 doi:10.20944/preprints201910.0200.v1

Climate change impact on future wildfire danger and activity in southern Europe: a review

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Abstract

Wildfire is the main disturbance in forested ecosystems of southern Europe and is due to complex interactions between climate-weather, fuels and people. Warmer and drier conditions projected in this region are expected to profoundly affect wildfires, which will impact ecosystems and humans. We review the scientific literature addressing the assessment of climate change impacts on wildfires in southern Europe, with a twofold objective: (i) report the trends in wildfire danger and activity projected under warming climate in southern Europe and (ii) discuss the limitations of wildfire projections under the specific biogeographical context of southern Europe. We identified 22 projection studies that examined future wildfire danger or wildfire activity at local, regional or continental scale. Under the scenario with the highest greenhouse gas emissions, we found that projections studies estimate an increase in future fire danger and burnt areas varying, on average, from 2 to 4 % and from 15 to 25 % per decade, respectively. Fire-prone area expansion to the north and to Mediterranean mountains is a concern, while climate-induced burnt area increase might be limited by fuel availability in the most arid areas. While all studies agreed on the direction of changes, further comparisons on the magnitude of increase remained challenging because of heterogeneous methodological choices between projections studies (climate models, projection period, spatial scale and fire metrics). We then described three main sources of uncertainty that may affect the reliability of wildfire projections: climate projections, climate-fire models, and the influences of fuel load/structure and human related factors on the climate-fire relationships. We finally suggest research directions to address some of these issues for the purpose of refining fire danger and fire activity projections in southern Europe.

Keywords

Global warming; projections; climate-fire relationship; FWI; burnt areas; forest fuels; Mediterranean forests.

1. Introduction

Wildfires are the main threat to forests in southern Europe because of their negative impacts on forest dynamics as well as on its environmental, economic and social values. Between 2007 and 2016, around 48,000 forest fires burned 457000 ha as annual average in the five southern European countries most affected by wildfires (Portugal, Spain, France, Italy and Greece) (San-Miguel-Ayanz et al. 2018). While recent statistics show a decrease in fire activity in most of these regions due to changes in land use/land cover or suppression policies (e.g. Turco et al. 2016, Curt and Fréjaville 2018, Silva et al. 2019), a number of studies have also shown an increase in fire danger during the same period (Piñol et al. 1998, Pausas 2004, Jolly et al. 2015, Fréjaville and Curt (2015), Ruffault et al. 2016). Moreover, 2017 has been one of the most devastating wildfire seasons on record in some of the southern Mediterranean countries, with a noteworthy increase in burnt area of 535 % for Portugal, 160 % for France, 105% for Italy and 95% for Spain, relative to the average values of the previous decade (San-Miguel-Ayanz et al. 2018).

Fuel moisture has long been recognized as a major component of fire danger (Brown and Davis 1973) and components of fire activity such as number of fires or burnt area are known to respond positively to increasing fuel dryness (e.g. Flannigan et al. 2016; Turco et al. 2017). Hence, the increase in temperature and decrease (or stagnation) in summer precipitation that are both projected for southern Europe (Kovats et al. 2014) are likely to increase fire danger and fire activity in this region. Flannigan et al. (2009) reviewed the literature addressing the impact of climate change on wildfires from a global perspective, censing all studies reporting projections of future wildfire danger or activity under global warming scenarios regardless of the spatial scale. At that time, they reported 38 studies mostly conducted at a regional or a national level in North-America or Australia. However, only two studies were dedicated to Europe, one addressing landscape vegetation changes under new climatic conditions in Corsica (Mouillot et al. 2002), and the other proposing the first projections of wildfire danger at the scale of southern Europe (Moriondo et al. 2006). There was at that time critical research needs in terms of projections of wildfire danger and activity in Europe. In contrast, in 2019, we found 22 studies reporting such projections from regional to continental scales, suggesting an increasing research effort in Europe on that topic. Accordingly, the general trends for wildfires in Europe have been briefly summarized by the experts of the IPCC in their fifth assessment report (Kovats et al. 2014): ‘Future wildfire risk is projected to increase in southern Europe, with an increase in the occurrence of high fire danger days and in fire season length. The annual burned area is projected to increase by a factor of 3 to 5 in southern Europe compared to the present under the A2 scenario by 2100. In northern Europe, fires are projected to become less frequent due to increased humidity'. Global fire projections, however, show more contrasted results for southern Europe: Scholtze et al. (2006) predicted a likely critical increase in wildfire frequency in most regions by the end of the century, Krawchuk et al (2009) a decrease or stagnation in burn probability, Moritz et al. (2012) a likely but slight increase in burn probability, and Flannigan et al. (2013) a 2 to 3-fold increase in fire season severity (i.e. a cumulative rating of the fire control difficulty). This supports a new review, based on the most recent research efforts in Europe and focused on forest fire, to refine such general trends.

In this paper, we review the scientific literature addressing the assessment of climate change impact on future fire danger and activity in southern Europe, including the Iberian Peninsula, France, Italy, Balkans, and Greece. The review includes projection studies, as well as studies addressing the understanding and modelling of climate-fire relationships in the European context. In the present paper, a projection study is defined as a study that projects fire danger indices or fire activity variables (fire number, fire size, burnt area) in the forthcoming decades based on climate series simulated under climate change scenario(s) and that explicitly reports future changes in these indices or variables. Projection studies were tracked with the following combination of keywords in the Web of Science: *climate change AND (wildfire OR forest fire) AND (projection OR projected)*. Among them, we selected the studies that effectively addressed the topic and were conducted in southern Europe, and we considered works published up to July 2019. We did not specifically include global fire projections in the review because they aim to address future changes in fire regimes or emissions at broad geographical scales or biome level, use coarse grid cells (often > 100 km), and often do not report rates of change of standard fire metrics. In section 2, we explain why modelling fire activity is challenging and then we give an overview of the models that were used in the studies to project fire danger or fire activity in Europe. In section 3, we present and compare the results of projections studies and attempt to summarize the main trends. In section 4, we disclose and discuss the limitations of current projections. Finally, we provide a synthetic view of expected trends in future fire danger and activity in southern Europe and propose some research directions to improve or complement current projections.

2. Projections methods

The basic couplings between climate, vegetation (fuel) and fire processes that drive the impact of climate change on fire activity have been identified (Figure 1). However, modelling climate change impact on wildfire activity remains highly challenging for several reasons. First, fire activity is primarily controlled by fuel continuity and availability (load, spatial structure, moisture), weather conditions (fire weather including wind, temperature, relative humidity, precipitation and atmospheric stability) and ignition sources (lightning or human causes). Biomass production, its availability to burn, fire weather and ignition have been described as a hierarchy of four switches that must be activated for fire to spread (Bradstock 2010). Ignitions and fuels are strongly impacted by human activities and infrastructures, land use, and prevention policies. Moreover, fire control operations tend to reduce the size of fires and the resulting burnt area. Hence, fire activity is the result of multiple, possibly interacting or correlated factors, making its modeling difficult, whether the approach is statistical or process-based. In this respect, projecting fire weather is comparatively straightforward. Second, a main impact of climate on fire activity comes through some changes in the moisture content of fuels (live and dead biomass). This impact is driven by a number of dynamical physical and biological processes involved in the soil-plant-atmosphere functioning at time scales ranging from hours to the season. In particular, water balance (evaporation, precipitation, transpiration, water storage and drainage) largely determines the water content of fuels as well as the production of dead fuel (Jolly and Johnson 2018). Although scientific research has produced representations of such dynamical processes, there are still fundamental and practical limitations to use them to predict fuel moisture (e.g. Jolly et al. 2014; Martin-StPaul et al. 2017; Jolly and Johnson 2018), even for dead fuel (e.g. Matthews 2014). Thus, more simple models are used to describe the climate impact on fires through fuel moisture dynamics, such as empirical fire danger indices or statistical models linking directly fire activity to weather or drought indices (e.g. Flannigan et al. 2016). Third, climate change will impact not only fuel moisture, but also fuel load/continuity and fuel structure, because climate is a major driver of biomass accumulation (through primary production) and vegetation composition and structure (Bradstock 2010). Furthermore, natural disturbances, including fire, affect forest and landscape dynamics, which induces strong feedbacks on vegetation and fuels (Seidl et al. 2011). Dynamic (Global) Vegetation Models (DGVM when global scale is addressed) are land biogeochemical models representing the climate-soil-vegetation interacting processes and have been coupled with fire models to study the role of fire in vegetation dynamics and in the terrestrial carbon cycle (Flannigan et al. 2009). These complex D(G)VM-fire models (Hantson et al. 2016) have been used to assess fire activity up to the global scale, as well as the contribution of vegetation fires to carbon emissions to the atmosphere. Predicting how forests and landscapes will change, and in turn how fuels will change, is thus highly challenging and by far exceeds the context of forest fire risk assessment.

Table 1 reports the main characteristics of the 22 projection studies that were reviewed in this paper. Among them, 8 studies were conducted at continental scale, 9 at national scale, and 5 at regional or local scale. 12 studies considered the A2/RCP8.5 scenario, 12 considered the A1B scenario, and few of them other scenarios. 14 studies used climate series from only one climate model to represent the future climate. Daily climate datasets were generally used and spatial resolution was often 25 km, ranging between 10 and 50 km. However, studies strongly differed by fire models and projected fire metrics, as detailed hereinafter.

A number of projection studies (13 among 22, Table 1) resort to the Fire Weather Index (FWI) System, a worldwide used fire danger rating system. The FWI System was developed by the Canadian Forest Service and was initially designed for pine fuel types (Van Wagner 1987). The FWI system empirically reflects the mechanistic impact of weather variables on fuel moisture and fire danger at daily to monthly time scales (Flannigan et al. 2016). It consists of six components: three moisture indices corresponding to three different fuel response times track the cumulative and dynamic influence of weather conditions on the moisture content of dead fuels (the Fine Fuel Moisture Code, FFMC; the Duff Moisture Code, DMC; and the Drought Code, DC); the other indices describe the potential for fire spread (the Initial Spread Index, ISI), fuel consumption (the Buildup Index, BUI), and fire intensity (Fire Weather Index, FWI), as a combination of the former indices. The indices are calculated daily from noon (12:00 LST) air temperature, relative humidity, wind speed and previous 24-hour accumulated precipitation. The FWI System also includes the Seasonal Severity Rating (SSR), which represents fire control difficulty over a season. The SSR is a seasonal average of the Daily Severity Rating (DSR), which is computed from the daily FWI.

Reviewed projection studies either directly projected the FWI or its components as measures of fire danger (studies 1,2,3,9,10,11,12,16,17,1819 in Table 1), or used the components of the FWI system as predictors of fire activity (studies 3,21). One study (4) used drought indicators not based on the FWI System, namely the standardized precipitation evaporation index (SPEI, Vicente-Serrano et al. 2010), to predict summer burnt areas. Few studies established direct correlations between seasonal fire number (22) or burnt area (13,15,22) and monthly weather variables by regression methods.

Some projection studies (11,16,19,20) assessed the impact of climate change on both wildfire activity and behaviour by simulation modelling. In this approach, fire events are explicitly run in the landscape under specified wind speed and fuel moisture conditions. In the context of future projections, these conditions must be specified from future climate scenario. In particular, fuel moisture was estimated either from the FFMC and DC codes of the FWI (16) or from empirical fuel moisture – weather relationships (19,20). Fire simulations take spatial variations in fuels and topography into account and provide variables measuring fire behaviour (rate of fire spread, fireline intensity, flame length) and fire activity (burn probability per pixel, fire size). This approach is well-suited for local to regional scales, but has also been applied nationally (11).

Finally, some studies (5,6,7,8) have projected burnt areas with DGVM-fire models, namely the CARAIB (5) and CLM-AB DGVM (6,8) coupled with a fire model inspired in the CETEM model (Arora and Boer 2005), and the LPJ-GUESS-SIMFIRE and LPJmL-SPITFIRE DGVM-fire models both used in the same study (7). Importantly, the physiological processes at play are represented in the DGVMs, which enables the capture of climate and CO2 effects on primary production and gives a basis for the estimation of fuel load dynamics. Except for LPJ-GUESS-SIMFIRE, fuel loads are computed from the carbon pools accounting for the above-ground biomass. In SIMFIRE, the annual maximum FAPAR (fraction of vegetation-absorbed photosynthetically active radiation) represents vegetation fractional cover and is used as a proxy for fuel load/continuity. In CARAIB and CLM models, soil moisture dynamics as driven by climate/weather variations are predicted from the coupling of plant and soil hydrological processes, and soil moisture is used to represent fuel moisture, which in turn conditions fire spread in the fire module. Both LPJ-GUESS and LPJmL DGVM use the Nesterov drought index to represent the effect of fuel moisture on fire. It is calculated using daily temperature, dew point (~relative humidity), and number of days since last significant precipitation event. This index is used to compute fuel moisture and a fire danger index that influences both the probability of ignition success and fire spread in SPITFIRE, while the maximum daily Nesterov index is used to calibrate the annual burnt area model in SIMFIRE. An important difference between LPJ-GUESS and LPJmL is that the former represents vegetation based on explicit-individuals, whereas the later uses average individuals. It must also be noticed that SPITFIRE is a detailed process-based fire model and includes fire effects (Thonicke et al. 2010), whereas SIMFIRE predicts fractional burnt area from a simple function of land cover type, mean monthly FAPAR, annual maximum of the Nesterov index and population density, which has to be parameterized from observed burnt areas (Knorr et al. 2013).

3. Projections results

A number of factors affecting projections of fire danger or activity renders the systematic comparison of quantitative results quite challenging. This includes the nature and associated statistics (mean, quantile, threshold exceedance) of fire metrics, the climate model(s) and run(s), the socioeconomic scenario(s), the historical and future periods selected for computing present and future metrics, the geographic area, as well as the climate-fire model used to predict the fire metric. Table 2 reports a selection of quantitative results that we extracted from the different studies for the purpose of studies comparison. We used the results reported in the text, tables, or data shown in the figures. Results were classified according to the nature of the fire metric and the geographic area (rows of Table 2), the emission scenarios (A1B and A2/RCP8.5) and the time-horizon considered (mid-century and end of century) (columns of Table 2). Too few studies dealing with other scenarios or other time-horizons have been carried out to be included in this table. The first part of Table 2 reports fire danger metrics based on the FWI system and the second part reports fire activity metrics derived from statistical-correlative fire models and process-based fire models. For the sake of comparison, we calculated, for each study, the relative rates of change of the fire metrics per decade up to the time horizon considered. For fire season length, we reported changes in days per decade. Normalizing by the number of decades reduces the differences resulting from the different definitions of the reference and future periods between studies. Finally, we felt it would also be relevant for the purpose of our review to report climate trends expressed as change by decade (e.g. Celsius degrees per decade), but this data was almost never available in the reviewed studies. Some studies were not included in Table 2 because no quantitative results were provided (e.g. only maps).

Table 2 reveals that the number of (apparent) replications of the results is small and that the different scenario/horizon combinations have not been equally explored. Regarding fire danger metrics, data mostly come from the three studies of Moriondo et al. (2006), Bedia et al. (2014a) and Amatulli et al. (2013) at the scale of Southern Europe, which all provide results down to national scales. Moriondo et al. (2006) and Bedia et al. (2014a) both report mean seasonal FWI and fire season length, while Amatulli et al. (2013) and Bedia et al. (2014a) report SSR. Four national or regional studies also provide the mean FWI. Regarding fire activity, most studies report burnt areas, whereas fire number or fire size are seldom reported. A single study reports national burnt areas (Amatulli et al. 2013). We provide detailed comments on the results of the studies and on Table 2 data in Supplementary material. In the following, we propose a tentative summary of these results.

All studies show future increase of fire danger and fire season length, everywhere in southern Europe, as measured through the FWI system. The relative increase in mean seasonal fire danger ranges between 2 and 4% per decade in the Mediterranean regions of Europe, and it reaches 7% per decade in France, where the fire-prone area is currently limited to the south. The projected increase in severity of the fire season, as measured by the SSR, is even higher (3-7% per decade in the Mediterranean area), and fire season lengths are projected to increase by 3-4 days per decade for the whole area of southern Europe. We note that these results mostly rely on three studies that differed in many aspects. One can claim that diversity in modelling options may bring robustness, but variations in definitions of fire danger metrics render comparisons between modelling results difficult, e.g. Bedia et al. vs Moriondo et al in Supplementary material.

Future burnt areas have mostly been studied at continental scales, with the noticeable exception of the Iberian Peninsula, in which several regional to national scale studies estimated future burnt areas. Projected changes strongly depend on the models used to rate climate change impact, and in fact on the drivers that they incorporate. When only seasonal fire weather or the coincident drought are considered, burnt areas are projected to increase everywhere in southern Europe. This result is similar to those obtained from potential fire danger projections, but corresponding rates of increase are substantially higher (15 to 25% per decade for most areas, and much more for Spain). When the effects of fuel load/continuity are considered, through vegetation dynamics in process-based models or climatic proxies (antecedent weather or drought conditions) in statistical approaches, burnt areas generally increase at much lower rate (not exceeding a few percent per decade) and can even decrease in the current most arid regions (e.g. south Iberian Peninsula). Hence, large uncertainty exists about future trends in these regions. For the northern margins of the current Mediterranean area, fuel load/continuity is not likely to become a limiting factor and future increase in fire activity is expected there. Hence area at risk should expand to new fire-prone regions, such as the western and central France, the mountains surrounding the Mediterranean basin, or central-eastern Europe.

Regarding fire number, we must expect an increase with potential fire danger, but very few results are available and do not allow to draw general conclusions.

Even though local climatology is sensitive to elevation, this factor has been seldom accounted for until now, with a few exceptions. For example, Moriondo et al. (2006) have adapted the length of

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their fire season to location (hence to elevation), and aggregate their results over an altitudinal gradient.

4. Limitations and uncertainties

Reliability of fire danger/activity projections depends on the biases and uncertainties resulting from both climate projections and climate-fire models. The evaluation of climate projection uncertainty in climate impact studies is addressed in numerous past and on-going researches, and goes far beyond the scope of the present review (e.g. Foley 2010, Maraun 2016). In the context of fire projections, the main issues relate to the large biases observed in climate model predictions of temperatures and precipitations, and to the difficulty of detecting robust trends in fire danger metrics from inter-annual and decadal fluctuations. For climate-fire models, the main issues relate to their intrinsic performance in reproducing fire metrics, but also to a number of fire factors of very different nature, which can be embedded in empirical climate-fire relationships. These factors include both fuels (load, structure, moisture content) or human-related factors (ignition patterns, fire management practices). Spatial and temporal variations in climate-fire relationships have already been observed in Europe or elsewhere (e.g. Littell et al. 2009, Bedia et al. 2014b, Higuera et al. 2015, Ruffault and Mouillot 2015), which raises the question of whether current empirical relations are applicable in the future.

In the following subsections, we develop these different points and specifically review studies that help to assess those sources of biases and uncertainty in the context of wildfire projections studies in southern European countries.

4.1. Uncertainty associated with climate projections

Partition of uncertainty

Uncertainty in climate projection arises from three distinct sources (e.g. Hawkins and Sutton 2009): internal or intrinsic variability of the climate system (natural fluctuations), model uncertainty (different models, or even different runs of a given model, respond differently to the same radiative forcing), and scenario uncertainty (different emission scenarios lead to different radiative forcing). For mean annual global temperature, projections uncertainty is dominated by intrinsic climate variability and model uncertainty over the next few decades (<30 years), whereas emissions scenarios led to the most variance at longer time scales (Hawkins and Sutton 2009). The most common approach for an assessment of climatic uncertainty is to generate a set of simulations (ensemble) from a set of models (multi-model) following contrasted scenarios or concentration pathways.

Several studies followed such a multi-model approach for fire danger/activity projections (refs 2,4,6,7,6,15,22 in Table 1). These studies consistently showed that uncertainties arising from climate models had important and significant impacts on wildfire projections. For instance, Sousa et al. (2015) provided ensemble means and inter-quartiles for burnt area trends in the Iberian Peninsula, and showed an uncertainty ranging from (roughly) +/-20 to +/-60% in 2075 (inter-quartile over mean predicted burnt area), depending on the region of interest. Turco et al. (2018) also reported that the uncertainty in burnt area projections in southern Europe was dominated by the spread in climate models. Similar results were obtained for burnt areas projected with DVGMs (Migliavacca et al. 2013a). It is also interesting to note that climate model uncertainty is modulated by the fire metric under study (Lung et al. 2013, Bedia et al. 2014a). For instance, Bedia et al. (2014a) showed that threshold-dependent statistics (e.g. number of days above some FWI threshold) exhibited much higher model uncertainty than mean or 90-th percentile FWI.

A number of reviewed studies have investigated the impact of scenario uncertainty on wildfire projections (refs 1,3,4,7,9,13,14,17,21 in Table 1). The first study by Moriondo et al. (2006) on FWI projections at the continental scale pointed out that increase in FWI by the end of the 21st century was much higher (+23%) under the A2 than under the B2 scenario (+16%). These findings have since been largely confirmed by studies at regional (e.g. Loepfe et al. 2012) and continental scale (e.g. Amatulli et al. 2013).

The uncertainties due to both models and scenarios were only addressed in two of the projection studies reviewed in the present paper (refs 4 and 7 in Table 1). However, none of them provided a thorough assessment of uncertainty partition and its evolution over time. Turco et al. (2018) used two scenarios (RCP4.5 and RCP8.5), but selected periods to achieve a predefined warming target of (+1.5, +2 or + 3 °C) for burnt area simulations. Wu et al. (2015) provided the most detailed assessment of uncertainty partition over time (see Fig 4 in Wu et al. 2015), but did not partition the different uncertainty sources and combined climate scenarios (RCP2.6 and RCP8.5) with population scenarios. Thus, a thorough assessment of the respective sources of uncertainty is still missing in wildfire projections studies in southern Europe. In particular, a quantification of when and how fire danger or activity would excess the intrinsic variability of the climate system is still missing (see the notion of time of emergence, for example in Abatzoglou et al. 2019).

Bias correction of climate model outputs

Another source of uncertainty in fire projections arises from the bias correction of climate model outputs. To date, General Circulation Models (GCM) are run at too coarse spatial resolutions for a direct use of outputs to project wildfire danger or activity. Besides, global and regional climate models are generally strongly biased and these biases are likely to have significant impacts on the estimations of climate change impacts, as the climate-fire relationship is not linear. In simulations of 13 RCMs over Europe, Christensen et al. (2008) found systematic biases in monthly mean temperature and precipitations as shown by their evaluation against observational data. Turco et al. (2013a) also reported large biases in seasonal precipitations over Spain, as provided by the ENSEMBLES regional climate projections. Thus, climate model outputs are generally not directly used as input for climate-fire models without any form of bias corrections, especially when fire models are calibrated against observations. However, the implications of bias corrections methods are still a matter of debate in the climate research field, because they alter the consistency of spatiotemporal fields and the relations between variables, and they violate conservation principles (see Boberg and Christensen 2012; Ehret et al. 2012).

Among the projection studies reviewed in this paper, we observed several approaches regarding bias correction of climate outputs. Some studies used raw climate output, i.e. uncorrected for bias, for FWI projections (e.g. Moriondo et al. 2006, Bedia et al. 2014a), while others used one or several bias corrections methods (e.g. Amatulli et al. 2013, Migliavacca et al. 2013a, Sousa et al. 2015, Turco et al. 2018). Turco et al. (2018) evaluated the impact of bias correction on burnt area projection (by comparing the results obtained with and without bias corrections) and reported differences between those two sets of simulations.

Bias corrections in climate impact studies are commonly applied on temperature and precipitations, but other variables such as wind speed or air humidity have been little considered so far (Haddeland et al. 2012, Li et al. 2019). In the reviewed studies, only temperature and/or precipitations were corrected when bias was considered. Yet both fire danger (here rated by the FWI) and fire activity are also sensitive to relative humidity and wind speed (eg Dowdy et al. 2010).

Furthermore, the choice of the bias correction method itself also has an impact on projection (Sousa et al. 2015). It should be noted that all bias correction algorithms used in the projection studies reviewed in this paper were applied to univariate time series and therefore neglected the dependence between different variables, which can be of importance for wildfire danger assessment (Cannon et al. 2018). In this regard, the recent developments in multivariate bias corrections procedure can allow some refinements in wildfire projections (Vrac and Firederichs 2015, Cannon 2018).

4.2. Climate-fire models

Fire Weather Index

Most projections of fire danger or fire activity in southern Europe have used the FWI as climate-fire model. The relevance of this approach depends on the representativeness of both fuel moisture dynamics by the different FWI moisture codes, and of fire behaviour and activity by the FWI itself, in the specific context of Mediterranean weather and fuel conditions.

The FFMC has been designed to represent the moisture of dead fine fuels (litter, elevated dead material, cured grass), which, with wind speed, determines fire-spread rate in a given fuel complex. Aguado et al. (2007) found that the FFMC correlated fairly well (r^2~0.5) with the fine fuel moisture of litter. Resco de Dios et al. (2015) confirmed such correlation, but also reported significant bias and dispersion errors in FFMC, as well as in other dryness indices tested in the study.

Shrubs are widespread Mediterranean fuels and the moisture of their foliage (live fuel moisture content, live FMC) can be an important fire driver (Yebra et al. 2013). Recent findings have confirmed the somewhat controversial effect of live FMC on fire spread and activity, motivating further attention to its prediction (Rossa and Fernandes 2018, Pimont et al. 2019). Several studies showed that the moisture content of some Mediterranean shrub species was correlated with the Drought Code (Castro et al. 2003; Ceccato et al. 2003; Pellizzaro et al. 2007; Viegas et al. 2001), but the strength of the correlations was moderate, especially when the moisture dataset included a variety of sites and species (Ruffault et al. 2018). An hypothesis that to date has been seldom accounted for is that the response of plants to drought varies among species type and biomes (McDowell et al. 2008, Vicente-Serrano et al. 2013, Martin-StPaul et al. 2017). Indeed, when applying the FWI system, the drought influence on plants is implicitly assessed from components (DC, DMC, FFMC) originally developed for dead fuels. These sub-components do not account for specific responses, and the same issue holds for other drought indices, including the SPEI used by Turco et al. (2018). Plants exhibit various strategies to resist drought (some avoid the desiccation of their living tissues whereas others allow some dehydration during drought), and such strategies could vary according to their habitat aridity. This might have a very important impact on climate-fire relationships calibrated over distinct regions.

Fire intensity is a fundamental fire behaviour variable as it measures the energy release rate of a spreading fire front and largely determines fire suppression difficulty and some fire effects (Van Wagner 1987). As mentioned by many projection studies among those reported in section 2, the FWI has been scaled with fire intensity, as it was designed to reflect variations in Byram's fire intensity, and the SSR builds on daily FWI values to represent fire control difficulty. This scaling was based on a set of 22 experimental fires in pine stands in Canada (Van Wagner 1974). However, the understanding of FWI-fire intensity relationships is quite limited, especially for European vegetation types. Palheiro et al. (2006) related the intensity (up to 100 MW m^{-1}) of experimental fires and wildfires in *Pinus pinaster* stands with the FWI or the ISI in combination with the BUI and succeeded in explaining 68-80% of the observed variation, depending on modelling option. Surface and forest floor fuel consumptions, which impact fire intensity, were found to be correlated with the DMC and BUI codes in Mediterranean pine stands, although the response ceases beyond moderate dryness levels (Palheiro et al. 2006; Fernandes and Loureiro 2013). However, similar attempts in shrublands, which are widespread in southern Europe, have been largely unsuccessful. This highlights the difficulty in extending the FWI System beyond its conditions of development and the need for FWI modifications, including in the representation of fuel moisture and fire behaviour (Anderson 2009). For instance Chelli et al. (2015) have calibrated the FFMC and the DMC of the FWI System to improve the prediction of measured fuel moisture content in two regions of Greece and Portugal.

Fire danger being not an observable variable, fire activity is often more relevant to decision makers and land fire managers than a fire danger index, even scaled with fire intensity. Yet there are clear evidences in Europe that fire danger as rated by the FWI is indicative of fire activity. Large fires in southern Europe (> 500 ha) are associated with high values of FWI codes (Camia and Amatulli 2009). In Sardinia and Corsica, Ager et al. (2014) found that 'an increase in the FWI from 30 to 60 produced on average an approximate eightfold increase in the odds of a large fire'. In Portugal, the increasingly high FWI relates to the development of increasingly larger fires (Fernandes et al. 2016a), with a steeper response for fires >2500 ha (Fernandes et al. 2016b). The FWI has successfully been used to define fire danger classes based on wildfire duration as observed by satellite sensors in southern Europe (DaCamara et al. 2014). The FWI codes may well correlate with observed burnt areas in Europe, but this depends on the region (Amatulli et al. 2013, Bedia et al. 2014a) and is likely to be affected by fuel conditions and anthropogenic drivers such as suppression policies or human activity and infrastructures (see sections 4.3 and 4.4).

Significance of FWI-based metrics

Studies projecting fire danger have often averaged the FWI across the territory of interest or over the fire season. According to the description of the FWI system, the FWI is considered 'not suitable for averaging and should be used as its single value daily' (Van Wagner 1987). As we already noticed, when an average fire danger over a season is desired, it is recommended to average the DSR, which scales with a 1.77 power of the FWI, resulting in the SSR. Only a few studies have used the SSR. According to Van Wagner (1987), the DSR reflects the fact that fire control difficulty rises sharply (not linearly) with the FWI. Moreover, Flannigan et al. (2013) have reminded that the DSR was originally created to compensate for the exponential increase in area burnt with fire diameter. This implicitly means that burnt area should scale exponentially with the FWI, suggesting that it should be more sensitive to climate change than the FWI. Hence we suggest that although means and percentiles of FWI have a statistical meaning (central tendency and dispersion of the distribution of values in a territory or over a season), they do not have a physical or an operational meaning (such as fire control difficulty in a territory or over a season). On the contrary, fire number and burnt areas are well-defined metrics with a physical and an operational meaning, and can be spatially or temporally integrated.

Fixed thresholds values of daily FWI have been used to define more or less high fire-danger days, and project how their number will evolve under climate change. It would be attractive to consider these thresholds as standards, but we rather suggest that they have limitations. Moriondo et al. (2006) referred to a report by Hanson and Palutikof (2005) to justify the use of 15 and 45 as threshold values for elevated (>15) and extreme fire danger (>45), and then later studies have used these values. This analysis was in fact published later on in Good et al. (2008): the FWI thresholds of 15 and 45 for elevated and extreme fire danger respectively, were obtained from an analysis of fire density against FWI in the vicinity of 7 meteorological stations in Greece and Italy. First, these thresholds were visually estimated and thus are somewhat arbitrary. Second, other threshold values might have been found if data were collected at other locations, and indeed, Karali et al. (2014) found that threshold corresponded to a given fire density highly dependent on the region of Greece considered. Hence we rather consider them as orders of magnitude.

Moreover, the number of days above thresholds is likely very sensitive to the method used for the computation of the FWI (see Supplementary material), as well as to the bias correction that might be applied to climate simulations (see section 4.1). In this way, the use of fixed thresholds was found to lead to important uncertainties as compared to other more stable metrics such as FWI percentiles (Bedia et al. 2014a), which moreover are location-dependent. Although the FWI computation is well-defined, several methods have been proposed for its computation from climate simulation datasets, because they often only include daily variables, while the FWI should be computed from 12:00 (LST) values of temperature, relative humidity and wind speed. This strongly impacts the FWI values (Herrera et al. 2013). Hence several proxies have been used to estimate the FWI from daily variables. These aspects, in addition to bias correction mentioned above, makes it difficult to define a stable reference level for the FWI among climate simulations.

In the reviewed projection studies, the fire season was most often defined as a fixed, but variable among studies, number of months, including the summer months, or sometimes its length was computed by setting a threshold value (15) of time-averaged (2 weeks) FWI (Moriondo et al. 2006). This likely had a strong impact on the reported metrics (Supplementary material). The drawbacks associated with a fixed period to report change in fire danger during the fire season are that the selection of this period applies to the whole area considered by the study, while the fire season likely depends on local characteristics, such as elevation, and that climate change may induce significant fire activity out of this period in the future. Hence we suggest that a variable fire season length should be preferred, but then, a criterion for defining the fire season must be adopted, which again raises the issue of defining when fire danger becomes significant. In the reviewed projection studies, a single threshold (suggested by Moriondo et al. 2006) has been used, while temperature-based thresholds have been used in other continents or globally. Then, in case the fire season expands in the future, reporting seasonal fire danger change as rated by the mean FWI or the SSR over the new fire season length could hide a more important change during the most severe part of the fire season, since additional, but relatively low danger days have been included in the computation of the mean corresponding to future conditions. This issue has been first raised by Flannigan et al. (2013) who introduced the Cumulative Severity Rating (CSR) to rate the seasonal fire danger. The CSR is the sum of the DSR values over the fire season, rather than its mean. Moreover, it can be computed in the future for both the historical and future fire seasons. This allows to separately estimate the contribution of fire activity increase during the historical fire season (due to increased fire intensity) and the contribution of fire season lengthening (more days with significant fire danger) to the total change in fire activity. We suggest that using the CSR or similar cumulative rating would be the best option for future studies.

Statistical-correlative fire models

Fire activity has been modelled through correlations with the FWI components (e.g. burnt area models of Amatulli et al. 2013) or by building direct correlations between fire metrics and climate variables, i.e. rather than using the FWI or any other fire danger index. Vázquez et al. (2012) built a series of statistical linear models for fire number and burnt area as function of a climate variable (monthly statistics) for 15 ecozones covering Spain. Each ecozone was represented by a potential vegetation type. The selected predictor variable was a temperature statistic in all models, but the statistics changed among ecozones, as well as the variances explained by the models that ranged from 20 to 68% for the number of fires and from 12 to 66% for the burnt area. Sousa et al. (2015) distinguished four pyro-regions (i.e. characterized by four different fire regimes) over the Iberian Peninsula and built a statistical linear model for the inter-annual variations of seasonal (i.e. summer, March depending on the pyro-region) burnt areas in each pyro-region. Selected predictor variables were mostly based on temperature and precipitation data, and were different among pyro-regions. Models explained 52 to 72 % of the variance. In Catalonia, Turco et al. (2013b) adjusted linear regression models to the log-transformed number of fires and burnt areas observed in summer, respectively accounting for up to 91 and 76% of the observed variance. These models were the basis for the Turco et al. (2014) projection study. Selected predictor variables were based on temperature and precipitation data, including both concurrent (summer) and antecedent conditions. These studies, among others in other continents, strongly suggest that the climate-fire relation can be strong, but is not unique and that its strength depends on the local or regional conditions.

In the reviewed studies most climate data were daily data, but the weather statistics (or fire danger indices) used as predictors in the burnt area models were monthly or seasonal variables. In some regions or at country level, these variables can explain a large part of the interannual burnt area variability, as illustrated above, but their temporal resolution is likely too low to capture the extreme fire events that much contribute to burnt areas (Hernandez et al. 2015).

Finally, an issue which is inherent to statistical approaches is that the future simulated climate can be outside the historical training climate used to adjust the climate-fire model, or some future frequent weather conditions might be rarely observed in the historical period and thus have low weight in the model used for projecting the future.

Spatio-temporal point-process models

Fire occurrence and subsequent burnt areas can be viewed as the result of a spatio-temporal point-process (Xi et al. 2019). Methods for the estimation of such a process in the frame of fire risk assessment have been developed from the seminal works of Brillinger et al. (2003) and Preisler et al. (2004). This modelling framework has been used for projecting future fire occurrence and burnt areas in California (Westerling et al. 2011). In Europe, it has been used for examining spatio-temporal patterns of fire occurrence in Sardinia and Corsica (Ager et al. 2014), but to our knowledge not for projecting future wildfire activity. Yet this modelling approach offers several advantages over statistical-correlative models. The probability of ignition and the expected fire size are modelled separately, acknowledging that ignition and spread result from distinct processes and factors; in reviewed studies, burnt areas have been projected with regression-type models with no simultaneous consideration for fire number, making it impossible to separate distinct sources of change in fire activity. Fire number and fire size distributions, hence not only means, are modelled and then fire events can be generated randomly, which allows to run ensemble fire simulations. Extreme events, which much contribute to total burnt area, can be taken into account by using heavy-tailed fire size distributions. Spatio-temporal effects can be modelled to avoid biases and confounding effects related to factors not explicitly taken into account. This probabilistic modelling approach is however limited by computational difficulties (size of fire events datasets, parameter estimation) that can be partially overcome through data aggregation (Poisson-additivity, Marchal et al. 2017) or efficient estimation techniques (Gabriel et al. 2017).

Spatially-explicit fire spread models

Simulation modelling of fires, as illustrated by the study of Lozano et al. (2017), could help overcome some of the limitations of climate-fire models currently used for projections of climate change impact. Indeed, simulation modelling permits to account for explicit effects of climate/weather variables on fire behaviour processes, through the fire spread equations. However, this approach requires additional estimation and modelling components, since fuel moisture content must be predicted; fuel types are explicitly distinguished and spatially-distributed, accounting for fuel variations and land use; and the effects of other fire drivers such as human-related factors (e.g. ignition patterns, suppression policies) can be parameterized separately. In addition, a variety of local fire behaviour outputs, instead of a single indicator, can be used to characterize fires. The study of Lozano et al. (2017), however, also relied on several important assumptions: ignition density patterns in the future do not depart from the historical period, all fire simulations (current and future) were carried out for exactly ten hours after ignition, and each land cover was represented by a single fuel type, selected among only three fuel models for the whole country. The outcomes of the study might be sensitive to these critical, but currently necessary, assumptions. Similarly, Kalabokidis et al. (2015) and Mitsopoulos et al. (2015) ran fire simulations under constant historical ignition density and constant fire duration. Hence, in these three projections studies, the impact of climate change was accounted for through changes in fire spread driven by the changes in the distribution of wind speeds (which are generally minor) and in fuel moisture levels, whereas the effects of climate change (in terms of weather or fuel moisture) on both ignition and extinction (or duration) of fires were ignored. Clearly, these studies provide insights on future climate-induced changes in fire behaviour variables and mean fire size conditional to specified ignition, duration and also fuel types (i.e. current fuel types are used), but the projections of fire activity are probably still incomplete.

DGVM-fire models

Here we only address the components of fire models used in projection studies that directly relate climate and burnt area in DGVM-fire models. The fuel load/continuity component is addressed in the next section. We first focus on the fuel moisture component, which is crucial in climate impact assessment.

SIMFIRE and SPITFIRE in Wu et al. (2015) use the Nesterov index to represent the fuel moisture effect on fire, as well as the fuel moisture itself in the case of SPITFIRE. The Nesterov index has shown poor correlations with litter or grass fuel moisture content and in fact the poorest correlation among the five metrics tested by Ganatsas et al. (2011) in Mediterranean conditions. This index was also the worse predictor of live fuel moisture content among the six categories of indices tested by Ruffault et al. (2018). In addition, evaluations of Nesterov index against fire danger have also shown the lowest correlations with fire density in Germany (Holsten et al. 2013), with Pearson correlation of 0.5 in order of magnitude, to be compared to 0.6-0.7 obtained with the FWI (highest correlation in this study). Hence, the Nesterov index at least in the Mediterranean does not seem to be the best option to represent neither fuel moisture dynamics nor moisture effect on fire.

The fire models used with the CARAIB DGVM in Dury et al. (2010) and with the CLM-AB DGVM in Migliavacca et al. (2013a) use the DGVM prediction of soil moisture as a surrogate for fuel moisture. Actual (i.e. measured) soil moisture content has been shown to be a good explanatory variable of litter or grass moisture content, better than weather variables or drought index in the case of litter (Ganatsas et al. 2011), which suggests that a modelling of litter or grass fuel moisture derived from soil moisture is a relevant option. More recently, Ruffault et al. (2018) showed that soil moisture ,as predicted by a water balance model (analog to hydrological models in CARAIB and CLM-AB), was also the best predictor of live fuel moisture content among the six categories of indices tested. Those findings suggest that using the hydrological module of a DGVM for representing live fuel moisture seems to be a relevant option, better than any drought index. Moreover, the hydrological module of CARAIB captured the spatial patterns of water runoff across Europe, although their magnitude was systematically underestimated (Dury et al. 2010).

Second, we focus on how well the DGVM-fire models used in projections studies predicted burnt areas. The maps shown by Wu et al. (2015, figure 1) reveal that with respect to fire databases burnt areas are overestimated for parts of Spain, half eastern France, some regions of central-eastern Europe, and the coastal margins of Turkey, especially with LPJmL-SPITFIRE, which for example predicts unrealistic fractional burnt areas per year in eastern France. In contrast, burnt areas are underestimated in the North-western of Iberian Peninsula, which exhibits the highest fire activity in southern Europe. According to Figure 2 in Wu et al. (2015), the two models do not seem to capture interannual variations in burnt areas in the Mediterranean basin, but temporal and spatial correlations are not reported. We already mentioned the large overestimation of burnt areas with the model used by Migliavacca et al. (2013a). This model results from an improvement of the original CLM-AB model through better parameterization of fire ignition/suppression (Migliavacca et al. 2013b): the seasonal variations and the summer peak in fire activity were reproduced well by the improved model, but the interannual variations (i.e. deseasonalized time-series) still exhibited modest (~0.4) or even low (0.17 for Portugal) correlations. In fact, time-series of monthly burnt areas over 1991-2009 show similar modelled peak fire activity every, whereas the interannual variation of the actual peak is large. Hence, definitely, the model does not capture interannual variability, which questions its ability to simulate the climate impact on burnt areas.

Burnt areas predicted by Dury et al. (2010) with the CARAIB-CTEM model underestimated the observed data, but in this study the objective was to simulate the potential fire regime without people, hence human-related factors were not considered in the simulation. The model reproduced interannual variability of burnt areas at European scale quite well (correlation 0.76).

Fire data issues

An additional limitation and source of uncertainty lies in the accuracy and resolution of fire datasets that are used to statistically derive or calibrate (in more process-based models) climate-fire relationships. National or regional fire datasets have been used in projection studies at the national level (e.g. Carvalho et al. 2010, Sousa et al. 2015). They provide ground-based statistics at fine temporal and spatial resolution over relatively long time periods (as early as in the 1970's in the Euro-Mediterranean). Unfortunately, such datasets do not systematically exist or are not publicly available. In addition, some inaccuracies have also been reported with significant impacts on burned area estimates (Pereira et al. 2011, Turco et al. 2013c, Ruffault and Mouillot 2015) and systematic evaluation of these datasets is currently lacking. Remote sensing products can also be used for calibration or evaluation of fire projections (e.g. Migliavacca et al. 2013a, Wu et al. 2015). Their benefits are undeniable where local ground-based statistics are lacking or incomplete, as it is the case for some countries in southern Europe. Thus, continental-scale projections of fire activity could use models for burnt areas derived from remote sensing products (e.g. Bedia et al. 2014a). Yet remote sensing products also bring a number of issues for projections, including inaccuracies in burnt area estimations because of omission and commission errors, difficulties when reporting small fires (< 40 ha), and they are also limited by the availability of images (early 2000's). We refer the reader to the comprehensive review of Mouillot et al. (2014) for further information on remote sensing products and their uncertainties. Regardless of the data source chosen to estimate fire activity, their uncertainty impacts on the form and parameters of climate-fire models are rarely evaluated and are currently unknown.

4.3. Influence of fuel load and fuel structure

Most projection studies have implicitly assumed a response of wildfires to fuel load/continuity that is constant both in time and space. However, there is evidence in southern Europe of both temporal and spatial variations in fire activity that can be attributed to fuel variation. Furthermore, climate warming, as well as the increase in the atmospheric CO_2 concentration, will impact primary production and plant water stress and distribution area, which in turn determine the amount and characteristics of fuels, although trends are still uncertain (e.g. Cheaib et al 2012; Lindner et al 2014).

The areas burnt during the summer season are strongly related to seasonal drought in southern Europe (Turco et al. 2017). However, antecedent conditions prior to the fire season (from a few months to a couple of years before), can influence fuel build-up and may also contribute to interannual variations in fire activity in the Mediterranean area (e.g. Turco et al. 2013b, 2014, Koutsias et al. 2013), even if such effect is not generalized in southern Europe (Turco et al. 2017).

In addition, it has been shown that there were spatial biases in current or future fire activity that could be related to the fact that fuel load/continuity is or will be insufficient to sustain fire spread in the most arid regions of southern Europe. Based on a statistical model of the climate-fire relationship that includes biomass effects in Mediterranean-type ecosystems, Battlori et al. (2013) found that in the currently warmest and driest areas a warmer-drier climate could result in decreased fire activity (e.g. south rim of the Mediterranean Sea for the Mediterranean Basin), whereas a warmer-wetter climate could further enhance fire activity (e.g. south of Spain). Similarly, Pausas and Paula (2012) studied how aridity triggered fire activity over the Iberian Peninsula, which encompasses a large productivity gradient owing to climate variation (from oceanic to dry-Mediterranean). They estimated local thresholds of aridity above which fire activity was significant. They reported lower thresholds in the less arid regions, which shows that fires can spread under less warm and dry weather conditions in less arid regions. They suggested that this pattern was explained by fuel continuity, which is higher in less arid regions, as fuel fragmentation increases with aridity. Loepfe et al. (2014) analyzed burnt areas of satellite-detected fires in Europe (including arctic regions) and North Africa. They found that fire size was not controlled by fuel moisture in regions above a given threshold of dryness. The authors suggested that burnt area was limited by insufficient fuel load in these dry regions. Beyond the FWI projections of their study, Bedia et al. (2014a) also examined the relation between burnt area and fire weather in different regions of France, Italy and Greece. This climate-fire relationship (i.e. sensitivity of burnt area to climate as represented by the 90th percentile of FWI in summer) changed among regions and was poor in the most arid and warmest areas where the fire regime is likely to be fuel-limited. We note that human factors such as fire preparedness might also have played a role in contrasting regions of elevated fire danger. Fernandes et al. (2016a) analyzed the variability in the size of large fires as determined by climate and 'bottom-up' factors, including fuels, in Portugal. Large fires occurred mostly under severe weather conditions (93% of the burnt area), but fuel composition, landscape-level fuel connectivity and spatial fuel patterns (as determined by fire frequency) were, by far, the primary explanatory variables of large fire size (fuel variables summing 82 % of explained variability).

These impacts of fuel load/continuity on fire activity suggest that neglecting spatial and temporal variations of fuels in projections is probably a simplistic assumption (Brotons and Duane 2019). We found three studies (Dury et al. 2010, Migliavacca et al. 2013a, Wu et al. 2015) attempting to project fire activity in Europe accounting for spatial variations and future potential evolution of fuels. As previously mentioned, these studies relied on simulations with DGVM-fire models, which model biomass production and estimate fuel load or proxies for fuel load. In the context of increasing CO_2 atmospheric concentration, one important uncertainty is the magnitude of the CO_2 fertilization effect on net primary production (Körner et al 2007) that drives biomass dynamics.

Dury et al. (2010) used the CTEM fire module (Arora and Boer 2005) coupled with the CARAIB DGVM to project the impact of global warming on net primary production and burnt areas in Europe by the end of the century. The CARAIB model reproduced the spatial pattern of net primary production derived from satellite data across Europe satisfactorily, compared well with the mean field estimate, but showed modest correlation with the local field estimates (Dury et al. 2010). In the Mediterranean area, the net primary production was found to increase when a CO_2 fertilization effect was considered and to decrease when fertilization was neglected. Burnt areas were found to increase 3 to 5-fold in the driest years in the Mediterranean area, owing to more frequent droughts, but the relative role of biomass (i.e. proxy for fuel load) in this trend was not described. The results from Migliavacca et al. (2013a) have already been presented in section 3, but interestingly, simulations revealed that the net primary production was the main driver of fire regime in the Mediterranean area, limiting the sensitivity of fire activity to climate change. As for the study by Wu et al. (2015), we already mentioned its contrasted results with the two DGVM-fire models used and explained this difference by the specific vegetation modelling options of the two models (see section 2). Moreover, both models were also run with the CO_2 fertilization effect on primary production enabled and showed increases in fuel loads ranging from 10 to 70% all over Europe. The CO_2-induced rise in fuel load had a relatively small effect on burnt area as compared to the climate effect, according to LPJ-GUESS, whereas in LPJmL it overrode the climate effect. But with this CO_2 effect included, both models predicted increasing burnt areas. Recently, Yuan et al. (2019) evidenced however that the CO_2 fertilization effect can be counteracted by the increase of vapor pressure deficit projected by several global climate models, leading to decreasing terrestrial primary gross production. This aspect might not be correctly included in DGVM yet.

An important issue when developing or evaluating models that attempt to predict fuel load dynamics and patterns is that to date only surrogates for fuel load are available at large scales. This important issue has already been identified in studies focusing on the assessment of wildfire emissions (e.g. Knorr et al. 2012). For example, fuels change among vegetation cover types, but fuel loads are not predictable just from vegetation cover attributes (Keane, 2015). Moreover, in forests, fuels that drive fires are firstly represented by the fine dead and live biomass at or near ground level, while most of the above ground biomass (predicted by D(G)VM models or estimated from remote sensing data) is represented by woody coarse elements in the tree overstory. A direct consequence of this lack of fuel load data at large scales is that previous studies obtained only indirect or model-based evidences for fuel load/continuity effects on fire regimes at these scales.

Hence it is of primary importance to develop methods for fuel load assessment at large scales. The two possible and likely complementary approaches are remote sensing and systematic field inventories of fuel data. Forest inventory in Portugal and Spain includes fuel-related data that can help estimate fuel load and structure (e.g. Fernandes et al. 2016b, Alberdi et al. 2017, González-Ferreiro et al. 2017).

Important shifts in the distribution of potential natural vegetation are forecasted for future, warmer climate conditions in Europe owing to subsequent changes in ecological conditions (e.g. Hickler et al. 2012; Costa et al. 2015). Moreover, changes in fire regimes could enhance or accelerate such shifts that affect fuel structure. On the long-term (several decades to centuries), changes in fire activity or behaviour with respect to the current situation could alter fuels (e.g. fragmentation, vegetation types) and in turn affect subsequent fires. At the landscape scale, a pioneering study by Mouillot et al. (2002) addressed the impact of long-term climate change scenarios on shrubland and pine forests in Corsica using functional modelling of vegetation dynamics. The time between two successive fires was predicted to decrease leading to a shrub-dominated landscape. Fire feedbacks are often not considered in current projections of climate change impacts on fires, and this is the case for most projections reported in section 3, with the exception of studies based on DGVM-fire models. In the models used by Dury et al. (2010) or Wu et al. (2015), fires consume fuels, decreasing fuel connectivity and the available fuel load for subsequent fires for some time, and thus the potential for fire spread and intensity. However we already reported that the agreement of these models with observed data is relatively poor and that their predictions can strongly diverge. Moreover, positive fire feedbacks are also possible. For example, positive feedbacks in fire severity (i.e. direct impacts on the ecosystem, often positively related with fire intensity and rated by fuel consumption) between consecutive fires have been reported in USA (Coppoletta et al. 2016) and Australia (Barker and Price 2018). These studies indicate that a fire severity increase is observed when a high severity fire occurs and a new event takes place within 10-15 years. On the contrary, low severity fires generate low severity fires in a re-burn scenario.

Hence, analysis of reviewed projections revealed the lack of established models for predicting trends in biomass, fuel load and fuel structure. The uncertainty in fuel projections, which also encompasses climate projection uncertainty, appears as a critical factor in predicting fire activity in southern Europe.

4.4. Influence of human-related factors

Humans influence fire activity in many ways including ignitions, suppression activity, or fuel modifications, in most regions of the world (Bowman et al. 2011). As a result, population density has been observed to influence fire ignitions, fire size and burnt areas (e.g. Knorr et al. 2013, Hantson et al. 2015). In Europe, fire ignitions are mostly anthropogenic (Ganteaume et al. 2013), particularly in human-dominated landscapes such as the Mediterranean, where human-caused ignitions exceed natural ignitions and human activities are modifying historical fire regimes (Rodrigues et al. 2016). Land use alters landscapes, decreasing or increasing forest continuity and inducing variation in vegetation cover and fuel load. Moreira et al (2011) reviewed a number of studies and found evidence of increased fire hazard since the 1950s in Mediterranean rural areas, mostly attributing it to agriculture abandonment, including the decline of pastoral activities, that resulted in increased fuel load/continuity. Pausas and Fernández-Muñoz (2012) found a drastic increase in fire size and burnt areas in eastern Spain in the 1970s. This shift followed the increase in fuel accumulation and continuity promoted by rural depopulation and agricultural land abandonment. The authors reported that fire occurrence was poorly related to climatic conditions before 1970, whereas fires were drought-driven after this date. Fernandes et al. (2014) drew similar conclusions from fire regime history in Portugal public forests. Martínez-Fernández et al. (2013) found that fire density was mostly influenced by variable related to agrarian activities, land abandonment, rural exodus and development processes. In Greece, Sarris et al. (2014) reconstructed climate and fire history from tree-rings and fire scars observed in mountain pine forests. The combination of extreme heat and drought events with fuel accumulation due to land abandonment explained the recent large fires in these forests by comparison to older fire events, suggesting that mountain forests could face large threats due to both climate and socio-economic changes.

Fire suppression has also drastically affected fire regimes in the recent decades, as suggested by a number of studies. Salis et al. (2014) found that fire regimes in Sardinia changed between the periods of 1980-1994 and 1995-2009 with a sharp decrease in both fire number and burnt area. Land use and associated fuels were marginally modified over the period, but fire suppression capabilities increased. Ruffault and Mouillot (2015) analyzed the weather conditions that explain the inter-annual variability of fire activity in a region of southeastern France. They suggested that the reinforced fire suppression policy implemented in the 1980s rapidly decreased fire activity, but also changed the weather conditions conducive to fire spread over a significant area, from fuel-dryness driven to fuel-dryness and strong-wind driven fires. Fire activity also decreased at the whole scale of southeastern France over the four last decades, while weather conditions conducive to fire were more frequent (Fréjaville and Curt 2015). Similarly, in northeastern Spain, both the burned area and number of fires decreased over the four last decades despite large inter-annual variations (Turco et al. 2013c). Likewise, and for Spain in general, Moreno et al. (2014) report a decrease in fire activity since the 1990s. More specifically, they pointed out that this decrease in fire activity was mostly observed in the Mediterranean region of Spain and in the growing season (from May to November) in the northwest and interior regions. Brotons et al. (2013) confirmed the impact of increased fire management efforts on burnt areas in northeastern Spain. At the scale of southern Europe, for the 1985-2011 period and data assembled from Portugal, Spain, southern France, Italy and Greece, Turco et al. (2016) have identified decreases of 66% and 59%, respectively in burned area and number of fires. It is likely that fire prevention and fire suppression policies did play a role in the observed decreasing fire activity. It must be noticed however that fire suppression does not seem to impact the incidence of large fires (San-Miguel-Ayanz et al. 2013), which has recently been confirmed in France by the analysis of large wildfire data based on extreme value theory (Evin et al. 2019).

This sample of studies illustrates the variety and the complexity (i.e. both spatial and temporal variations of drivers) of the influence of human-related factors on fire activity in southern Europe and suggests that disentangling these influences from the climate impact on fire activity by statistical approaches is a challenging task. Such factors should not be neglected, also because changes in human drivers can induce important variations in fire activity that can counterbalance or exacerbate the impacts of climate change.

5. Summary and future directions

Projected trends. Despite the heterogeneity in methods and results of reviewed studies, all projection studies based on the FWI system agree on a generalized future increase in fire danger and fire season length in southern Europe. The relative increase in mean seasonal fire danger up to the end of the century under the pessimistic climate change scenarios ranges between 2 and 4% per decade in the Mediterranean regions of Europe, and it reaches 7% per decade in France. When fuel load/continuity dynamics are ignored, burnt areas are projected to increase everywhere in southern Europe, just as the potential fire danger does but with substantially higher rates of increase (15 to 25 % per decade for most areas, and much more for Spain). Large uncertainties remain when considering fuel dynamics. Area at risk should expand to new fire-prone regions, such as the western and central France, the mountains surrounding the Mediterranean basin or central-eastern Europe, where fuel load is not expected to be a limiting factor. In the warmest and driest fire-prone regions (e.g. central and southern Iberian Peninsula), fuel availability is or would become the main limiting factor of fire activity.

Need for projection standards and meaningful fire metrics. A lack of standards has been identified in the definition of some fire metrics, in their computation, and in the way the results are reported, which was a major obstacle to compare studies' results. The reviewed studies differed by the climate-fire model used. It is of high interest to get comparable results from different models in order to estimate model uncertainties and confidence intervals, similarly to ensemble climate modelling. However, reviewed projections studies were found to be highly heterogeneous beyond the diversity of fire models, making comparisons difficult and precluding replication. We suggest that the scientific fire community works on deriving common definitions and standards of the fire danger metrics to be reported in future studies. This must include a sound evaluation of the fire danger concept and how to rate this danger. In this respect, we suggest that fire activity variables such as fire density (number of fires per time and per area) and fractional burnt area (burnt area per time and per area) are the key operational data that need to be related with fire danger metrics. Fire number and burnt areas are well-defined metrics that have a physical and an operational meaning, and they can be spatially or temporally aggregated, hence they do not have the same drawbacks as fire danger metrics. Another promising area of work is the standardization of the rate of change in fire metrics with respect to projected change in climate (basically, rate of change in temperature and precipitation). Indeed, climatic projections differ among scenarios, climate models and associated methods and data such as bias correction or climate reanalysis, leading to important variations in projected climatic variables. However, the current status and the future trends of the climatology are rarely reported in projection studies. Reporting such quantities in addition to fire danger metrics would ease the comparisons among studies. Finally, performing error estimation and uncertainty analysis in projection studies should also become a standard. Reviewed projections in Europe lacked error estimation and at best provided an incomplete analysis of the uncertainties associated with

 doi:10.20944/preprints201910.0200.v1

climate projections, while the uncertainty associated with fire models is ignored. We acknowledge that the state of knowledge, data and resources can hinder uncertainty analysis, but this is a fundamental aspect that questions the reliability of depicted trends and requires further research.

Fuel processes. Fuel load/continuity have been reported to significantly alter the climate-fire relationship in Europe, and a specific response to live fuel dryness could also play a role. These fuel aspects should hence be incorporated in projections to avoid spatial or temporal bias arising from spatial or temporal fuel variations. This involves important research efforts for understanding fuel processes and predicting fuel load and fuel moisture. Indeed, commonly-used drought indices are poorly correlated with both dead and live fuel moisture content. For dead fuels, other options have been developed, including tractable methods based on vapor pressure deficit. For live fuels, there is a need for more fundamental research to understand the physiological processes driven by water potential in plant and soil that ultimately govern water content dynamics. Fuel moisture prediction not only involves the prediction of water content dynamics, but also of dry matter content of fuel elements (i.e. mass per area), hence both the carbon and water cycles in plants. Considering fuel load dynamics involves the processes of vegetation dynamics and carbon fluxes, which in turn will be influenced by both climate warming and CO_2 increases. Reviewed studies based on DGVM-fire models suggested that CO_2 fertilization itself could play a role as important as climate warming on fuel dynamics. Thus, the process-based modelling of fuels in relation to climate appears as a challenging pathway, involving plant functioning and biogeochemical cycles, to project climate change impacts on fire activity or behavior. To date the complex fuel processes have generally been ignored in simple climate-fire models such as fire danger indices or statistical models, which likely weakens the accuracy of their predictions.

Vegetation shifts. The long-term evolution of fuels under future climate is another large source of uncertainty, as it involves both change in ecological niches of plant species and human impacts in terms of forestry and wildland management. D(G)VM-fire models aim at accounting for changes in fuel structure and fire severity associated with vegetation transitions, in addition to fuel load dynamics. A number of DGVM-fire models have been developed to date, including either empirical or process-based fire modules, and the community has recently initiated a project of global fire models inter-comparison (Hantson et al. 2016, Rabin et al. 2017). More generally, evaluation and further developments of these models and of their fire and vegetation components, at both global and regional scales with different degrees of refinement, is certainly a good option to gain new understanding and better prediction capabilities of fire regimes. Indeed, in the reviewed studies, it was found that the agreement of these models with observed data is relatively poor and that their predictions can strongly diverge.

Anthropogenic processes. Most projection studies do not account for the impact of fire management and socio-economic drivers on fire activity. Burnt areas declined since about the 1990s in most fire-prone regions of Europe, which is largely explained by fire control policies. It is of great importance to assess how the fire danger increase might affect the success of these policies, especially because fire suppression does not seem to impact the incidence of large fires. In that respect, the capacity of fire suppression policies to contain fires that occur under extreme fire weather and are likely to become extreme fire events, is of central importance. There is also critical need to assess the impact of continued land abandonment that may foster increasingly large fires in non-fuel-limited environments. More generally, long-term variations in human-driving fire influences need to be better understood. Then, projections could be carried out under various policy scenarios to inform the decision-making process.

Scale of projections. Global or continental fire projections deliver possible future trends in large scale patterns of fire activity. At these scales, drought and fire danger indices inform how the potential for fires will change in current fire-prone areas or biomes and where fires could emerge as a new, significant threat to people or disturbance to ecosystems. Still, at these scales, DGVM-based projections attempt to incorporate climate-vegetation-fire interactions, in particular fuel dynamics and vegetation shifts, pursuing the objective of achieving more realistic predictions, but large uncertainties remain. To date, projection studies at regional (i.e, subcontinental) scales in southern Europe are still rare. Yet, in fire-prone areas, fire activity datasets at regional scales are often large enough to set up the models, while accurate data characterizing fire drivers such as fuels, human population or infrastructures can be made available (which is more difficult to achieve at larger scales).

Updated modeling approaches. Contemporary probabilistic approaches such as those used in the framework of spatio-temporal point-processes are well-suited for fire regime modelling at regional scales and could overtake regression techniques to improve fire process understanding and prediction. Such probabilistic modeling approach could be coupled with refined DVMs to account for climate-vegetation-fire interactions. We recommend developing the use of such approaches rather than landscape simulation approaches based on fire behavior models when exploring current and future fire regimes. The use of landscape fire models at regional scales, which involves multiple fire simulations over a multitude of weather and ignitions scenarios, does not solve *per se* the issues of predicting fire-fighting, fuel moisture or fuel load trends, as well as future fire ignition density and patterns or fire duration, under climate change. The example studies found in southern Europe rather suggest these landscape simulation approaches are more useful for exploring future changes at landscape scales in fire control, fire exposure or fire severity, conditional to ignition and burnt area regimes. They could provide valuable detailed exploration of changes in fire damages to ecosystems or of the effectiveness of fuel, forest or land management options for fire risk mitigation in the context of climate change.

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Table1. Main characteristics of the European projection studies

Reference	Spatial extent, location	Time periods(1)	Climate simulations				Climate-fire model	Projected fire metrics
			Scenario	Models (2)	Spatial resolution	Temporal resolution		
1 Moriondo et al. 2006	Continental, southern Europe	1961-1990, 2071-2100	A2, B2	One RCM (HadRM3) driven by one GCM (HadCM3) (PRUDENCE project)	0.44°x0.44° (~50km)	Daily	FWI	Mean seasonal FWI, number of days above FWI threshold, fire season length
2 Bedia et al. 2014a	Continental, southern Europe	1971-2000, 2011-2040, 2041-2070, 2071-2100	A1B	6 RCM-GCM couplings driven by 2 GCMs (ENSEMBLES project)	25 km	Daily	FWI	Mean seasonal and 90th percentile FWI, number of days above FWI threshold, fire season length, SSR
3 Amatulli et al. 2013	Continental, EU-Med countries	1961-1990, 2071-2100	A2, B2	One RCM (HIRHAM) driven by one GCM (ECHAM) (PRUDENCE project)	50 km	Daily	Multivariate regression-type models for monthly burnt area by country based on monthly FWI subcomponents	Annual burnt area by country, SSR
4 Turco et al. 2018	Continental, EU-Med countries	1971-2000, +1.5, +2, +3°C	RCP4.5, RCP8.5	9 simulations from 4 RCM and 5 GCM combinations (EUROCORDEX).	NUTS3 level (~50 km)	Daily	Regression-type models for summer burnt area by administrative regions (NUTS3) based on a drought index (SPEI, standardized precipitation evapotranspiration index)	Changes in summer burnt areas for +1°C, +2°C and +3°C warming scenarios
5 Dury et al. 2010	Continental, Europe, including Scandinavia, Finland, Russia and Turkey	1981-2000, 2081-2100	A2	One GCM (Arpege-Climate)	0.5°x0.5° (~55km)	Daily (3)	CARAIB DVM with a fire module inspired by the fire algorithm developed by Arora and Boer 2005	Annual burnt area
6 Migliavacca et al. 2013a	Continental, Europe, including Scandinavia, Finland, Russia and Turkey	1960-1990, 2010-2040, 2040-2070, 2070-2100	A1B	5 RCM-GCM couplings (ENSEMBLES project)	0.25°x0.25° (~25 km)	Daily	CLM DVM with a fire module inspired by the fire algorithm developed by Arora and Boer 2005	Annual carbon fire emissions, annual burnt area, maps of fire occurrence probability and burnt area fraction
7 Wu et al. 2015	Continental, Europe, including Scandinavia, Finland, Russia and Turkey	1981-2000, 2081-2100	RCP2.6, RCP8.5	4 ESM (2) (CMIP5 experiment)	ESM outputs interpolated to 0.5°x0.5° (~55km)	Daily(3)	Integrated fire-vegetation models, LPJ-GUESS-SIMFIRE and LPJmL-SPITFIRE	Annual burnt area
8 Khabarov et al. 2016	Continental, Europe, including Scandinavia, Finland, Russia and Turkey	2000-2008, 2026-2035, 2046-2055, 2086-2095	A2	3 GCM (CMIP3 experiment)	Not specified(6)	Monthly(4)	Same framework as Migliavacca et al. (2013), with a standalone fire model calibrated for Europe	Annual burnt area
9 Chatry et al. 2010(5)	National, France	1961-2008, 2031-2050, 2051-2070, 2081-2100	A1B, A2, B1	One GCM (Arpege-Climate)	50 km (statistically downscaled to 8 km)	Daily	FWI	Annual FWI, number of days above FWI thresholds
10 Karali et al. 2014	National, Greece	1961-1990, 2021-2050 2071-2100	A1B	One RCM (RACMO2) driven by one GCM (ECHAM5) (ENSEMBLES project)	25 km	Daily	FWI	Number of days above FWI thresholds

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11 Lozano et al. 2017	National, Italy, and Corsica (France)	1981-2010, 2011-2040, 2041-2070	A1B	One RCM (CMCC-CLM)	14 km	6 hours	FFMC and DC (FWI system), Randig (~FLAMMAP fire simulator)	Frequency distributions of FFMC and DC, mean values and maps of burn probability, flame length and fire size
12 Carvalho et al. 2011	National, Portugal	1981-2000, 2041-2060	Radiative forcing: +3 W/m2 in 2050 (~RCP8.5)	One RCM (MM5) driven by one GCM (MUGCM)	10 km	Daily	FWI	Frequency distribution of FWI and its subcomponents
13 Vazquez et al. 2012	National, Spain	1961-1990, 2071-2100	A2, B2	One RCM (PROMES) driven by one GCM (PRUDENCE project)	50 km	Daily	A simple regression model for monthly fire number and burnt area by ecozone based on one monthly weather variable	Annual fire number and burnt area by ecozone
14 Vazquez et al. 2015	National, Spain	1974-2005, 2071-2100	A2, B2	-	-	-	Ratio values of fire activity by scenario and by ecozone between future and present time slices, from Vazquez et al. 2012	Fire frequency and rotation period by woodland types
15 Sousa et al. 2015	National, Portugal and Spain	1981-2001, 2001-2025, 2026-2050, 2051-2075	A1B	4 RCM-GCM couplings (ENSEMBLES project)	25 km	Daily	Multivariate regression-type models for monthly burnt area by pyro-region based on monthly weather variables and statistics	Seasonal (summer, March) burnt area
16 Arca et al. 2012	National, Italy (FWI) Regional, Sardinia	1961-1990, 2071-2100	A1B	One RCM (EBU-POM)	25 km	6 hours	FWI, FlamMap fire simulator	Annual FWI, maps of mean burn probability
17 Faggian 2018	National, Italy	1971-2000, 2021-2050	A1B, RCP4.5, RCP8.5	One RCM from Med-CORDEX (for fire danger analysis)	12, 25 km		FWI	Number of fire danger days, SSR
18 Pellizzaro et al. 2010	Regional, Sardinia, Italy	1961-1990, 2071-2100	A1B	One RCM (likely EBU-POM, see Arca et al. 2012)	20 km	6 hours	FFMC (FWI system)	Frequency distribution of FFMC
19 Kalabokidis et al. 2015	Regional, Greece (3000 km^2)	1961-1990, 2071-2100	A1B	One RCM (RACMO2) driven by one GCM (ECHAM5) (ENSEMBLES project)	25 km	Daily	FWI, Randig (~FLAMMAP fire simulator)	Monthly FWI statistics, number of days with extreme fire danger. Maps of conditional burn probability and flame lengths, fire size distribution
20 Mitsopoulos et al. 2015	Local, Greece (160 km^2)	1991 – 2000 2045 – 2055 2065 – 2075 2091 – 2100	A1B	One RCM (RACMO2) driven by one GCM (ECHAM5) (ENSEMBLES project)	25 km	Daily	FLAMMAP fire simulator, specific empirical fuel moisture model	Fire behavior variables
21 Loepfe et al. 2012	Three distinct areas of 700-800 km^2 in Catalonia, Spain	1968-2005, 2001-2100	A2, B1	One GCM (HadCM3)	Not relevant	Daily	Yearly maxima of FFMC, DC and FWI, FIRE LADY fire simulator	Annual fire number and burnt area
22 Turco et al. 2014	Regional, Catalonia, Spain	continuous, 1970-2050	A1B	11 RCM-GCM couplings (ENSEMBLES project)	25 km	Monthly	Multivariate regression-type models for monthly fire number and burnt area based on monthly weather variables and statistics	Annual fire number and burnt area

[1] A reference historical period and one or several future periods for change assessment. [2] GCM (Global Climate Model), RCM (Regional Climate Model), ESM (Earth System Model).[3] Interpolation or stochastic generation from monthly GCM/ESM outputs. [4] Transformed to daily by adding monthly anomalies to historical daily data.[5] Chatry et al. (2010) used projection data from the technical report of Meteo-France (Clopet and Regimbeau 2009)

Table 2: changes in fire metric (in % or days per decade)

		Scenario A1B		Scenario A2 or RCP8.5	
	Area	Mid-term	End of century	Mid-term	End of century
Mean seasonal FWI (%)	Southern Europe	3.3[2]	4.0[2]		2.1[1]
	Balkans	2.6[2]	3.4[2]		2.3[1]
	France (< 48° lat)				2.6[1]
	France	5.9[2], 5.2[9]	6.9[2], 6.1[9]	4.9[9]	7.2[9]
	Greece	1.8[2]	1.9[2], 2.5[19]		2.2[1]
	Italy	3.2[2]	4.3[2], 1.8[16]		2.3[1]
	Portugal	2.7[2]	3.1[2]	9.1[12]	1.5[1]
	Spain	3.1[2]	3.7[2]		2.1[1]
Seasonal severity rating SSR (%)	Southern Europe	5.0[2]	6.5[2]		3.7[3]
	Balkans	4.0[2]	5.5[2]		
	France – MED				4.7[3]
	France	10[2]	12[2]		
	Greece	3.0[2]	3.3[2]		3.9[3]
	Italy	5.1[2]	7.4[2]		2.6[3]
	Portugal	4.2[2]	5.0[2]		4.9[3]
	Spain	4.8[2]	6.3[2]		4.3[3]
Length of fire season (days)	Southern Europe	3.4[2]	3.4[2]		3.5[1]
	Balkans	2.3[2]	2.5[2]		3.4[1]
	France (< 48° lat)				3.5[1]
	France	5.2[2]	5.4[2]		
	Greece	3.1[2]	2.4[2]		4.3[1]
	Italy	2.6[2]	2.5[2]		3.2[1]
	Portugal	2.6[2]	2.3[2]		3.3[1]
	Spain	3.1[2]	3.0[2]		3.8[1]
Fire number (%)	Spain				32[13]
	Regional (NE Spain)	20[22]			
	Local (NE Spain)				20-23[21]
Burnt area (%)	Europe	3.7[6]	4.5[6]	10[8]	6.4[7], 10[7], 24(1.9)[8]
	Southern Europe	1.4[6]	1.9[6]	14(9.7)[4], 9.0[8]	16[3], 25(13)[4], 3.7[7], -7.6[7] , 20(-2.5)[8]
	France-MED				14[3]
	Greece				18[3]
	Italy				4.8[3]
	Portugal				19[3]
	Spain				93[3], 51[13]
	Iberian P.	23(16)[15], 2.7[6]	3.6[6]		
	Regional (NE Spain)	-15[22]			
	Local (NE Spain)				9-96[21]
Fire size (%)	Italy (+Corsica)	0.7[11]			
	Regional (Greece)		6.9[19]		
	Local (Greece)	0.5[20]	2.3[20]		

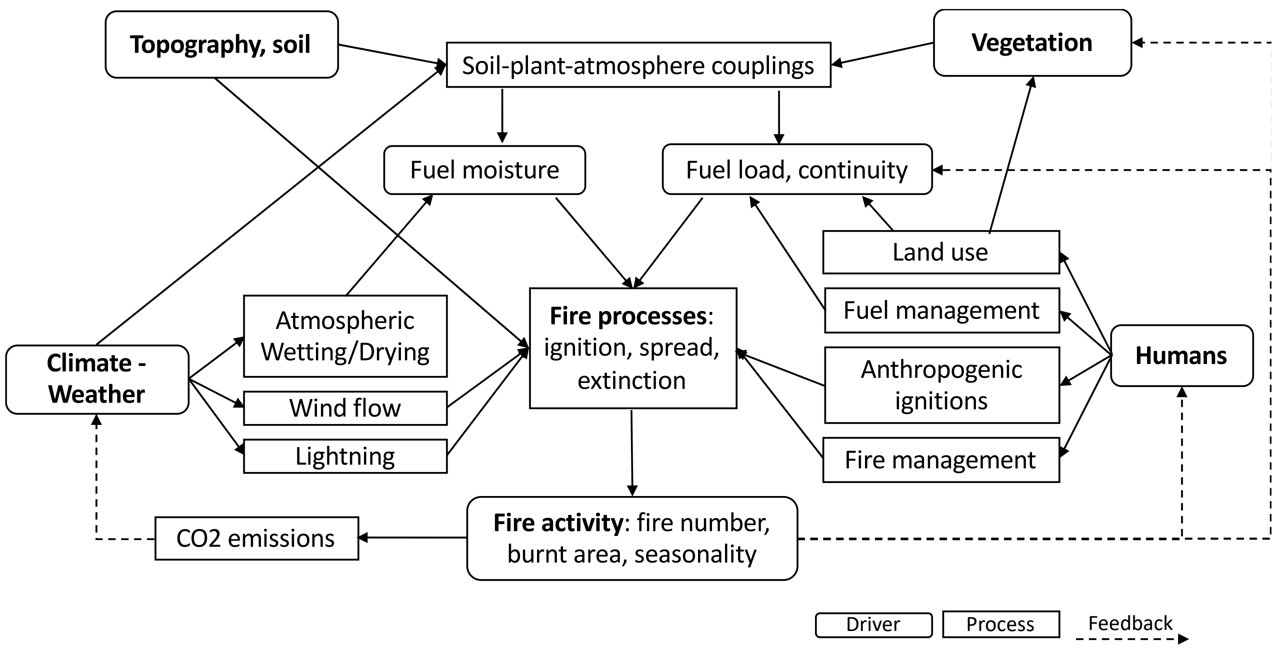

Figure 1. Wildfire drivers, processes and feedbacks

Supplementary material

In the following, we provide detailed comments on the results of Table 2, with the aim to understand differences or similarities between studies.

Fire danger

For the Balkans, Italy, Portugal and Spain, the increases in mean FWI reported by Moriondo et al. (2006) by the end of the century are lower than those reported by Bedia et al. (2014b), though they considered a less severe scenario (A1B instead of A2). For France and Greece, they are slightly higher. When comparing the two studies, several important differences must be kept in mind. First, as pointed out by Bedia et al., Moriondo et al. used only one RCM exhibiting a strong positive bias in FWI with respect to a climate reanalysis of the historical period in several regions of southern Europe and the lowest spatial correlation among the six models that Bedia et al. selected. This model was thus discarded in the Bedia et al. study. Note that Moriondo et al. did not report whether the model bias was corrected. Second, as shown by Bedia et al. again, the proxy used by Moriondo et al. to compute the daily FWI (defined at noon) from daily meteorological variables resulted in lower FWI values compared to the reference values derived from hourly (noon) values, hence a negative bias that could compensate for the positive bias caused by the climate model. In contrast, Bedia et al. used a different proxy providing FWI values closer to the reference values. Third, the mean FWI was computed for a fixed period of the year (June to September, 120 days) in Bedia et al., while Moriondo et al. computed the mean FWI on a locally variable fire season length, ranging between 55 days and 127 days in the historical period according to the country. Only Portugal (127 days) and Spain (110 days) in Moriondo et al. study had a mean fire season length close to the 120 days used by Bedia et al. to compute the mean FWI; in other countries, fire season lengths were lower. Keeping in mind that this mean number hides large local disparities following elevation in each country, on the historical period, this difference between the two studies should nevertheless increase mean FWI values in Moriondo et al. as compared to Bedia et al., since the period is more or less centred on summer. Despite the above differences, it is worth noting that except for the particular case of France for which geographical areas of the two studies are also different, both studies show similar historical values of the mean FWI, ranging between 28 and 33 in Moriondo et al. and between 23 and 35 in Bedia et al. This suggests that compensations effectively occurred among the sources of variation in mean FWI reported above. On the future period, the fire season length increased for all countries according to Moriondo et al., exceeding the 120 days used by Bedia et al. for Greece, Portugal and Spain.

Bedia et al. (2014a) also computed fire season lengths using the same FWI threshold value (15) as Moriondo et al. (2006). The fire season lengths computed by Bedia et al. in the historical period (not shown) however are roughly 2 to 3-fold the values computed by Moriondo et al. It is attracting to explain this strong difference by the negative bias caused by the Moriondo et al. proxy for noon FWI estimation, however some compensation from the positive bias due to the climate model should also be expected. In France, the current fire season length was 108 days in Bedia et al. (2014a), whereas it was only 55 days in Moriondo et al. (for more southern latitudes, $< 48^{\circ}$). We consider that the value by Bedia et al. (2014a) is largely overestimated since the operational fire season lasts typically two months and half in the most-fire prone region of France (South-East). This questions the use of either the threshold FWI value of 15 or the magnitude of FWI values in Bedia et al. Both studies predict increases of fire season length of about 3 days per decade up to the end of the century. Moriondo et al. predicted slightly higher increases than Bedia et al. in Mediterranean countries (Balkans, Greece, Italy, Spain and Portugal), but lower in France (where we remind again that the geographical area was different in the two studies).

Both historical and future SSR values predicted by Amatulli et al. (2013) under the A2 scenario are lower than those reported by Bedia et al. (2014a) under the A1B scenario, especially for France and Italy. This is consistent with the fact that SSR was computed from May to November in Amatulli et al., while Bedia et al. used the June to September period. The absolute increases in SSR predicted by Bedia et al. (roughly 0.6 per decade) are also much higher than those predicted by Amatulli et al. (roughly 0.2 per decade), which also makes sense because of the difference in fire season lengths.

Other studies that report mean FWI are from Chatry et al. (2010) in France, Arca et al. (2012) in Italy, Carvalho et al. (2011) in Portugal, and Kalabokidis et al. (2015) in a region of Greece.

In an exploratory study of fire danger evolution in France, Chatry et al. reported annual means of FWI (and number of days above several FWI thresholds). They found an increase of the annual mean FWI of 6.9% per decade for the whole area of France in scenario A2, whereas Moriondo et al. (2006) found an increase of the seasonal FWI of 2.6% for the southern half of France (latitude $<48^{\circ}$). This great difference could be partly explained by the respective geographic areas of the two studies, but also by the respective periods considered for the computation of the mean FWI (whole year versus a variable fire season). In contrast, relative increases reported by Chatry et al. under scenario A1B are similar for both horizons to those reported by Bedia et al. (2014a). However, Chatry et al. found annual mean FWI values of 4.4 and 7.4, while Bedia et al. found mean summer (June to September) FWI values of 12 and 20, for the historical and future (end of century) periods respectively.

Arca et al. (2012) reported present and future mean FWI for the four seasons of the year and found an increase of the mean summer (July to September) FWI of 1.8% per decade for Italy under the A1B scenario, while Bedia et al. (2014a) found an increase of 4.3% per decade for a similar season (June to September). The mean FWI values in Arca et al. are 26 and 31, while they are 23 and 33 in Bedia et al., respectively for the historical and future periods. Note that Arca et al. found the same FWI increase (+5) in spring and in summer, while Bedia et al. found an increase of 10 for the June to September period, hence the difference is clearly not due to the definition of the season. Another difference between the two studies is that Arca et al. used only one RCM with no bias correction.
Carvalho et al. (2011) found a mean relative FWI increase of 9.1% per decade under A2 scenario up to mid-century in Portugal, while Bedia et al. (2014a) found a 2.7 % per decade increase under A1B scenario. The mean FWI values in Carvalho et al. are 10 and 15, while they are 32 and 38 in Bedia et al., respectively for the historical and future periods. Carvalho et al. computed the mean FWI from February to October, which is likely to explain the important difference between the FWI levels of the two studies, but the absolute increases are similar. Moreover, when using Carvalho et al. data to compute change in mean FWI for the upper classes of FWI (e.g. FWI >15), hence values likely more concentrated in the summer period, the relative increase drops to 2.6% per decade, close to the prediction of Bedia et al. Therefore, it seems that the predictions by Bedia et al. and Carvalho et al. are compatible, contrary to what the data reported in Table 2 suggest at first glance.
When using the monthly FWI values reported by Kalabokidis et al. (2015) for a region of Greece, the increase in seasonal (June to September) FWI is 2.5% per decade up to the end of century under the A1B scenario, which is slightly higher than the increase of 1.9% per decade by Bedia et al. (2014a) for the whole Greece. The mean FWI values in Kalabokidis et al. are 27 and 34, while they are 35 and 41 in Bedia et al., respectively for the historical and future periods, hence the FWI levels strongly differ between the two studies, but the increases are similar.
One could argue that it would be more valuable in our review to compare statistics such as number of days above threshold values instead of means (or quantiles) of the FWI. Some studies report such statistics, but using different threshold values, and the pertinence of these thresholds might be location-dependent. Hence, again, comparisons are complicated by different choices and we were not able to show comparisons of such statistics.

Fire activity

Two types of models, statistical (regression on climate variable, fire danger indices or drought indices: 3,13,15,22) and process-based (coupled DGVM - fire model: 6,7,8), have been used to project future burnt areas. Among projection studies at continental scale, only the Amatulli et al.

(2013) study also reports the results down to national scale. Many reports and scientific papers refer to the Amatulli et al. study to mention expected changes in future burnt areas in Europe. Amatulli et al. built regression models of burnt area on components of the FWI at a monthly time scale for the Mediterranean countries of the European Union. Projected relative burnt area increases was 16% per decade under A2 scenarios for Mediterranean Europe (or 2.4-fold increase by the end of century), ranging between 5% (Italy) and 93% (Spain) per decade according to the different countries.

Turco et al. (2018) projected burnt area in Mediterranean Europe, assuming that seasonal fire activity is driven by the coincident seasonal drought, as supported by recent work analysing historical burnt areas (Turco et al. 2017). They found that the sensitivity of burnt area to drought conditions, as measured by monthly statistics based on the SPEI, was lower in sub-regions of southern Europe exhibiting the highest temperatures. For this reason, they built both stationary (sensitivity to SPEI is constant in time) and non-stationary (sensitivity to SPEI decreases with time-averaged temperature, hence decreases in the future) models for burnt area by ecozones of Mediterranean Europe. The lower sensitivity in the hottest region was suggested to reflect some human and vegetation adjustment/adaptation. The stationary model predicted a 25% burnt area increase per decade at the scale of southern Europe, higher than the one reported by Amatulli et al. (2013) (16% per decade). Note that Amatulli et al. used climate data from one GCM/RCM, whereas Turco et al. (2018) used 9 simulations from several GCM/RCM couplings. The non-stationary model logically resulted in lower increases in burnt area (13% per decade).

At continental scale the two studies by Migliavacca et al. (2013a) and Wu et al. (2015), which both use DGVM-fire models, exhibit much lower increases than the studies by Amatulli et al. (2013) and Turco et al. (2018), which both use statistical models. DGVM-fire models incorporate vegetation and fuel dynamics that can lessen the impacts of fire weather increase on fire activity when fuel availability becomes critical, but such low increases could also have other reasons.

Using the CLM-AB DGVM with a fire model adapted from Arora and Boer (2005), Migliavacca et al. (2013a) found very low relative increases in future burnt areas (e.g. 1.9% per decade for southern Europe), which in fact is likely due to the model largely overestimating the historical burnt areas: for instance the predicted historical (1990-2010) burnt areas were e.g. 800 000 ha for the Iberian peninsula, whereas the actual historical mean burnt area is 130 000 ha according to the European Forest Fire Information System. The absolute increase by the end of century predicted by the model was 130 000 ha for the Iberian Peninsula, hence a two-fold increase relative to the actual, historical burnt area in the future period. Such large discrepancy between modelled and observed historical burnt areas is also visible in the data by Migliavacca et al. (2013a) at the whole European scale (all these data are shown in a Supplementary file). This strongly questions the reliability of the low relative increases that the authors claim to be more conservative estimates than previous dramatic increases of say 3 to 5-fold obtained without considering fuel dynamics (Amatulli et al. 2013).

Wu et al. (2015) used two coupled DGVM-fire models to project future burnt areas in Europe and, for the Mediterranean area of the study, they found low increase in burnt area (3.7% per decade) with LPJ-GUESS-SIMFIRE, as compared to Amatulli et al. (2013), or even decrease in burnt area (-7.7% per decade) with LPJ-mL-SPITFIRE. Moreover, the maps of changes in burnt area reported by Wu et al. reveal the following spatially-explicit trends within the Euro-Mediterranean area: LPJ-GUESS-SIMFIRE predicts slight increases in burnt area almost everywhere; in contrast, LPJmL-SPITFIRE predicts decreases in burnt area for the southern half of the Iberian peninsula, the south of Bulgaria and the north of Greece (Macedonia region), while it predicts increases for the north of Iberian Peninsula, France, Italy, the western Balkans and the rest of Greece, and these increases are higher than with LPJ-GUESS-SIMFIRE. Hence, LPJmL-SPITFIRE produces higher spatial variability.

To explain these opposite trends, the authors point out the divergent trends in fuel loads: LPJmL-SPITFIRE predicts an important decline in fuel loads in the Mediterranean area due to climate warming, which limits fire spread, whereas LPJ-GUESS-SIMFIRE predicts a slighter decrease in fuel loads largely offset by the increase in climatic fire danger. Several differences can explain diverging fuel load trends, since the models do not treat fuel load estimation, fuel effects on fire and fire feedbacks on fuels in the same way. Noticeably, SIMFIRE is a simple model with few parameters, which could make it less sensitive to input conditions or feedbacks than SPITFIRE. LPJ-GUESS uses the FAPAR as a proxy for fuel load and continuity, while LPJ-mL estimates the litter fuels from the carbon pools of the DGVM. Moreover, according to Wu et al., SPITFIRE likely overestimates fire-induced feedbacks to vegetation composition and structure, as compared to SIMFIRE, because the two associated DGVMs represent the vegetation differently (see section 2).

Khabarov et al. (2016) used a modelling framework similar to Migliavacca et al. (2013a), but with a non-dynamic (fixed) vegetation, which likely explains that the increase in burnt area was much larger than in other studies using DVGM coupled with a fire model.

Interestingly, a significant number of studies provide results for Spain or for the Iberian Peninsula, which is not the case for other countries. For Spain, Amatulli et al. (2013) found a drastic but likely unrealistic 8-fold increase by the end of the century, or a 93% increase per decade, under the A2 scenario. According to the authors, it is likely that the drought components of the FWI, which are not bounded, no longer reflect fire activity under the extreme climatic conditions that are projected for most of the Iberian Peninsula by the end of the century. Still for Spain, Vazquez et al. (2012) found a 51% burnt area increase per decade under the A2 scenario from regression models by ecozone built on monthly weather variables. For the Iberian Peninsula, Sousa et al. (2015) also built regression models of burnt area on climatic variables statistics by pyro-regions and projected a 23% increase per decade up to the mid-century under the A1B scenario. Hence, the studies of Vazquez et al. (2012) and Sousa et al. (2015), which both use regression on weather variables, are compatible in order of magnitude, and predict a much lower increase than Amatulli et al. (2013), who instead used unbounded FWI components as predictors, which tends to confirm the overestimation of future increase in burnt area by the latter. In contrast, even when using the actual historical burnt area as a reference, we computed from Migliavacca et al. (2013a) data (A1B scenario) a 12% increase per decade only for the Iberian Peninsula. This low increase is qualitatively in line with the maps of burnt area changes reported by Wu et al. (2015) that show either slight increase (LPJ-GUESS-SIMFIRE) or both large increases and large decreases (LPJmL-SPITFIRE) across the Iberian Peninsula, as reported above. For a region of Spain (Catalonia), Turco et al. (2014) projected increased fire number but decreased burnt areas in Catalonia in the future, based on regression models on climate variables. The burnt area model exhibited a negative sensitivity to antecedent (2 years lag) seasonal (February to November) temperatures, which was selected as one of the predictors. According to the authors, this effect of antecedent weather was associated with fuel build-up, which, in a warm and dry climate, should be higher in seasons with higher precipitations and lower temperatures. The trend in burnt area would convey decreasing fuel load/continuity under a warmer climate in an arid region. Also for Catalonia, Loepfe et al. (2012) used two simple models for fire number and burnt area based on yearly maxima of the Drought Code to project future fire activity in three distinct sub-regions. They found similar relative increase in fire number (20-23% per decade) in all sub-regions but contrasted relative increases (9-96% per decade) in burnt areas: the currently wetter and cooler sub-region, with forests located at higher altitudes and infrequent fires, exhibited the highest relative increase. These results are thus, for burnt area, opposite to the findings of Turco et al (2014). This makes sense since only seasonal drought drives seasonal fire activity in Loepfe et al., and it is expected to be more frequent and intense in the future, whereas in Turco et al., antecedent weather conditions can counterbalance the seasonal increase in fire danger through decreased fuel loads.