit of the probability of exceedance. Spatial effect by SER from the Besag component in the 100 ha exceedance (*k*).

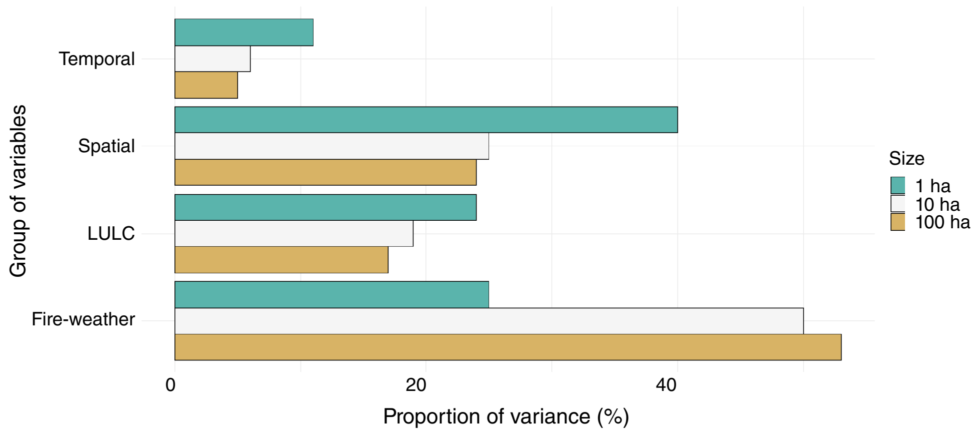

Fig. 5. Partition of spatial variance according to each group of explanatory variables, expressed as a proportion for the full model. Spatial variances are computed for log Poisson intensities (Supplementary Material S2).

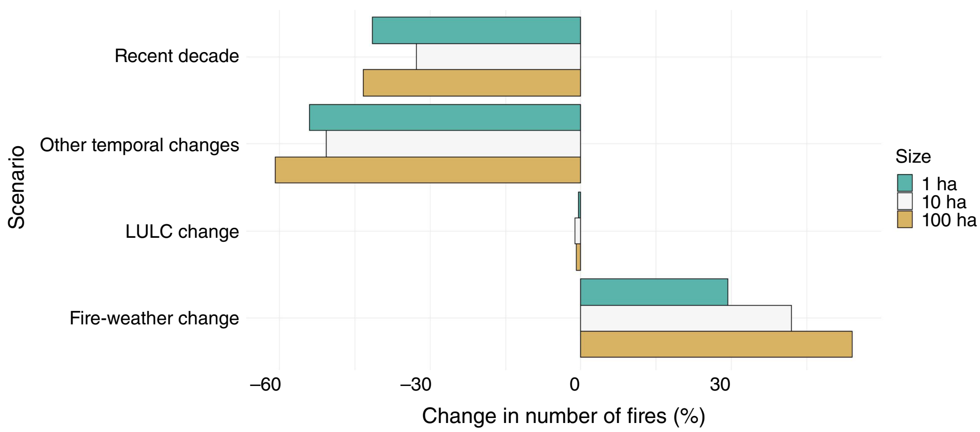

Fig. 6. Comparison of simulations of fire activities between the past decade (1990–2003) and the recent decade (2009–2018) scenario and three alternative present scenarios in mean yearly fire numbers per pixel.

selected in our fire occurrence model, while fuel rating, usually not included in previous studies, was found to be a better predictor. On the contrary, the models for exceedance probability of 10 and 100 ha selected vegetation cover variables as predictors, with either positive (shrubland and conifer) or negative (broadleaves) effects, which is consistent with previous models for fire size (Díaz-Avalos *et al.* 2016), and land cover fire-proneness studies in Europe (Moreira *et al.* 2009). Vegetation cover variables were also found to be more influential on fire sizes than on fire occurrence in the United States (Hawbaker *et al.* 2013).

Road density had the strongest effect on fire occurrence among all LULC in our model, confirming the key role of accessibility to forest areas found in other regions of Europe (e.g. Vilar *et al.* 2010; Serra *et al.* 2014). However, this factor was not selected in size models, in contrast to previous studies in the United States that selected accessibility (distance to roads) (Dickson *et al.* 2006; Ager *et al.* 2013; Hawbaker *et al.* 2013). As observed by Costafreda-Aumedes *et al.* (2017), interfaces between forest/wildland, agriculture and urban areas, and vegetation cover, were also found to be highly influential on fire occurrence.

LULC variables played an important role in fire occurrence, explaining ~25% of its spatial distribution, (Fig. 4), with the same order of magnitude as fire-weather, and in accordance with previous results on the western part of the study area (Ruffault and Mouillot 2017). Nonetheless, unexplained spatial factors and their temporal changes still represented half of the spatial variability in occurrence, meaning that these commonly used predictors did not fully explain the fire occurrence hot-spots observed in western areas and Corsica, or cold-spots observed in mountainous areas or alluvial plains (Fig. 2). For the size models, the fire-weather explained the major part of the spatial distribution, and the share of the LULC and unexplained spatial effects were smaller. This might partly be explained by the less

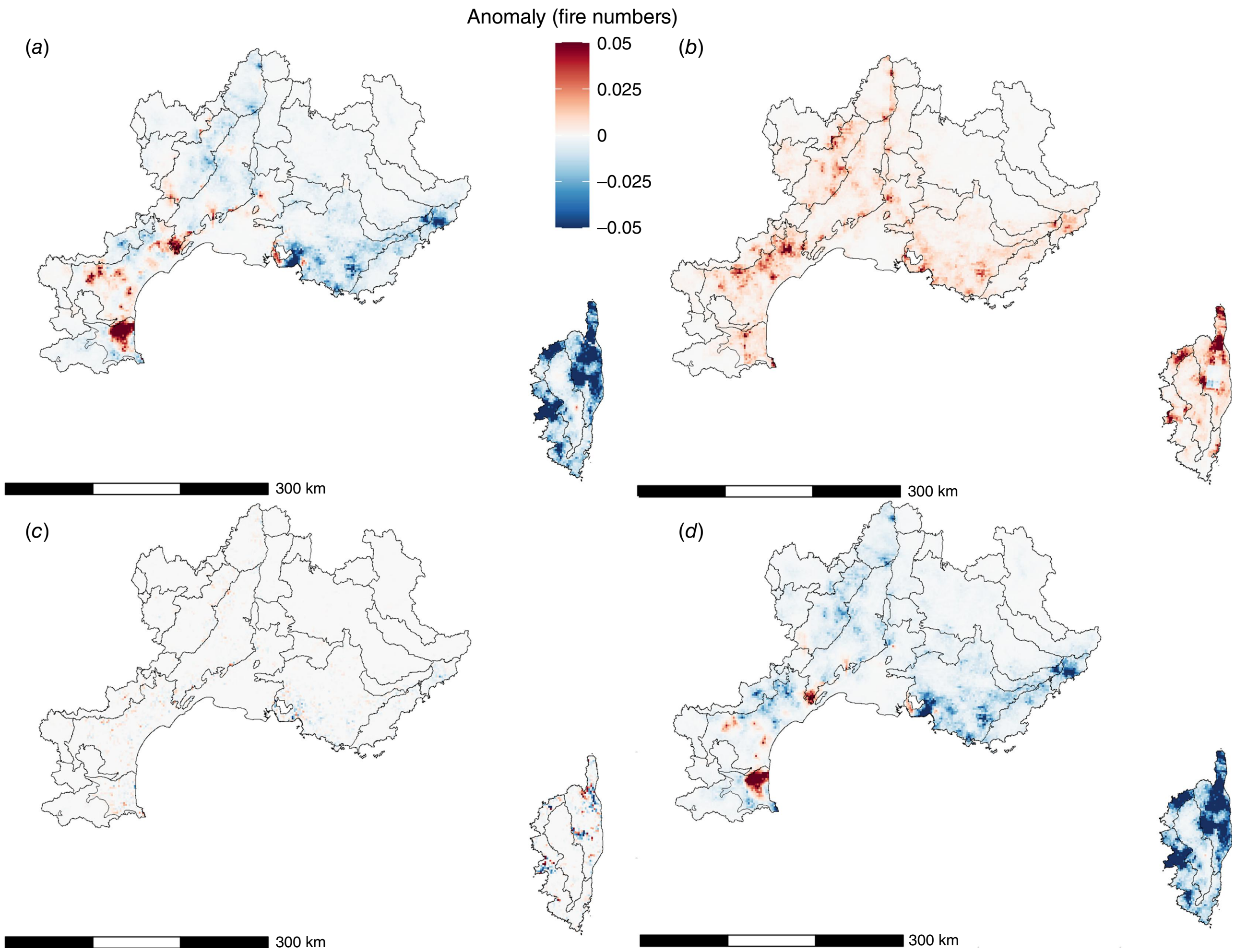

Fig. 7. Spatial distribution of anomalies (in mean yearly fire numbers per pixel) between the 1993–2002 and 2009–2018 decades for 1 ha fire numbers. Same figure for 10 and 100 ha are shown in Supplementary Figs A3, A4. (*a*) Recent decade; (*b*) fire-weather; (*c*) LULC, (*d*) other temporal changes.

sophisticated spatio-temporal effects for exceedances. However, the larger picture that emerges is that fire occurrence was explained equally by fire-weather and by landscape and socio-economic drivers, and once a fire has been ignited, the major driver for its size was the weather during the fire event.

Temporal trends in the fire regime

Fire-weather change alone was found to drive significant increases in potential fire activity, due to a shift of the distribution of the FWI values between the two periods of our study. Around 50% of this increase in fire-weather has already been attributed to anthropogenic climate warming (Barbero *et al.* 2020). Despite the importance of LULC variables over the spatial distribution of fires, LULC changes alone induced marginal changes in fire activity. Temporal changes related to unexplained factors were the main driver, compensating the climate-induced change, contrasting with the findings of Viedma *et al.* (2018) in a west-central Spanish landscape, who documented virtually no trend in fire-weather, but substantial dynamics in landscape drivers of fire, with significant associated trends in fire activity using a 10 km pixel-grid.

Figs 3*j*, 4*j* and Supplementary Fig. A2*j* give an indication of overall temporal changes associated with unexplained factors, allowing us to conclude that the decay was mostly caused by a major reduction in escaped fire numbers after 2003, and that posterior evolution has been limited. Few variations were detected on exceedance probabilities, especially in the recent years. It is very likely that fire suppression policy reduced the number of escaped summer fires, as suggested for the 1973–2005 period in the western part of the region (Ruffault *et al.* 2015), or for the 1976–2009 period in most areas of the region (Fréjaville and Curt 2017); similar trends were reported in Spain by Moreno *et al.* (2014). Indeed, following the record-breaking year 2003 in terms of burnt area in France, the suppression was reinforced with new fire-fighting material and better training capacities, but such changes were not easy to capture with quantitative variables.

No more reduction has been detected since 2007. In particular, the capability to limit the escaped fires that become large (>100 ha) has not been improved, especially during the past decade, matching with Evin *et al.* (2018), who reported a successful suppression strategy, but no significant trend on larger fires. Those findings may put in question the capacity of the French prevention and suppression system to absorb future increases in fire activity associated with climate change, especially given the fact that large fire numbers are expected to increase faster than 1 ha fires (Fargeon 2019).

The spatial distribution of unexplained changes revealed new interesting patterns, providing more insights into the possible temporal drivers of the observed evolution. The positive effect of the fire-weather was concentrated in the current fire activity hot-spots, whereas the unexplained temporal changes were negative in almost all the eastern part of the region. Positive unexplained temporal trends in the south-west would be, according to fire managers, associated with areas of agricultural abandonment, raising the ignition potential of this area. It is also likely that suppression policies were less reinforced in these traditionally less fire-prone areas and struggled to face the observed fire-weather increase.

Conclusion

Analysing factors of fire activities at regional scales is highly challenging because of the stochasticity and the non-stationarity of both these factors and the fire activities. The modelling framework and the simulation plan allowed us to reveal important changes in fire activity and gain insights on some of their drivers. The simulation-based approach allowed us to disentangle the relative contribution of usual explanatory variables to spatial fire activities and to identify differences between fire sizes. We also further explored recent changes in fire regimes and found that the main temporal changes observed over recent decades were driven by unexplained factors suggesting an important contribution of prevention and suppression policies to these trends. Our study further revealed that, if very significant reductions on the number of escaped fires (1 ha fires) was observed after the 2003 heatwave, no significant overall reduction could be detected over the last decade, neither on fire numbers nor on the ability of escaped fires to turn into large fires, even if strong regional differences were detected along a west to east gradient. In a context where climate change is expected to further increase fire weather in this region in the next decades (Fargeon 2020), this raises the question as to how long current low levels in fire activity could be maintained by ongoing efforts in fire suppression and prevention.

Supplementary material

Supplementary material is available online.

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Data availability. The data that support this study comes from six sources with different availability conditions: (1) data for CLC available at Copernicus (Land Monitoring Service) https://land.copernicus.eu/; (2) fire records available at Prométhée database https://www.promethee.com/; (3) landscape descriptive geographical layers from the French IGN (Institut national de l'information géographique et forestière) at https://geoservices.ign.fr/catalogue; (4) population data available from the French Insee (Institut national de la statistique et des études économiques) at https://www.insee.fr/fr/statistiques?theme=0; (5) climatic SAFRAN data available under demand via SICLIMA Extraction application at https://www6.paca.inrae.fr/agroclim/Demande-des-donnees-de-Meteo-France; and (6) fuel classification is not publicly available as it is managed by the French ONF (Office National des Forêts).

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