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Climate change impacts on wildfires in a Mediterranean environment

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Abstract We analyse the observed climate-driven changes in summer wildfires and their future evolution in a typical Mediterranean environment (NE Spain). By analysing observed climate and fire data from 1970 to 2007, we estimate the response of fire number (NF) and burned area (BA) to climate trends, disentangling the drivers responsible for long-term and interannual changes by means of a parsimonious Multi Linear Regression model (MLR). In the last forty years, the observed NF trend was negative. Here we show that, if improvements in fire management were not taken into account, the warming climate forcing alone would have led to a positive trend in NF. On the other hand, for BA, higher fuel flammability is counterbalanced by the indirect climate effects on fuel structure (i.e. less favourable conditions for fine-fuel availability and fuel connectivity), leading to a slightly negative trend. Driving the fire model with A1B climate change scenarios based on a set of Regional Climate Models from the ENSEMBLES project indicates that increasing temperatures promote a positive trend in NF if no further improvements in fire management are introduced.

Keywords Climate change · Regional impact scenarios · Forest fires · Mediterranean ecosystems

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1 Introduction

The Mediterranean region is one of the "hot-spots" of climate change (Giorgi, 2006). In this area, wildfires have a significant impact, with about 50'000 fires burning 400'000 hectares every year on average (San-Miguel-Ayanz et al, 2013). Although anthropogenic ignition is dominant in most Mediterranean regions (Ganteaume et al, 2013), the variations in the ease of ignition and in the burned area are governed by the presence, amount and connectivity of fuel (fuel structure) and by its moisture content (fuel flammability; Pausas and Ribeiro, 2013). Thus, given the sensitivity of wildfires to climate, estimating the impact of present and future climate change on wildfires is a key topic in risk assessment and adaptation strategies, and it has become a strategic issue in national and international climate programs (e.g. the European FUME project, `http://www.fumeproject.eu`).

Several studies support the hypothesis that in Mediterranean type ecosystems, climate is a primary driver of the interannual variability of fires, controlling fuel flammability and fuel structure (see, e.g. Pausas, 2004; Pereira et al, 2005; Koutsias et al, 2012; Bedia et al, 2014a). Increased fuel flammability due to warmer and drier conditions (changes in fuel conditions), is one of the fire responses to climate change. Fire activity is also favoured by the presence of fine fuel, which can be produced during antecedent periods with favourable climate conditions and reduced during warm and dry periods (changes in fuel loading). In general, under changing climate conditions, several possible pathways of wildfire response can be identified, depending on the magnitude of climate change as well as on differences in how fires, vegetation and humans respond to such changes (Hessl, 2011; Moritz et al, 2012).

The past and the possible future evolutions of wildfires due to climate change in European Mediterranean regions are subject to active investigation (see Moreira et al, 2011, for a review). In particular, the relative importance of changes in fuel flammability and fuel loading, due to climatic changes, remains largely unexplored in these areas mainly owing to data limitations and because of difficulties in disentangling the several drivers of change (e.g. changes in human behaviour and environmental factors).

In a previous study, we analysed the interannual climate-fire relationship in a typical Mediterranean environment (NE Spain; Turco et al, 2013a), and we developed a Multi Linear Regression model (hereinafter MLR) that links year-to-year changes in summer fires and climatic drivers in the period 1983-2007. In this model we considered coincident (i.e. same summer) temperature and precipitation values as proxies for the climatic factors that affect fuel flammability, and antecedent climate variables, as proxies for the climatic factors that influence fuel structure. Analysing the recent evolution of fires since 1970 in NE Spain, we showed that both the burned area and the number of fires display a decreasing trend (Turco et al, 2013b). The potential drivers of these fire trends are changes in climate, vegetation, land use and human activities (see e.g. Moreno et al, 2014). An increasing effort in fire management, considering both fire prevention and fire extinction, is presumably one of the main causes for the observed change. For instance, after the big fires in the 1980s, fire management strategies were improved (Turco et al, 2013b; Moreno et al, 2014), including: the generation of daily maps of fire risk, combing weather forecasts and vegetation maps obtained by satellite and aerial photography; the presence of fire-guard in areas of risk of fire; the use of specific aerial means (e.g. Canadairs); the increasing awareness of the population and its coordination with fire-fighters (`http://www.gencat.cat/medinatural/incendis/`).

In this study we investigate long-term climate-driven changes in burned area and number of fires applying the MLR model to wildfires in NE Spain since 1970, disentangling the drivers responsible respectively for gradual and year-to-year changes. The objectives of this study are threefold: (1) to provide a quantitative estimate of the impacts of observed climate trends on fires, (2) to assess the applicability and uncertainties of the MLR model driven by Regional Climate Model (RCM) outputs, and (3) to explore the fire response to an ensemble of regional climate projections. We focus on the statistical evidences of climate change impacts on fires and provide an estimate of the overall uncertainties in fire response. We also perform several sensitivity tests to assess the robustness of the results to three sources of uncertainties: the choice of the fire model, its uncertainties, and the uncertainty in RCM scenario outputs.

2 Climate and fire data

High-quality data on the Number of Fires (NF) and Burned Area (BA) in summer months (June, July, August and September; JJAS) are obtained from the Forest Fire Prevention Service of the "Generalitat de Catalunya", in the period 1970-2010, for the area of Eastern Catalonia (NE Spain; see Turco et al (2013b) for an exact definition of this area). The study area has typical Mediterranean geographical and climatic features: complex coastline, rich orography, dry and hot summers, sporadic but heavy rain, high fire regime and large climate variability at interannual and interdecadal scales (Llasat, 2009). To obtain homogeneous series, we restrict the analysis to fires with burned area of at least 0.5 ha.

Climate data are provided by the recently developed SPAIN02 gridded dataset ($0.2^\circ \times 0.2^\circ$, period 1950-2007; Herrera et al, 2012). Simulated climate data (1970-2050) were obtained from state-of-the-art Regional Climate Model (RCM) simulations at 25 km resolution provided by the EU-funded ENSEMBLES Project (van der Linden and Mitchell, 2009). This dataset includes eleven ERA40-driven and eleven GCM-driven simulations for the 20C3M control period (1970-2000) and for the A1B scenario (2001-2050). The ENSEMBLES subset used here has been extensively validated (see Herrera et al, 2010; Turco et al, 2013c for more details).

In addition to mean values of precipitation, maximum and minimum temperature, we evaluate also the indices of extremes defined by the World Meteorological Organization (WMO) CC1/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI; for more details see `http://etccdi.pacificclimate.org/` or WMO, 2009). These indices describe different aspects of climate extremes, including metrics related to drought (e.g. number of days with precipitation lower than 1 mm; DD hereinafter, or consecutive dry days index) and to extreme temperature (e.g. number of days with maximum temperature greater than 25°C or greater than 35°C).

Monthly regional means of climate data are used. Before computing the spatial average over the region of interest, we standardize the individual series from each grid point to unit variance and zero mean, in order to reduce the presence of possible biases in the regional average. For the time series produced by future climate projections, standardization consisted in subtracting the climatological mean and dividing by the standard deviation computed over the historical period 1970-2000. This calibration approach reduces possible biases in the outputs of the regional models while preserving possible trends.

3 Model setup

3.1 Fire response to climate trends

To assess the impact of observed climate trends on wildfire statistics, we follow a trend attribution method which is widely used to analyse the effects of climate change on crops (see, e.g. Lobell et al, 2007, 2011). First, we model the year-to-year changes in the response fire variables (the predictands) by a multiple linear regression model (MLR), using a set of detrended climate variables as predictors:

$$Y' = \sum_j \beta_j X'_j + \epsilon \tag{1}$$

where $Y' = Y - \alpha t - \alpha_0$, and $X'_j = X_j - \gamma_j t - \gamma_{0,j}$ are, respectively, the linearly detrended fire variable and the j-th climate variable. Since both BA and NF follow approximate log-normal distributions we normalize the variables by applying a log transformation (i.e. $Y = \ln(BA)$ or $Y = \ln(NF)$). The parameters α, γ_j represent the linear temporal trends of the fire and climatic variables, including both anthropic effects (such as a gradual increase in fire management effort) and environmental/climatic changes. The parameters β_j are the j-th regression coefficients, and the term ϵ represents the model residuals. The dependence on time of Y, Y', X'_j and ϵ is omitted for ease of notation.

From eq. 1, we obtain an expression for the non-detrended variables:

$$Y = \alpha_0 + \alpha t + \sum_{j=1} \beta_j X'_j + \epsilon = \delta_0 + \delta t + \sum_{j=1} \beta_j X_j + \epsilon \tag{2}$$

where δ an δ_0 depend on α, γ_j, α_0 and $\gamma_{0,j}$. The term δt includes all climatic and anthropic linear trends, while the expression:

$$Y^{climate} = \delta_0 + \sum_{j=1} \beta_j X_j + \epsilon \tag{3}$$

explicitly depends only on the climatic variables. Clearly, the residuals include the effect of possible year-to-year management changes; to assure that no structured process is missed, it is important that the residuals are Gaussian and uncorrelated in time and, possibly, with small variance. This type of model also assumes that fires respond similarly to year-to-year climate fluctuations and to longer-term trends in climate.

3.2 Statistical fire-climate models

The MLR model development follows the same procedure as in Turco et al (2013a). In addition to calibrating this model over Eastern Catalonia for a longer period

Variable	Months	τ	r (ln(NF)')	Variable	Months	τ	r (ln(BA)')
$P'_{(5-8)}$	May-Aug	0	-0.77	$DD'_{(6-7)}$	Jun-Jul	0	0.73
$P'_{(5-7)}$	May-Jul	0	-0.73	$DD'_{(5-8)}$	May-Jul	0	0.67
$Tx'_{(6-8)}$	Jun-Aug	0	0.68	$Tx'_{(6-7)}$	Jun-Jul	0	0.59
$Tx'_{(6-9)}$	Jun-Sep	0	0.72	$Tx'_{(6-8)}$	Jun-Aug	0	0.56
$Tn'_{(4-4)}$	Apr-Apr	0	-0.35	$Tn'_{(4-4)}$	Apr-Apr	0	-0.42
$Tn'_{(4-5)}$	Apr-May	0	-0.25	$Tn'_{(4-5)}$	Apr-May	0	-0.31
$P'_{(1-7)(2)}$	Jan-Jul	2	0.38	$P'_{(2-3)(2)}$	Feb-Mar	2	0.42
$P'_{(1-8)(2)}$	Jan-Aug	2	0.34	$P'_{(1-5)(2)}$	Jan-May	2	0.41
$Tx'_{(1-2)(2)}$	Jan-Feb	2	-0.46	$Tx'_{(1-11)(2)}$	Jan-Nov	2	-0.52
$Tx'_{(12-2)(2)}$	Dec-Feb	2	-0.40	$Tx'_{(2-11)(2)}$	Feb-Nov	2	-0.52
$Tn'_{(1-2)(2)}$	Jan-Feb	2	-0.32	$Tn'_{(2-10)(2)}$	Feb-Oct	2	-0.46
$Tn'_{(2-2)(2)}$	Jan-Jan	2	-0.29	$Tn'_{(1-10)(2)}$	Jan-Oct	2	-0.46

Table 1 Cross-correlations (r) between the detrended climate variables $X'_{(k-l)(\tau)}$ and the detrended fire variables (log-transformed NF and BA in JJAS). The climate variables considered are the number of dry days (DD), precipitation (P), maximum temperature (Tx) and minimum temperature (Tn), during the months from k to l at the time lag τ, in years.

(1970-2007), in this study we extend this model exploring the potential fire response using indices of climate extremes (ETCCDI indices). For more details on the original implementation of MLR model, the readers are referred to Turco et al (2013a). Briefly, its practical implementation is summarized here.

First, we select the key climate variables for model development, systematically exploring same-year and lagged cross-correlations between fires and multi-month values of climatic variables. Specifically, we compare the fire variables (detrended log-transformed BA and NF in JJAS), to the detrended climate variables, $X_{(k-l)(\tau)}$, including indices of extremes and mean values of precipitation, maximum and minimum temperature, during the months from k to l with a time lag of τ years (omitted if $\tau = 0$). The results of the cross-correlations between climatic data and fire statistics are reported in Table 1. For sake of compactness, only the two highest correlations for each variable with similar features (with a confidence level of at least 95%) are shown. As expected, BA and NF are correlated with coincident summer maximum temperature and precipitation (proxies for the climatic factors that affect the fuel dryness) and with antecedent variables (proxies for the climatic factors that influence the fuel structure): high rainfall and low temperatures of two years before presumably allow fine fuel to be produced, ensuring fuel continuity. Besides, also low temperature, or frost, in the spring immediately before the fire season seems to play a role in increasing the fuel amount. Interestingly, we find that in general the indices of extremes, based on daily data, do not show a significantly higher correlation with fire variables compared to mean climate variables based on monthly data. The only exception is represented by the dry days index: $DD_{(6-7)}$ has a greater correlation with the Burned Area (0.73), than the mean precipitation, $P_{(6-7)}$ (-0.65), suggesting that this index is a better proxy of climate condition affecting fuel moisture.

Next, we fit all the possible models with the selected predictors and we retain only those models with lowest AIC (Akaike Information Criterion), whose residuals satisfy the hypothesis of normality, zero autocorrelation and no trend. Applying the procedure described above we obtain the following optimal parsimonious models :

$$\ln(BA)' = 0.92DD'_{(6-7)} + 0.36T'_{x(6-7)} - 0.48T'_{n(4-4)} - 0.69T'_{x(2-11)(2)} + \epsilon \quad (4)$$

and

$$\ln(NF)' = -0.36P'_{(5-8)} + 0.34T'_{x(6-9)} - 0.16T'_{n(4-5)} + 0.08P'_{(1-8)(2)} + \epsilon \quad (5)$$

The explained variance of the models (Eqs. 4 and 5) is, respectively, 0.67 and 0.71. The optimal selection of predictors and the coefficients are very similar to those found in Turco et al (2013a) for a shorter period and for all Catalonia. In both cases we identify similar climatic variables from the antecedent years as efficient predictors. This highlights the importance of the year-to-year climate variability not only in regulating fuel flammability, but also fuel structure. Among the potential models (4095) considering different combinations of the twelve predictors reported in Table 1, several models (290 models for BA and 284 for NF) perform reasonably well ($R^2 > 0.5$), with residuals that satisfy the hypothesis of normality, zero autocorrelation and no trend. For this reason the choice between the models is delicate; in the following we test the sensitivity of the results to the choice of the model.

In order to estimate the uncertainty of the regression parameters we use bootstrap resampling, where the predictand and predictor pairs are drawn randomly with replacement 1000 times and new regression models are fit to the data. The confidence interval is defined by the 5th and the 95th percentiles of the ensemble of the 1000 regression models.

4 Results

4.1 Recent climate trends and future projections

Figure 1 shows a representative set of observed and simulated key climate variables used in the regression models (Eq. 4 and 5), over the common period 1970-2000, and shows future projections up to 2050. RCM simulations driven by ERA40 and by global GCMs are plotted separately. The trends in the climate predictors for NF and BA are similar. The observed temperature trend indicates climate warming (around +0.60/0.80 °C/10y depending on the aggregation months; $P < 0.01$), coherent with the observed regional and global warming (see Turco et al, 2012, and reference therein). No significant trends are observed in the mean precipitation values or the number of dry days (Turco and Llasat, 2011).

The ERA40-driven RCMs capture quite well the observed trends and the year-to-year variability. Since the GCM-driven RCMs are climatic runs, we cannot compare their year-to-year changes with historical observations. However, the model statistical properties agree with the observations: The GCM-RCMs correctly reproduce the observed trends, even though with a slight underestimation (not shown), and have an interannual variability which is consistent with that of the observations. Future projections indicate a significant sustained increase in temperature,

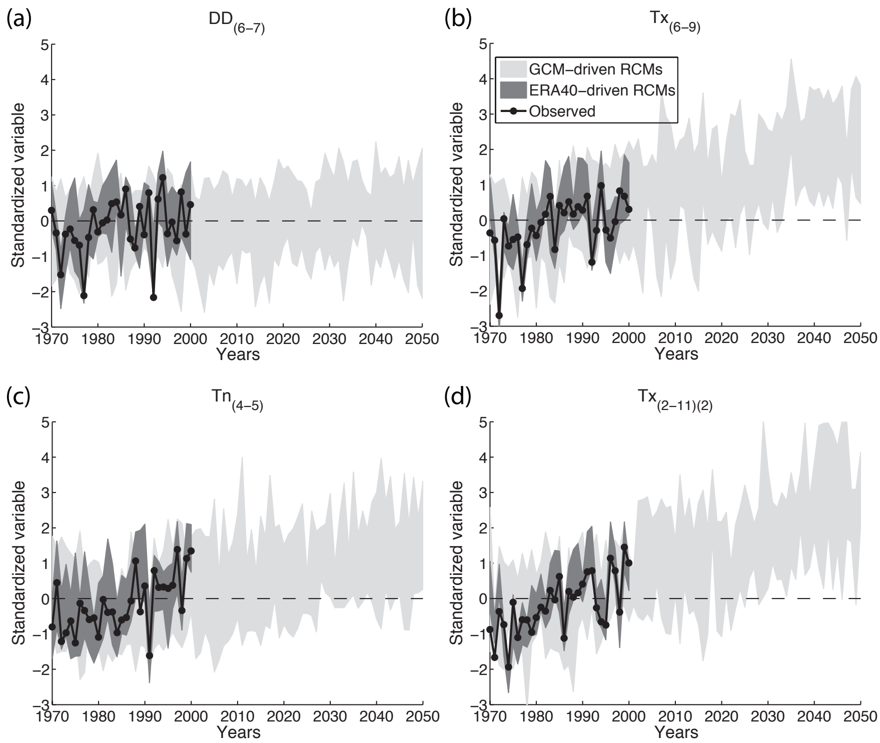

Fig. 1 Observed (1970-2000) and simulated (1970-2050) representative key climate variables: **(a)** Dry days index between June and July ($DD_{(6-7)}$); **(b)** Maximum Temperature between June and September ($T_{x(6-9)}$); **(c)** Minimum Temperature between April and May ($T_{n(4-5)}$); **(d)** Maximum Temperature between February and November with a time lag of two years ($T_{x(2-11)(2)}$). The black line with solid circles indicates the observed data (*Spain02*). The dark shaded band spans the values for the ERA40-driven RCMs and the light bands span the values for the GCM-RCM model chains.

particularly in summer, at a rate that continues the historical trend. Trends in precipitation and DD are non-significant (decreasing and increasing respectively). Uncertainty in the GCM ensemble propagates also to the RCM ensemble and in general the uncertainty spanned by RCMs driven by GCMs is larger than that of RCMs driven by ERA40.

4.2 Historical fire response to recent climate trends

Figure 2 shows the output of the MLR model using eq. 2 and eq. 3 and the coefficients of eq. 4 and 5. The impact of climate change on NF is evident (Fig. 2a). While the actual trend is negative (-0.042 y^{-1}, $P < 0.05$), climate forcing alone would have led to a positive trend in $\ln(NF)$ (+0.016 y^{-1}, $P < 0.05$). This suggests that, in the absence of fire management, we would have had a significant increase in NF. This result also indicates that for NF the direct effect of a warmer climate (i.e. higher fuel flammability) might be more important than the indirect effects (i.e. lower fine fuel availability). While also the BA trend is negative (Fig. 2b; -0.049 ln(ha)/y, $P < 0.05$), the BA response to the climate trend alone is very small, with a non-significant, slightly negative trend (-0.013 ln(ha)/y). This could be associated with the importance of antecedent climate conditions for this variable: warmer conditions can act on the fuel structure by limiting the availability of fine fuel and favouring fuel gaps, thus reducing the spread of large fires.

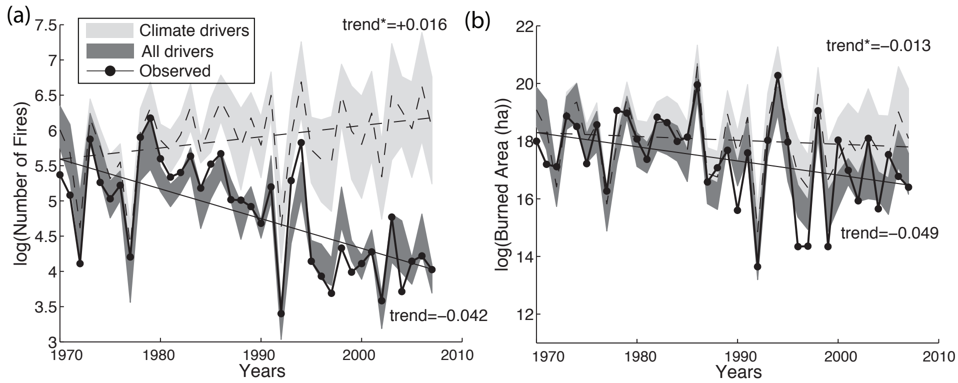

Fig. 2 Model results for **(a)** Number of Fires and **(b)** Burned Area, considering two set of drivers: (i) "all drivers", that is, the *MLR* consider the year-to-year climate variation added to the overall trend (eq. 2), and (ii) only the climate drivers (eq. 3). The continuous line with solid circles represents observed data. The light shaded band refers to the "climate drivers" and includes 90% of the members of 1000 different bootstrap replicates, while the dark band spans the uncertainty of the simulation with "all drivers".

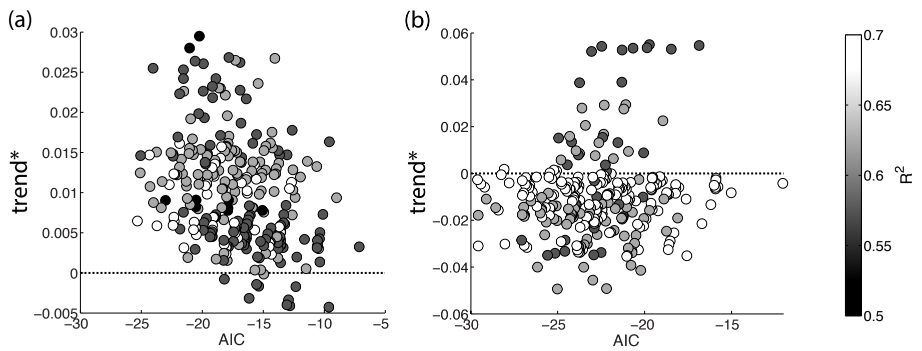

Fig. 3 Potential fire trends (trend*) due to climate trends only, based on several combinations of model parameter choices from table 1, for **(a)** Number of Fires and **(b)** Burned Area. Lower *AIC* values indicate better models (i.e. those in the left part of the graphs). Different R^2 are shown in gray-scale. We retained only those models with R^2 greater than 0.5 and whose residuals satisfy the hypothesis of normality, zero autocorrelation and no trend.

Figures 3a and 3b provide information on the sensitivity of the results to the details of the fire model. The figure shows the trends of the fire variables in response to climate forcing alone (eq. 3) for several model specifications with different predictors combination (see Table 1), versus their Akaike Information Criterion score (AIC). The best models (i.e. those with lower AIC) suggest a positive contribution to the trend of $\ln(NF)$ (Fig. 3a), indicating that the results on the NF response to climate trends is robust to variations in the model details. For $\ln(BA)$, the best models indicate a negative contribution of climate trends (Fig. 3b), but the pattern is less clear, with relatively good models (i.e. R^2 greater than 0.60 and low AIC values) indicating both a steady or slightly negative trend, or, in some cases, a slightly positive trend.

4.3 Impact of future climate change projections on wildfires

Figure 4 shows the results provided by the MLR models (eq. 4 and 5) driven by observed data (SPAIN02) and RCMs forced by ERA40 (past) and GCMs (future). The climate-fire model reproduces well the historical data, using both the SPAIN02 series and the ERA40-driven RCMs. For future projections, we drive the models using only climate variables as predictors (eq. 3), that is, assuming no further improvement in future fire management. The results indicate that warmer conditions in the A1B scenario lead to an increase in NF and to steady or slightly decreasing BA.

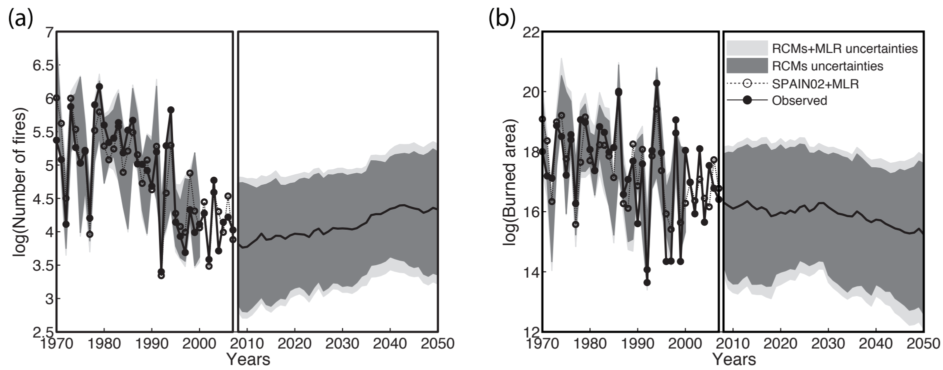

Fig. 4 Observed behaviour and future projections for **(a)** Number of Fires and **(b)** Burned Area. Solid circles and continuous line represent the observed fire data. Empty circles and dashed line represent the MLR output forced with SPAIN02 data. The dark shaded band spans the values for the RCM projections while the light band shows 90% the confidence interval accounting for both RCM and MLR uncertainties (1000 bootstrap replications x 11 RCMs). Future projections are shown as 10-year moving averages to emphasize gradual changes rather than year-to-year fluctuations.

In the RCM-MLR model chain, different sources of uncertainty are active. RCM model uncertainty is estimated by the spread of the ensemble of 11 RCM projections (dark gray bands in the figure). Total uncertainty (that is, RCM uncertainty combined with the uncertainty in the parameter estimation for the fire model) is estimated by the spread of 1000 MLR bootstrap replications for each of the 11 RCMs (light gray bands in the figure). There is only a small difference between the two bands, suggesting that the overall uncertainty is dominated by the RCM spread.

5 Discussion and Conclusions

In this paper we provided a parsimonious mathematical framework to statistically analyse the impact of climate change on forest fires, disentangling the effect of climate variables from other drivers. In addition to mean values of precipitation and temperature, we explore the potential fire response to the ETCCDI indices of extremes. Except for the dry days index, using these indices does not improve the correlations with fires, likely because of data limitation, but also since the specific spatio-temporal scale of our modelling approach. Indeed, at these relative broad scales, the monthly scale aggregation of the climate variables is likely sufficient to explain some of the main processes determining the effects of climate variability on fires, as suggested by the high R^2 of our fairly simply models. Instead, extreme weather conditions likely capture crucial processes for fire occurrence and behaviour at finer scales (see e.g. Pereira et al, 2005).

The observed trends of the key climate variables affecting wildfires indicate a clear increase of temperature, particularly in summer, and a slight, non-significant, decrease in precipitation. Considering the simulated data, the RCMs reproduce well the historical characteristic of the key climate variables and indicate increasing temperature and substantial steady precipitation up to mid-century in the A1B scenario.

The climate trends lead to a positive trend for NF, suggesting that for NF the direct effect of climate (higher fuel flammability) is more important than the indirect effect due to antecedent climate conditions. The relatively strong link of NF with summer precipitation and temperature suggests that the mechanism by which climate affects NF is, on the whole, simple: warmer and drier summers lead to more fires. However, in the past forty years the measured trend of NF is negative, indicating that past improvements in management actions have more than counterbalanced the climatic trend. For future conditions, keeping management actions unchanged will not be able to balance climatic trends and NF is expected to increase in absence of further improvements in fire management.

The climate change impact on BA is more complex. The BA response to climate trends is slightly negative (although not statistically significant), possibly because the direct effect of climate in regulating fuel flammability is balanced by the indirect effect of climate on fuel structure. However, this result should be taken with caution since (i) the indirect relationship between climate, vegetation and fires is complicated and (ii) it could be more model-dependent than the behaviour of NF. As shown in fig. 3b, small differences in the parameters used in the regression model, and their weights, can lead to different BA trends.

The main conclusions presented here are consistent with previous findings in other regions with similar Mediterranean type ecosystem, which showed that fires may not increase uniformly in these areas throughout the century, since both fuel amount and fuel moisture constraints (Westerling and Bryant, 2008; Krawchuk et al, 2009; Batllori et al, 2013; Bradstock et al, 2014).

We have found that the NF might be more closely related to fuel flammability conditions and that it is projected to increase if climate variables were the only driver. This result is consistent with several recent studies for the European Mediterranean region, that predict increased fire activity under climate change in the future, through an increase of the Fire Weather Index (see e.g. Bedia et al, 2013, 2014b). On the other hand, our results pose some caveats on the applicability of the FWI in climate change studies, as BA is influenced also by the amount and structure of available fuel. Ignoring antecedent climate variables corresponds to assuming that the direct climate effects on fuel flammability are more important than variations in fuel loading.

Past studies on Burned Area (BA) projections in these areas show a rather controversial picture, mainly owing to the variety of models assumptions. Amatulli et al (2013) apply a time series model to simulate BA by using the Fire Weather Index (FWI), showing a significant increase of the Burned Area in European Mediterranean countries. However, the authors also warn that the potential decrease in fuel load is not taken into account. A recent study of Migliavacca et al (2013) considers the impact of climate change on fires in Europe with a process-based model forced by different Regional Climate Models (RCM). Their results show an increase in BA during the 21st century, in particular in the Mediterranean basin, although this increase is lower than in other studies that did not consider the effect of climate on net primary productivity.

To summarize, in our analysis of NE Spain we find a potential increase of NF and a steady or slight decrease of BA in warmer scenarios. Although obviously the greater losses are due to the bigger fires, the increase in NF is of concern. The value of BA is largely determined by a few large fires (70% of the burned area is associated with fires > 500 ha) whose dynamics could be governed by complex mechanisms and under extreme weather conditions, big fires can propagate out of control and can be very difficult to extinguish. On the other hand, NF results mainly from numerous small fires (but with burned area larger than 0.5 ha), for which suppression could be more effective and, despite their size, they may have a negative impact in an increasingly vulnerable environment. Besides, if the fuel load and connectivity will increase, for example due to land-use and land-cover changes, the increasing number of fires might increase the chance of large fires. Thus, the results reported here indicate the need for an increased effort in future fire-management policies, combing prevention (e.g. increasing efforts to avoid ignitions during those days with adverse weather conditions; reducing fuel load and continuity with prescribed burning and with fuel-breaks) and suppression strategies (in particular investing in the early stage of extinction). These strategies should be focused on areas of high value, since these efforts may not be of the same intensity everywhere.

Clearly, more precise projections for NF and BA would require assumptions on future fire management policies, land-use and land-cover change, which go beyond the scope of this study. Also, we did not consider fire changes due to the introduction of invasive species and changes in ignition patterns, mainly because reliable projections for these drivers are not available. Despite these limitations, the ability to separate the impact of climate change on wildfires from other drivers, as done here, is crucial to identify key actions in adaptation strategies. Overall, our study advances the understanding of the impact of climate change on wildfires in Mediterranean environments, providing a climate change-fire model framework that can be adopted in other geographical regions.

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