1 Global patterns in the sensitivity of burned area to
2 fire-weather: implications for climate change

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14 **Abstract**

15 Fire is an integral Earth system process, playing an important role in the
16 distribution of terrestrial ecosystems and affecting the carbon cycle at the
17 global scale. Fire activity is controlled by a number of biophysical factors,
18 including climate, whose relevance varies across regions and landscapes. In
19 light of the ongoing climate change, understanding the fire-climate relation-
20 ships is an issue of current interest in order to identify the most vulnerable
21 regions. Building upon recent global observations of burned areas and cli-
22 mate, we investigate the sensitivity of fire activity to fire-weather across the
23 world's major biomes. We identify the biomes susceptible to inter-annual
24 fire-weather fluctuations, unveiling a non-linear relationship with a satura-
25 tion threshold past which the area burned can be considered insensitive to
26 increasing fire-weather. Our results depict an unambiguous spatial pattern
27 that identifies the world regions where short-term climate fluctuations are

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28 unlikely to produce any significant effect on current fire activity, and those
29 most sensitive to fire-weather changes. In particular, the boreal forests and
30 extensive areas of tropical and subtropical moist broadleaf forests (excluding
31 Africa) as well as sizeable areas of temperate broadleaf forests are identified
32 as highly sensitive. We then present near-future fire-weather scenarios (pe-
33 riod 2026-2045) using a state-of-the-art ensemble of Earth System Models
34 (ESMs) from the CMIP5 database, considering a moderate and a high emis-
35 sion scenario (RCPs 4.5 and 8.5). The projected anomalies in fire-weather for
36 the vulnerable temperate biomes are small in magnitude and their direction
37 is either negative or just slightly positive, although significant differences in
38 the projected probability density functions suggest that disruptions of fire
39 regimes may occur locally. Other sensitive ecosystems, like the rain forests
40 of the Amazon basin may experience a significant increment in fire-weather
41 that may result in severe impacts on fire regimes as a direct consequence of
42 climate change in the next decades.

43 *Keywords:* biomass burning, forest fires, Fire Weather Index, CMIP5,
44 pyrogeography, fire risk

45 1. Introduction

46 Fire plays an important role in shaping the composition and functioning
47 of terrestrial ecosystems (Scott and Glasspool, 2006). It is an important
48 agent affecting atmospheric composition (Andreae and Merlet, 2001) and a
49 major factor of disruption in the global carbon cycles (van der Werf et al.,
50 2004; Bowman et al., 2009). It has even been argued that several of the
51 world’s major biomes owe their distribution and ecological properties to fire
52 regimes (Bond et al., 2005; Bond and Keeley, 2005).

53 Fire is the result of a complex interplay between different drivers operat-
54 ing at varied spatial and temporal scales (Krawchuk et al., 2009; Archibald
55 et al., 2013), reflected by an heterogeneous global distribution of fire activ-
56 ity (Chuvieco et al., 2008). Global fire activity is controlled by four hier-
57 archical processes (Archibald et al., 2009), namely (i) biomass production,
58 (ii) its availability to burn, (iii) fire-weather and (iv) ignition. The un-
59 derlying biophysical factors influencing these processes can be regarded as
60 “switches” (*sensu* Bradstock, 2010) that need to be simultaneously activated
61 for fire to occur. As a result, the limits of fire vary spatially across regions de-
62 pending on what hypothetical switches are activated at each moment. Knowl-
63 edge on the relative frequency with which these switches are activated is the
64 key to identify the processes driving/limiting fire at any particular ecosys-
65 tem. In light of the ongoing climate change, important alterations of fire
66 regimes are anticipated worldwide (Power et al., 2008; Pechony and Shindell,
67 2010; Westerling et al., 2011; Moritz et al., 2012; Batllori et al., 2013). Thus,
68 understanding the current fire-climate relationships is of utmost importance
69 in order to assess the potential impacts that projected climate may exert in

70 the near future. This requires the identification of the most sensitive areas
71 (i.e., those regions where climate can be considered the “limiting switch”).

72 It is well known that the fire-climate relationships are mediated by fu-
73 els. Ecosystems can be arranged in an aridity-productivity gradient along
74 which fire is constrained either by fuel availability on one extreme (fuel-
75 driven fires), and potential for fire spread on the other (drought-driven fires).
76 This is known as the ‘intermediate fire-productivity hypothesis’ (Krawchuk
77 and Moritz, 2010; Bradstock, 2010; Moritz et al., 2012; Pausas and Ribeiro,
78 2013). In arid ecosystems the prevailing meteorological conditions are gener-
79 ally favourable for fire to spread, but productivity is low due to the perpetual
80 water deficit. Thus, the low and fragmented fuel loads constrain fire occur-
81 rence. On the opposite side of the gradient (productive ecosystems) fuels are
82 abundant, but fire propagation is limited by the adverse humid conditions.
83 Thus, fire activity peaks at intermediate levels of this gradient, describing a
84 humped response. As a result, in many ecosystems the bulk of burned area
85 is due to relatively infrequent large fire events that can take place only when
86 particular conditions prevail so that fire can spread (Pereira et al., 2005; Meyn
87 et al., 2007). These conditions are governed by fire-weather and mediated by
88 fuel availability and connectivity (Krawchuk and Moritz, 2010; Pausas and
89 Paula, 2012). Air temperature, humidity and wind speed (referred to as *fire-*
90 *weather* variables) directly influence the rate of spread of fires and the degree
91 to which fires can bridge the gaps in the fuel layer (Rothermel, 1972). By
92 integrating these variables in a single numerical value, fire-weather indices
93 provide a synthetic measure of the state of the fire-weather switch in a par-
94 ticular place at a given time. They allow for a more realistic representation

95 of the climatic conditions conducive to fires, as they respond simultaneously
96 to the different meteorological variables affecting fire. For instance, while a
97 steady warming trend may occur over an extensive region, local differences
98 in air moisture or precipitation patterns may yield a varying response of the
99 fire-weather index (e.g., as described at both sides of the Urals by Grois-
100 man et al., 2007). Furthermore, fire-weather indices also provide an indirect
101 measure of antecedent conditions and not strictly a snapshot of the current
102 meteorological state. As a result, high values of fire-weather indices, indi-
103 cating an extreme fire danger potential, are highly improbable without a
104 concurring severe drought (Bradstock, 2010). For this reason, the usefulness
105 of fire-weather indices for the assessment of fire danger potential is widely
106 recognised, having been integrated into more complex fire danger rating sys-
107 tems used for decades by different protection agencies throughout the world.
108 Beyond the daily scale for what they are conceived, fire-weather indices have
109 been also proposed as a useful tool for the provision of current and future
110 fire danger climatological maps, as an easily interpretable and meaningful
111 information for fire managers (e.g. Williams et al., 2001; Hennessy et al.,
112 2005; Flannigan et al., 2000, 2013).

113 In this study we investigate how the sensitivity of fire activity (and in
114 particular burned area) varies globally in response to the fire-weather switch.
115 Whilst some previous studies addressed the global variability of different fire
116 drivers (see e.g. Krawchuk and Moritz, 2010; Archibald et al., 2013), a direct
117 empirical relationship between fire-weather and burned area remains to be
118 established, potentially useful for assessing the most direct, short-term effects
119 of climate change on fire activity. The analysis is focused on the fire season,

120 as estimated at the grid-box scale. The use of a fire season (a “fire year”
121 *sensu* Boschetti and Roy, 2008) significantly limits the potential sources of
122 error, particularly when the climatic conditions that prevail during the fire
123 season are significantly different from the entire year. This is important to
124 obtain consistent yearly statistics, and ensures that the analysis is done dur-
125 ing the period of bulk fire activity. We empirically identify the world regions
126 where fire-weather is a chief driver of fire activity, and quantitatively assess
127 the magnitude, direction and degree of future fire-weather projections using a
128 multimodel of state-of-the-art earth system models (ESMs) from the CMIP5
129 project, and two different scenarios (representative concentration pathways,
130 RCPs). The empirical fire-climate links presented are discussed from a py-
131 rogeographical perspective. It is expected that climate change will alter
132 the fuel distribution patterns, as well as the fire season onset and duration,
133 affecting the current fire-climate relationships. Thus, for simplicity, we as-
134 sume that neither vegetation types, nor the fire season start and end dates
135 change during the period of analysis. For this reason, we present fire-weather
136 projections for the near future (period 2026-2045), avoiding the analysis of
137 longer-term projections for the last decades of 21st century. Furthermore,
138 the period selected is well suited to a reasonable time horizon potentially
139 useful for decision-makers involved in conservation and forest management
140 planning.

141 2. Material and Methods

142 2.1. Fire data

143 2.1.1. Fire season determination and ‘non-burnable’ mask definition

144 Active fires satellite data, acquired by the MOderate Resolution Imaging
145 Spectroradiometer instrument (MODIS, Giglio et al., 2003), were screened
146 for non-vegetation fires (Oom and Pereira, 2013), aggregated at the grid-
147 box level and composited in 16-day intervals for the entire 2002-2012 period.
148 Based on GLC2000 (Bartolomé and Belward, 2005), all grid-cells covered
149 entirely by land cover classes devoid of vegetation were masked from the
150 analysis. In addition, we excluded the grid-cells with very low fire activity
151 (less than 10 fire counts in the study period). For the remaining grid-cells, a
152 mixture of normal circular distributions (von Mises Fisher, 1995) were fitted
153 to the active fire time series for the whole period. The number of distri-
154 butions used varied from 1 to 2, corresponding to unimodal and bimodal
155 distributions, respectively. The single independent variable was the day-of-
156 year. Model performance was evaluated through the model efficiency index
157 (MEF), and only grid-cells with MEF above 0.6 were classified. If the dif-
158 ference between the unimodal and bimodal MEFs was lower than 0.15, the
159 cell was classified as unimodal, otherwise it was classified as bimodal. For
160 each fire season, we calculated the start/end days according to the 5% and
161 95% confidence intervals. For unclassified grid-cells (5% of grid-cells), we set
162 the fire season to the entire year. In the case of bimodal distributions, the
163 main fire season was defined as the season encompassing the major number
164 of fire events (Benali et al., *submitted*). In order to focus on the period of
165 bulk area burned, subsequent analyses were carried out considering the main

166 fire season (Fig. S1).

167 2.1.2. Burned area data

168 Monthly burned area data (BA hereafter) were retrieved from the fourth
169 generation of the Global Fire Emissions Database (GFED4, Giglio et al.,
170 2013), encompassing the period 1996-2012 (Fig. 1c), providing data at 0.25°
171 resolution for the entire globe, obtained through the combination of differ-
172 ent satellite sources. GFED4 database is available via ftp ([http://www.](http://www.globalfiredata.org/Contact/index.html)
173 [globalfiredata.org/Contact/index.html](http://www.globalfiredata.org/Contact/index.html)).

174 2.2. Fire Weather Index and input climate data

175 The Canadian Forest Fire Weather Index System (FWI system), consists
176 of different components that account for the effects of fuel moisture on dif-
177 ferent fuel layers and wind on fire behaviour and spread. The combination
178 of the different components leads to FWI, a daily-based, dimensionless in-
179 dicator rating the potential fire intensity as a function of the meteorological
180 conditions (van Wagner, 1987). Although initially conceived to be applied to
181 the forests of Canada, FWI has demonstrated to be useful in other regions
182 of the world, such as the Mediterranean basin (Viegas et al., 1999; Dim-
183 itrakopoulos et al., 2011), Indonesia and Malaysia (deGroot et al., 2006),
184 New Zealand (Briggs et al., 2005) or the South Pacific (Taylor and Alexan-
185 der, 2006) among others. We used FWI for the characterization of global
186 fire-weather given its broad international application and its relative ease of
187 calculation. FWI requires four meteorological input variables, namely tem-
188 perature, relative humidity and wind speed, recorded at “noon local standard
189 time” (Stocks et al., 1989), together with 24-hourly accumulated precipita-

tion. These variables are not straightforward to be used for FWI calculation when using global climate databases (Herrera et al., 2013; Bedia et al., 2014). Climate data at an appropriate temporal resolution were obtained from the publicly available WATCH Forcing Dataset-ERA Interim (WFDEI, Weedon et al., 2011), with a native spatial resolution of 0.5° and 3-hourly time resolution. As a proxy of noon local time, we used the time of maximum solar incoming radiation of the WFDEI dataset for each grid cell and day of the year.

As FWI is computed on a daily basis, we tested several options in order to obtain a meaningful seasonally integrated FWI measure. In particular, we tested the 90th percentile of seasonal FWI and the seasonal severity rating (SSR, a seasonal average of DSR, an exponentially scaled version of FWI, van Wagner, 1970), the latter often applied for aggregation of fire danger over time (e.g. Flannigan et al., 2013). In all cases, we attained similar fractions of explained variance in area burned, so we decided to use mean FWI for subsequent analyses (see Harrington et al., 1983, for an analysis of time aggregates of FWI as predictors of burned area).

2.3. *Global biomes distribution*

We used the biomes delineated in the Global Map of Terrestrial Ecoregions (Olson et al., 2001), freely available from the World Wildlife Fund (<https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world>). As biomes are classified according to the predominant climate-vegetation characteristics, they explicitly bring the fuels into consideration for interpreting the results, providing a suitable basis for data aggregation. We rasterized the original vectorial map to match the grid of

analysis (see Sec. 2.5.1), resulting in 13 biomes from the original 14 of the dataset, after exclusion of Mangroves, represented only by polygons too small for the global scale of our analyses (Fig. 1a).

Figure 1: Summary of the datasets used for the analysis. **(a)** Map of the world’s biomes. Their names are indicated together with the abbreviated codes used in the next figures. Numbers in parenthesis indicate the percentage of grid cells occupied after masking. **(b)** fire-weather climatology (mean fire-weather Index of the fire seasons 1981-2000). **(c)** Total (log10) burned area for the period 1996-2012 (GFED4 database). All data are presented in the reference regular grid of 1.5° resolution. Land blank areas correspond to the masked grid-cells not considered in the analyses (mainly deserts and ice sheets, see Sec. 2.1.1).

2.4. Future fire-weather projections

We used the state-of-the-art climate projections from an ensemble of earth system models (ESMs) of the Coupled Model Intercomparison Project (CMIP5) database. From all the available models (in January 2014), only seven included the required variables for FWI calculation at an adequate time resolution (Sec. 2.2), an issue often limiting the application of climate databases in fire danger studies (Herrera et al., 2013; Bedia et al., 2014). In

225 addition, two ESMs did not have future simulations available, but just the
 226 historical run. We retained all of them for greater model diversity in the
 227 validation stage (Sec. 2.5.2). The future projections were computed consid-
 228 ering the ensemble of the remaining five models using the period 2026-2045.
 229 Two different representative concentration pathways (RCPs 4.5 and 8.5) are
 230 available for all five ESMs, spanning a reasonable range of conditions, from
 231 moderate to high emission scenarios, respectively. The final set of ESMs is
 232 detailed in Table 1. The future FWI climatologies were computed using the
 233 “delta method” (Winkler et al., 2011), in order to extract the climate change
 234 signal from model simulations while significantly alleviating the problems
 235 linked to model biases. More details on this particular method applied to
 236 FWI are provided in Bedia et al. (2014).

237 2.5. Data analysis

238 Prior to the analysis, all data (FWI, BA and biomes) were interpolated
 239 to a common grid of 1.5° resolution, as a compromise between the high
 240 resolution of the GFED and WFDEI databases, and the coarser resolution
 241 of the ESMs used for the future climate projections (1 to 2.8° , Table 1).

242 2.5.1. Regression methods

243 All data were seasonally aggregated according to the fire season at the
 244 grid-box level (Sec. 2.1.1), by summing and averaging the original series of
 245 BA and FWI respectively. Thus, the analysis of interannual variability is
 246 equivalent to the analysis of the variability between fire seasons (Boschetti
 247 and Roy, 2008), hereafter referred to as *annual data*. We fitted annual BA
 248 against fire-weather (FWI) using a simple linear regression model for each

Id	ESM Name	Reference	Modeling Center	Hor. Res.	Hist.	RCPs
1	ACCESS-1.0	Bi et al. (2012)	Bureau of Meteorology and Commonwealth Scientific and Industrial Research Organisation	$1.875^\circ \times 1.25^\circ$	yes	yes
2	GFDL-ESM2G	Dunne et al. (2012)	NOAA Geophysical Fluid Dynamics Laboratory	$1.5^\circ \times 2^\circ$	yes	yes
3	IPSL-CM5A-MR	Dufresne et al. (2013)	Institut Pierre-Simon Laplace	$1.5^\circ \times 1.27^\circ$	yes	yes
4	MIROC-ESM	Watanabe et al. (2011)	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	$2.8^\circ \times 2.8^\circ$	yes	yes
5	MRI-CGCM3	Yukimoto et al. (2011)	Meteorological Research Institute	$1.125^\circ \times 1.125^\circ$	yes	yes
6	CNRM-CM5.1	Voldoire et al. (2013)	Centre National de Recherches Météorologiques - Groupe d'études de l'Atmosphère Météorologique and Centre Européen de Recherche et de Formation Avancée	$1.4^\circ \times 1.4^\circ$	yes	no
7	GISS-E2-R	Schmidt et al. (2014)	NASA Goddard Institute for Space Studies	$1^\circ \times 1.25^\circ$	yes	no

Table 1: Summary of the Earth System Models (ESMs) used in this work. The availability of historical scenario (*Hist.*, used for ESM validation) and RCPs 4.5 and 8.5 (*RCPs*, used for future FWI scenarios) is also indicated. The *Id* number is used in the Taylor diagrams displayed in Fig. 6. Note that only those ESMs bearing both RCPs have been used for the future FWI projections.

249 grid-box encompassing the period 1996-2012 period ($N = 17$ years). We as-
250 sume that the fire season (estimated for the period 2002-2012) is valid for the
251 analysis period, considering the 10-year overlap of both. A robust regression
252 approach was followed by removing from the regression models highly influ-
253 ential data points, identified by leave-one-out deletion diagnostics using the
254 ‘influence.measures’ function in the R software (v3.2.0, R Core Team, 2015).

255 The regression coefficient was used as an indicator of the sensitivity of BA to
256 fire-weather. The FWI threshold was calculated as the breakpoint estimate,
257 fitting a linear regression model with segmented relationships (Muggeo, 2003)
258 between the slope coefficient and the mean FWI for each grid-box, using the
259 R package ‘segmented’ (v0.5-1.1). Prior to regression, a spatial moving win-
260 dow of 5×5 grid-cells, centred at each pixel, was applied in order to aggregate
261 seasonal BA and FWI into larger spatial units (their size is indicated by the
262 black squares around selected points in Fig. 3a). The resulting smoothed
263 predictor (FWI) and response (BA) allow to reinforce the deterministic com-
264 ponent of the FWI-BA relationship by reducing its inherent stochasticity.
265 At the same time, it helps to minimize the effect of sub-grid scale processes
266 potentially affecting their relationship.

267 The linear regression approach allowed the estimation of a breakpoint,
268 describing a ‘threshold effect’ (*sensu* Pausas and Paula, 2012) of fire-weather
269 on fire activity, based on the slope parameter. Thus, regression coefficients
270 below the threshold value indicate that BA is insensitive to FWI variability
271 (i.e. increments in FWI do not produce significant increments in BA), while
272 on the contrary, large coefficients indicate a high sensitivity. However, one
273 major drawback of this approach is the existence of multiple confounding
274 factors affecting area burned, that may obscure the link with fire-weather.
275 In order to ascertain the explained variance attributable to fire-weather alone,
276 we built a similar linear model using absolute year-to-year changes in FWI
277 against the corresponding changes in BA (i.e. first-difference time series),
278 following a simple attribution approach. This method is intended to remove
279 the effects of trends in the variables of interest (e.g. FWI and BA). The

280 main assumption behind the application of this method is that other factors
281 affecting fire (e.g. land use ...) have much lower year-to-year changes than
282 FWI, thus minimizing their effect on burned areas (see e.g. Lobell et al.,
283 2007; Lobell and Field, 2007; Turco et al., 2014, the latter focusing on fire
284 activity).

285 *2.5.2. Validation of the historical ESM simulations*

286 The validation of the historical runs for the seven ESMs available was
287 performed with regard to the observed FWI for the 20-year reference period
288 1981-2000, as computed from the WFDEI dataset (Sec. 2.2). In addition, we
289 also assessed the input fire-weather variables simulated by the different ESMs.
290 We computed the following parameters: spatial correlation (Spearman's *rho*
291 correlation coefficient), root mean square error and standard deviation. All
292 the validation analyses were undertaken using the fire season data at the grid
293 box scale (Sec. 2.1.1).

294 *2.5.3. Analysis of future fire-weather projections*

295 We analysed both the magnitude of the projected FWI anomalies, with
296 regard to the observed FWI climatology (Sec. 2.2) and the degree of mul-
297 timodel agreement. In order to avoid a misleading spatial representation
298 of the degree of model consensus in areas of weak signal (i.e., FWI anoma-
299 lies close to zero, either positive or negative, see e.g. Tebaldi et al., 2011) we
300 discretized the anomalies in intervals, considering an interval around zero en-
301 compassing both low negative/positive values. All values within this interval
302 are considered to have a null signal (i.e., no changes with regard to current
303 FWI). Multimodel agreement was then assessed by comparing the number

304 of models projecting anomalies within the same interval. For instance, if 2
305 or less models lie in the same anomaly interval, agreement is of 40% or less.
306 If 3 models coincide, agreement is of %60 and so on, until reaching a total
307 agreement (100%) when all five models project anomalies falling in the same
308 interval.

309 **3. Results and Discussion**

310 *3.1. Global fire-weather patterns*

311 The recent global fire-weather climatology (1981-2000) depicts areas char-
312 acterized by high FWI values during the fire season (Fig. 1b), notably the cen-
313 tral and western part of the Australian sub-continent, the Mexican Plateau
314 and California in Central and North America, the Sahelian belt and vast land
315 areas south of the Equator in the African continent. In Europe, the Mediter-
316 ranean area shows the highest values of FWI, especially in the East (Greece,
317 Turkey and Balkans; see Bedia et al., 2014, for a regional zoom). In Asia, the
318 highest FWI areas lie in the Middle East and the Arabic Peninsula, Turkey,
319 central India and south of Pakistan, Iran, the steppes of Kazakhstan and
320 north-western China. In South America, north-eastern Brazil is the most
321 remarkable high-FWI region. At the biome scale, the lowest annual FWI
322 corresponds to the Tundra (median $\simeq 7$), the boreal/taiga forests of north-
323 ern areas (9), the temperate broadleaf and conifer forest of the intermediate
324 latitudes (11) and the tropical moist broadleaf forests (11, Fig. 2). The last
325 two biomes show a much higher dispersion. On the other hand, deserts and
326 tropical savannas and grasslands, two of the biomes with largest coverage
327 at the global scale (Fig. 1) exhibited the highest climatological FWI, al-
328 though in both cases the spread was large indicating a remarkable climatic
329 heterogeneity (Fig. 2).

330 *3.2. Relationship between FWI and burned area*

331 FWI and annual BA were significantly correlated over extensive world
332 areas (Fig 3a). R-squared values were above 0.6 in many world regions, some

333 of them highlighted in Fig 3a. The first-order differences regression approach
334 on the same data strongly reinforced the relationships found over large world
335 areas (Fig 3b), particularly in South and Central America, South East Africa,
336 North East Asia and East of Australia, supporting the role of climate as a
337 chief driver of fire activity in these regions.

338 While a significant relationship between burned areas and fire-weather
339 is found across a diverse range of climates and biomes, from the boreal re-
340 gions to the intertropical zone, not all areas exhibit the same sensitivity to
341 FWI variability. The highest sensitivity is found in Boreal Asia and North
342 America, as well as in Equatorial Asia (Fig. 4a). These areas are character-
343 ized by two contrasting biomes, mostly boreal forests/taiga and a few tundra
344 grid-boxes in the first case, and tropical moist broadleaf forests in the latter.
345 However, from a climatological point of view both exhibit a relatively low
346 mean FWI during the fire season. In fact, at the global scale, the BA sensitiv-
347 ity and mean FWI describe a non-linear relationship, with a saturation FWI
348 threshold above which burned area is insensitive to further interannual FWI
349 variations (Fig. 4b). As a result, sensitive world areas coincide with those
350 characterized by a climatological FWI below this critical threshold. These
351 biomes are not completely linked to mild climates (e.g. temperate broadleaf
352 forests), but also to warm climates in which humid conditions prevail (e.g.
353 tropical moist broadleaf forests, Fig. 2).

354 In line with the intermediate fire-productivity hypothesis, the link be-
355 tween burned area and fire-weather is completely lost in most arid ecosys-
356 tems (deserts and xeric shrublands (Figs. 1a and 3). In these areas FWI is
357 high (Figs. 1b and 2) as a result of prolonged water deficits and low relative

358 humidity, possibly in combination with high temperatures. It must be noted
359 that some desert areas may still experience rare fire events, although at long
360 return intervals, much longer than the period of analysis in this study (see
361 e.g. Archibald et al., 2010).

362 Continuing along the aridity-productivity gradient, fires in the savanna
363 ecosystems are tightly controlled by the seasonal rainfall cycles. Once the dry
364 season begins, fuels (mostly ephemerals and grasses) dry rapidly and become
365 available to burn, fuelling large extensive surface fires (e.g., Archibald et al.,
366 2009). As a result, fire-weather fluctuations during the fire (dry) season do
367 not affect this dynamic significantly. An exception is found in south east
368 of Africa, where we found a very significant correlation between fire-weather
369 and burned area (3a-b and lower right scatterplot). Although we do not have
370 an explanation for this particular case, the regression coefficient indicates a
371 low sensitivity to further changes in mean FWI, and therefore interannual
372 FWI variability is not expected to translate into drastic changes in area
373 burned. Deserts and tropical savannas, areas where fire-weather does not
374 play a key role, occupy a significant fraction of the total area studied (about
375 one quarter, Fig. 1a) and the assessment of climate change impacts on fires
376 should focus on longer-term changes in precipitation seasonality as the most
377 important climate driver.

378 In the same vein, it is expected a higher sensitivity to FWI in productive
379 ecosystems, like the tropical moist broadleaf forests. As a result, significant
380 areas belonging to intermediate productivity biomes proved sensitive to fire-
381 weather, in particular the boreal forests, but also the temperate broadleaf
382 forests and the temperate coniferous forests, all of them lying on the left

side of the FWI threshold (Fig. 2). In consequence, the FWI threshold shown in Fig. 4b can be regarded as an empirical climate-based indicator of the transition between drought and fuel-driven fire regimes, useful for the identification of potentially sensitive areas to fire-weather fluctuations.

Independently of climatic conditions, the ignition switch, affected by anthropogenic activity is not homogeneous across the globe (Bowman et al., 2011). People interfere with annual fire cycles in many areas of the world, anticipating as well as extending the fire season (Le Page et al., 2010). Human intervention thus affects the ignition switch exerting an important control of fire activity beyond its “natural” constraints, undermining the fire-climate relationship. Its effect is widespread throughout the globe rather than particular of certain biomes or fuel types (Archibald et al., 2013), partly explaining why many areas of the intermediate latitudes, where in principle fire regimes should be weather-driven, did not exhibit sensitivity to the fire-weather switch. Some of these regions can be identified for their relatively long fire season lengths (Fig. S1), often characteristic of human intervention (Le Page et al., 2010), for instance many areas of the Mediterranean Basin, South east of the United States or east of China among others. In light of the ongoing global change, burned area in many areas of the world not identified as sensitive in our analysis are probably more susceptible to the ignition switch owed to human action (e.g. through landscape fragmentation, urbanization, etc.; Syphard et al., 2007; Viedma et al., 2015) than to changes in the fire-weather switch, that won’t probably have an immediate effect in fire activity. As an example, it has been shown that the availability of ignitions, and not fire-weather, is the limiting fire switch in South African

408 *fynbos* (Van Wilgen et al., 2010) or Californian *chaparral* shrublands.

409 3.3. Future fire-weather projections

410 The spatial pattern of FWI depicted by the historical run of the mul-
411 timodel ensemble (1981-2000, Fig. 5a) is in agreement with the observed
412 FWI climatological map for the same period (Fig. 1b), with a low to mod-
413 erate model spread (Fig. 5b). All models attained high spatial correlation
414 coefficients ($0.75 < \rho < 0.92$) and both low to moderate standard deviation
415 ($0.50 < \sigma < 0.75$) and error ($0.50 < RMSE < 0.75$, Fig. 6). The validation
416 results justify the suitability of the selected ensemble of ESMs for the global
417 projection of future FWI (Table 1). The highest uncertainty is linked to the
418 poor representation of wind speed in the models. In this sense, the scale of
419 our analysis and the coarse resolution of ESMs is not representative of local-
420 scale factors affecting fire regimes. This is particularly true for wind, highly
421 affected by fine-scale factors (e.g. topography) beyond the scale of analysis.

422 With this regard, significant fire-climate relationships not found in this
423 study may be unveiled at finer-grained scales (e.g. Littell et al., 2009). Simi-
424 larly, the assessment of regional/local future fire-weather shifts would require
425 the use of Regional Climate Model simulations (Giannakopoulos et al., 2009;
426 Bedia et al., 2014) or adequate statistical downscaling methods (Abatzoglou
427 and Brown, 2012; Bedia et al., 2013), able to capture the local scale fire-
428 weather conditions.

429 Fire-season FWI projections do not indicate a generalized increment of
430 fire-weather in most sensitive areas. On the contrary, most of the biomes show
431 very weak positive signals or even negative anomalies in mean fire-weather
432 conditions for both RCPs analysed (Fig. 2). However, some particular re-

433 gions exhibit positive FWI anomalies, that are cancelled when averaging with
 434 other areas where negative trends are projected, such as the fire-weather sen-
 435 sitive boreal forests/taiga biome (Fig. 5c-d). This is shown in the comparison
 436 of Figs. 2 and 7. The latter depicts the probability density only for those
 437 pixels previously identified as sensitive (Fig. 4), while Fig. 2 shows the pro-
 438 jected anomalies for the whole biome. In spite of the weak positive signal
 439 found in the Tundra and the Boreal Forests biomes, the projected anomalies
 440 in fire-weather may translate in important local impacts in burned area, as
 441 a result for instance of an increased frequency of high FWI events (Fig. 7).
 442 Although the fire-weather anomalies are positive only locally, in these areas
 443 important carbon losses from the large available stocks may occur as a result
 444 of an increased fire frequency (Turner et al., 2014). It is also worthy of
 445 mention the significant positive signal in fire-weather conditions projected
 446 for the Mediterranean basin and also the rest of mediterranean climate-type
 447 areas of the world (Chile, California, South Africa). Notably, the pattern
 448 and magnitude of projected FWI for the Mediterranean is similar to the
 449 finer-scale projections obtained using an independent multi-model ensemble
 450 of GCM/RCM couplings for this region (Bedia et al., 2014). These results
 451 align with a growing body of evidence pointing to a transition from drought-
 452 driven to fuel-limited fire regimes in Mediterranean-type ecosystems (Pausas
 453 and Fernández-Muñoz, 2012; Batllori et al., 2013). In south America, the
 454 high probability of the projected positive FWI anomalies (Fig. 5) over a
 455 particularly sensitive area like the the Amazon basin, in conjunction with
 456 human-induced alterations, may result in widespread, possibly irreversible
 457 changes in the rainforest ecosystems and a massive carbon release (Cochrane,

2003; Brando et al., 2014). Other tropical moist broadleaf forest areas identified as sensitive (Papua New Guinea and Indonesia) show a null FWI anomaly with a high degree of multimodel agreement, with the exception of southernmost Islands (Java, Sumatra ...) for the more extreme RCP 8.5, where positive anomalies are projected.

In the long term, climate-induced fire season length variations can be expected in many areas of the world (Jolly et al., 2015), and therefore the future fire-weather shifts described may be aggravated in some areas due to fire season lengthening or the eventual emergence of a second fire season in some places. Also, start and end dates of the fire season may experience important shifts in some areas and therefore caution must be taken in the extrapolation of fire-weather considering the current fire season to the last decades of the transient period.

471 4. Conclusions

472 We investigated the global patterns of the sensitivity of burned area to
473 fire-weather variability (i.e. the fire-weather switch). We found significant
474 relationships over extensive land areas of the world, but not all proved equally
475 sensitive to these changes. The areas of the world most sensitive to changes
476 in fire-weather are those characterized by a lower climatological FWI in the
477 fire season. In particular, the most sensitive areas have been empirically
478 identified as those with a FWI below 17, where fire regimes can be considered
479 mostly driven by fire-weather variability. The spatial extent and strength of
480 the fire-climate relationship in these regions was globally reinforced when
481 other confounding factors were removed using a first-difference regression
482 approach, as compared to the results from the ordinary regression analysis
483 that enabled the estimation of the FWI threshold.

484 Future fire regimes in large areas of the world proved insensitive to cur-
485 rent fire-weather, and may be more susceptible to factors related to other
486 fire switches not explicitly modelled, such as vegetation productivity or hu-
487 man action. As a result, in these areas, future fire-weather projections are
488 of lesser importance in order to assess near-future climate impacts on fire
489 activity. On the contrary, our FWI projections anticipate impacts that may
490 be locally important in sizeable areas of the current boreal forests of Canada
491 and Siberia, particularly at the East of the Urals, and in the tropical moist
492 broadleaf forests of the Amazon basin and south of Indonesia. These are sen-
493 sitive areas in terms of biodiversity conservation and are important global
494 carbon stocks. Here, fire-weather indices may prove the most adequate tools
495 for the assessment of fire risk.

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Figure 2: Current and projected distribution of fire-weather climatology across world's biomes. The current fire-weather climatology, computed as the mean of the annual FWI (period 1981-2000) across all pixels belonging to each biome is indicated by the black violins. Violins are envisaged to provide the same information as standard boxplots (drawn inside) together with a probability density estimation across the range of values of the continuous variable. The yellow-shaded areas indicate the corresponding projected distribution for the future period (2026-2045, no boxplot is drawn), according to the RCP 8.5. FWI threshold (FWI = 17) is indicated by the red dashed vertical line.

Figure 3: Global relationship between burned area and Fire Weather Index. (a) displays the results of the regression of (log10-transformed) burned areas against mean fire season FWI ($N = 17$ years). The colour map represents the adjusted R-squared of the robust linear fit between both variables. The red dots in the grid-cells of the map indicate a significant relationship ($p < 0.05$). Scatter plots for selected representative locations are displayed for the ordinary (black) and robust (red) linear fits (for the latter, outlying points removed are marked with red crosses). X-axis represents FWI, and Y-axis the log10-burned area (ha). Significance of the linear models is indicated in the scatterplots by the asterisks next to the r^2 values [$p.value < 0$ ***; 0.001 **; 0.01 *; >0.05 n/s , at the 95% confidence interval]. In (b) the same is presented, but considering the first-order differences of BA and FWI δ approach (see Sec. 2.5.1).

Figure 4: Global sensitivity of burned area to interannual fire-weather variability. The slope of the robust linear regression models displayed in Fig. 3a is shown in (a). Only the significant models ($p < 0.05$, red dots in map of Fig. 3a) are represented. Grey crosses correspond to masked land areas (see Sec. 2.1.1). (b) Scatterplot of mean FWI (average of the 17 years) plotted against the slope for each grid-cell value displayed in (a). The red line represents the piecewise linear model fit, with the break point at $FWI = 17$, indicating the threshold above which FWI variability has a negligible effect on the magnitude of burned area. Points are colored according to their biome (Fig. 1a).

Figure 5: Multimodel projections of fire-weather climatology for the historical (1981-2000) and future (2026-2045) periods. The time period and the color scale in (a) is the same as depicted in Fig. 1a, for better comparison of observed and simulated maps. The spread of the multimodel (standard deviation) is shown in (b). Projected fire season FWI anomalies by the multimodel ensemble for future period (2026-2045) are shown for RCPs 4.5 (c) and 8.5 (d). Colour tones in panels (c-d) indicate the magnitude (and direction) of the projected anomalies, while colour intensities represent the degree of the multi-model agreement (expressed as the fraction of coincident models, see Sec. 2.5.3). The hatched areas have a significant FWI-BA relationship according to the first-order difference regression approach (Fig. 3b).

Figure 6: Summary of the validation of the different ESM's with regard to the reference baseline climatology (WFDEI dataset). Results are presented in the form of Taylor diagrams (Taylor, 2001). The similarity between model and observations (point labelled “obs” on the x-axis) is quantified in terms of their spatial correlation (blue lines), their centred root-mean-square difference (proportional to the distance of the model point to the “obs” point) and the amplitude of their variations (represented by their standard deviations in the y-axis). In addition, the bias of the different ESM's is represented by the color bar. The surface variables displayed are the inputs for the calculation of FWI: *tas* = (2 m) air temperature; *wss* = (10 m) wind speed; *pr* = last 24-h accumulated precipitation; *hurs* = (2 m) relative humidity. *FWI* and its 90th percentile (*FWI90*) are also included in the bottom panels. See Table 1, to see the ESM numbering used for point labels. The results

Figure 7: Current and projected probability density functions (PDFs) of mean fire season FWI in sensitive biomes. Black line corresponds to the current FWI. Shaded area indicates the range of the projections of each model of the ensemble for both RCPs (period 2026-2045). The FWI threshold (FWI=17) is indicated by the red vertical line. Note that, unlike Fig. 2, only sensitive pixels to fire-weather variations (highlighted in Figs. 4 and 5) have been used to produce the PDFs.