



1 **The status and challenge of global fire modelling**

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48 **Abstract.** Biomass burning impacts vegetation dynamics, biogeochemical cycling, atmospheric chemistry, and
49 climate, with sometimes deleterious socio-economic impacts. Under future climate projections it is often expected
50 that the risk of wildfires will increase. Our ability to predict the magnitude and geographic pattern of future fire
51 impacts rests on our ability to model fire regimes, either using well-founded empirical relationships or process-based
52 models with good predictive skill. A large variety of models exist today and it is still unclear which type of model or
53 degree of complexity is required to model fire adequately at regional to global scales. This is the central question
54 underpinning the creation of the Fire Model Intercomparison Project - FireMIP, an international project to compare
55 and evaluate existing global fire models against benchmark data sets for present-day and historical conditions. In this
56 paper we summarise the current state-of-the-art in fire regime modelling and model evaluation, and outline what
57 lessons may be learned from FireMIP.

58

59 1. Introduction

60 Each year, about 4% of the global vegetated area is burned (Giglio et al., 2013; Randerson et al., 2012). Fire is the
61 most important type of disturbance and as such is a key driver of vegetation dynamics (Bond et al., 2005), both in
62 terms of succession and in maintaining fire-adapted ecosystems (Furley et al., 2008; Staver et al., 2011; Hirota et al.,
63 2011; Rogers et al., 2015). Fires play an essential role in ecosystem functioning, species diversity, plant community
64 structure and carbon storage. The impact fire has on the ecosystem depends on the local fire regime, including fire
65 frequency, intensity, seasonality etc. Fire is also important through its effect on radiative forcing, biogeochemical
66 cycling and biogeophysical effects (Bond-Lamberty et al., 2007; Bowman et al., 2009; Ward et al., 2012, Yue et al.,
67 2015).

68 Global carbon dioxide emissions from biomass burning are estimated to be about 2 PgC ($P = 10^{15}$) per year of which
69 approximately 0.6 PgC/yr comes from tropical deforestation and peat fires (van der Werf et al., 2010). This is
70 equivalent to ca 25% of those from fossil fuel combustion (Ciais et al., 2013; Boden et al., 2013), although a
71 significant fraction of these emissions is taken up during vegetation regrowth after fire. Together, fire significantly
72 decreases the net carbon gain of global terrestrial ecosystems by 1.0 Pg C yr⁻¹ averaged across the 20th century (Li et
73 al., 2014). Fire emissions are also an important driver of inter-annual variability in the atmospheric growth rate of
74 CO₂ (van der Werf et al., 2004; van der Werf et al., 2010; Prentice et al., 2011; Guerlet et al., 2013) and a significant
75 contribution to the atmospheric budgets of CH₄, CO and many other atmospheric constituents. As a source of aerosol
76 (including black carbon) and ozone precursors (Voulgarakis and Field, 2015), emissions from fires contribute
77 directly and indirectly to radiative forcing (Myhre et al., 2013; Ward et al., 2012), reducing net shortwave radiation
78 at the surface and warming the lower atmosphere, thus affecting regional temperature, clouds, and precipitation
79 (Tosca et al., 2010; Tosca et al., 2014; Ten Hoeve et al., 2012; Boucher et al., 2013) and regional to large-scale
80 atmospheric circulation patterns (Tosca et al., 2013; Zhang et al., 2009). Through their impacts on ozone, and as a
81 source of CO and other volatile organic compounds, fires also affect the atmospheric abundance of the OH radical,
82 which determines the atmospheric lifetime of the greenhouse gas methane (Bousquet et al., 2006). In addition, ozone



83 produced from fires is directly harmful to plants, reducing photosynthesis (Pacífico et al., 2015) and fire-emitted
84 aerosol can shift the balance between diffuse and direct radiation (Mercado et al., 2009; Cirino et al., 2014).
85 Deposition of fire produced N- (Chen et al., 2010) and P-aerosols (Wang et al., 2015) can enhance productivity in
86 nutrient limited ecosystems.

87 Fire also has direct effects on human society: more than 5 million people globally were affected by the 300 major
88 fire events in the past 30 years, with economic losses of more than US\$ 50 billion (EM-DAT; <http://www.emdat.be>).
89 Air quality is regionally affected by the occurrence of fire due to increases in aerosol and ozone that are harmful to
90 human health. At a regional scale, hospitalisations and human deaths increase in major fire years (Marlier et al.,
91 2013). The degradation of air quality caused by fire is estimated to result in 260,000 to 600,000 premature deaths
92 globally each year (Johnston et al., 2012).

93 Given that fire impacts so many aspects of the earth system, there is considerable concern about what might happen
94 to fire regimes in response to projected climate changes in the 21st century. However, as the IPCC Fifth Assessment
95 Report (AR5) made clear, “There is low agreement on whether climate change will cause fires to become more or
96 less frequent in individual locations” (Settele et al., 2014). This is in large part due to the complexity of the
97 interactions and feedbacks between vegetation, people, fire and other elements of the earth system (Fig. 1), which is
98 not well represented in current Earth System Models. Fire, vegetation and climate are intimately linked: changes in
99 climate drive changes in fire as well as changes in vegetation that provides the fuels for fire, and in return fire alters
100 vegetation structure and composition, with feedbacks to climate through changing surface albedo, ecosystem
101 properties, transpiration, and as a source of CO₂, other trace gases, and aerosols, altering atmospheric composition
102 and chemistry (Ward et al., 2012). Human activities strongly affect fire regimes (Archibald et al., 2013) due to the
103 use of fire for land management, while the use of fire as a tool in the deforestation process is still occurring in the
104 tropics (e.g. Morton et al., 2008). Humans may also suppress fire directly or indirectly through land-use change
105 (Bistinas et al., 2014; Knorr et al., 2014; Andela and van der Werf, 2014). Grazing herbivores (the densities of which
106 are also often controlled by humans) can also decrease fire occurrence by reducing fuel loads (Pachzelt et al. 2015).

107 Statistical models (e.g. Moritz et al., 2012) have been used to examine the potential trajectory of changes in fire risk,
108 i.e. the possibility of fire occurring based on climate conditions and fuel availability. Fire risk is not quantitatively
109 related to area burnt, fuel consumption, or fire emissions. This prevents an assessment of feedbacks to climate
110 through fire-driven changes of land-surface properties, vegetation structure or atmospheric composition. It is
111 important to understand such feedbacks quantitatively, as they have the potential to exacerbate or ameliorate the
112 effects of future climate change on ecosystems, as well as affect the security and well-being of people.

113 In contrast to statistical models, fire-enabled dynamic global vegetation models (DGVMs) and terrestrial ecosystem
114 models (TEMs) can address some of the feedbacks between fire and vegetation. Coupling fire-enabled DGVMs with
115 climate and atmospheric chemistry models in an Earth System Model (ESM) framework allows the feedbacks
116 between fire and climate to be examined. There has been a rapid development of fire-enabled DGVMs in the past
117 two decades with many DGVMs currently including fire as a standard process. Four out of the 15 carbon-cycle
118 models in the MstMIP (Multi-scale Synthesis and Terrestrial Model) intercomparison project, 5 out of 10 carbon-



119 cycle models in TRENDY (Trends in net land-atmosphere carbon exchange over the period 1980-2010), and 9 ESM
120 in CMIP5 (fifth phase of the Coupled Model Intercomparison Project) provide fire outputs. The complexity of the
121 fire component of these models varies enormously—from simple empirically-based schemes to predict burnt area,
122 through models that explicitly simulate the process of ignition and fire spread, to models that incorporate fire
123 adaptations and their impact on the vegetation response to fire. However, to date there has been no systematic
124 comparison and evaluation of these models, and thus there is no consensus about the level of complexity required to
125 model fire and fire-related feedbacks realistically.

126 The Fire Model Intercomparison Project (FireMIP), initiated in 2014, is a collaboration between fire modelling
127 groups worldwide to address this issue. Modelling groups participating in FireMIP will run a set of common
128 experiments to examine fire under present-day and past climate scenarios, and will conduct systematic data-model
129 comparisons and diagnosis of these simulations with the aim of providing an assessment of the reliability of future
130 projections of changes in fire occurrence and characteristics. Here, as a background to the FireMIP programme, we
131 present an overview of the current state of knowledge about the drivers of global fire occurrence. We indicate how
132 these have been treated over time in different fire models and describe the state-of-the-art fire-enabled DGVMs.
133 Finally, we outline the FireMIP philosophy and approach to model benchmarking and evaluation.

134

135 2. The controls on fire

136 Fire is driven by complex interactions between climate, vegetation and people (Fig. 1), the importance of which vary
137 depending on temporal and spatial scales. On meteorological time scales (i.e., minutes to days) and limited spatial
138 scales (i.e. metres to kilometres), atmospheric circulation patterns and moisture advection determine the location,
139 incidence and intensity of lightning storms that produce fire ignitions. Weather and vegetation state also determine
140 surface wind speeds and vapour-pressure gradients, and hence the rates of fuel drying, which in turn affect the
141 probability of combustion as well as fire spread. However, topography also affects the spread of fire: fire fronts
142 travel faster uphill because of upward convection of heat while natural barriers such as rivers, lakes, and rocky
143 outcrops can act as natural barriers to fire fronts.

144 On longer time scales (i.e., seasons to years) and larger spatial scales (i.e. regional to continental), temperature and
145 precipitation exert a major effect on fire because these climate variables influence net primary productivity (NPP),
146 vegetation type and the abundance, composition, moisture content, and structure of fuels. Burnt area tends to be
147 lowest in very wet or very dry environments, and highest in areas of intermediate water availability. Related to this,
148 burnt area is greatest at intermediate levels of NPP and decreases with both increases and decreases in productivity.
149 These unimodal patterns along precipitation or productivity gradients emerge due to the interaction between moisture
150 availability and productivity: dry areas have low NPP which limits fuel availability and continuity, while NPP and
151 hence fuel loads are high in wet areas but the available fuel is generally too wet to burn. Temperature exerts an
152 influence on the rate of fuel drying in addition to its influence on NPP. Seasonality in water availability also plays a
153 role here: for any given total amount of precipitation, fire is more prevalent in seasonal climates because fuel



154 accumulates rapidly during the wet season and subsequently dries out. While the vegetation and fuel exert an
155 important control on fire occurrence, fire impacts vegetation distribution and structure, causing important vegetation-
156 fire feedbacks. At a local scale fires create spatial heterogeneity in fuel amount, influencing subsequent fire spread
157 and limiting fire growth.

158 While natural factors are important drivers of global fire occurrence, human influences are also pervasive. People
159 start fires, either accidentally or with a purpose, for example for forest clearance, agricultural waste burning or fire
160 management. People can also affect fire regimes through land conversion from less flammable (forest) vegetation to
161 more flammable (grassy) vegetation. The introduction of flammable invasive species is another cause of changing
162 fire occurrence. Changes in land use can also reduce fuel loads through crop harvesting, grazing and forestry. Human
163 activities lead to fragmentation of natural vegetation which affects fire spread and fires are also actively suppressed.
164 There is a unimodal statistical relationship between burnt area and population density. At extremely low population
165 densities, increasing population is associated with an increase in fire numbers and burnt area. At high population
166 densities, increasing population is associated with a decrease in burnt area. However, in general when climate and
167 vegetation factors are accounted for, there is a monotonic negative relationship between burnt area and human
168 population, i.e. burned area decreases with increasing human presence (Bistinas et al., 2014; Knorr et al., 2014). The
169 unimodal statistical relationship of burnt area with population density (and other socio-economic variables such as
170 gross domestic product, GDP, that are linked to population density) results from the co-variance of population
171 density with vegetation production and moisture. Low population densities are found in very dry or cold climates
172 where vegetation productivity and fuel loads are also minimal. High population densities are (generally) found in
173 moist environments with high vegetation productivity but where moist conditions limit fire spread.

174

175 3. History and current status of global fire modelling

176 While not explicitly representing fire occurrence, early vegetation models often included a generic treatment of
177 disturbance on plant mortality. There are two basic types of fire models that are applied in global vegetation models
178 (Fig. 2): (a) top-down “empirical models” based on statistical relationships between key variables (climate,
179 population density) and some aspect of the fire regime, usually burnt area; and (b) bottom-up “process-based
180 models” which represent small scale fire dynamics (i.e. by simulating individual fires), before scaling up to calculate
181 fire metrics for an entire grid cell. The boundaries between these two types are not rigid, however, and some models
182 combine features of both.

183 3.1 Empirical global fire models

184 The absence of global-scale fire information before remotely sensed burnt area products became available was a
185 common challenge to the development of fire models and hindered testing and parameterisation of empirical
186 algorithms. The GLOBal FIRE Model (Glob-FIRM) (Thonicke et al., 2001) was the first global fire model, based on
187 the notion that once there is sufficient combustible material burned area depends on the length of the fire season. The



188 fire season length is calculated as the summed daily “probability of fire” which is a function of the fuel moisture
189 (approximated by the moisture in the upper soil layer), and the moisture of extinction. The functions relating
190 moisture content, fire season length, and burnt area were calibrated using site-based observations. In addition, Glob-
191 FIRM has a threshold value of 200 gC/m² to represent the point at which fuel becomes discontinuous and the
192 probability of fire occurring is zero. Glob-FIRM was initially developed for inclusion in the Lund-Potsdam-Jena
193 (LPJ) DGVM (Sitch et al., 2003), but has since been coupled into several other DGVMs (with some modifications),
194 including the Common Land Model (Dai et al., 2003), the Community Land Model (CLM) (Levis et al., 2004), the
195 ORganizing Carbon and Hydrology In Dynamic EcosystEms (ORCHIDEE) (Krinner et al., 2005), the Lund-
196 Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) (Smith et al., 2001), and the Biosphere Energy-Transfer
197 Hydrology model (BETHY) (Kelley, 2008; Kaminski et al., 2013). A simple fire model with a similar structure to
198 Glob-FIRM, has also been included in the JSBACH global vegetation model (Reick et al., 2013).

199 Some empirical models include human impacts on fire occurrence. Typically, algorithms are used that link fire
200 probability/frequency to both an estimate of lightning ignition and to human population density. Pechony and
201 Shindell (2009) proposed an algorithm whereby the number of fires increases with population, levelling off at
202 intermediate population densities and then decreasing to mimic fire suppression under high population densities
203 (Table 1). The simulated number of fire counts are then converted into burnt area using an “expected fire size”
204 scaling algorithm (Pechony and Shindell, 2009). The human ignition and suppression relationships described by
205 Pechony and Shindell (2009) have been adopted by several other, both empirical and process based fire-vegetation
206 models (Table 1). In an alternative approach, Knorr et al. (2014) used a combination of weather information (to
207 account for fire risk) with remotely-sensed data of vegetation properties that are linked to fire-spread and information
208 on global population density to derive burned area in a multiple-regression approach. This model has been coupled to
209 LPJ-GUESS DGVM (Knorr et al., 2016).

210

211 **3.2 Process-based global fire models**

212 MC-FIRE (Lenihan et al., 1998; Lenihan and Bachelet 2015) was the first attempt to simulate fire via an explicit,
213 process-based, Rate of Spread (RoS) model. MC-FIRE calculates whether a fire occurs in a grid cell on a given day,
214 based on whether the grid cell is experiencing drought conditions and that the “probability of ignition and spread,” as
215 jointly determined by the moisture of the fine fuel class and the simulated rate of spread, is greater than 50%. The
216 rate of spread is calculated based on equations by Rothermel (1972), which represent the energy flux from a flaming
217 front based on fuel size, moisture, and compaction. Canopy fires are initiated using the van Wagner (1993)
218 equations. All of the grid cell is assumed to burn if a fire occurs, i.e. the original MC-FIRE was designed to simulate
219 large, intense fires. Later work introduced functions to suppress area burned by low-intensity and/or slow-moving
220 fires (Rogers et al., 2011). MC-FIRE inspired the development of several process-based RoS based models, and
221 many fire-enabled DGVMs still use a similar basic framework (Table 1).



222 The Regional Fire Model (Reg-FIRM: Venevsky et al., 2002) introduced a new approach in fire modelling by
223 simulating burned area as the product of number of fires and average fire size. Reg-FIRM assumes a constant global
224 lightning ignition rate, and includes human ignitions depending on population density. It then uses the Nesterov
225 Index, an empirical relationship between weather and fire, to determine the fraction of ignitions that start fires. Every
226 fire occurring during a given day in a given grid cell is assumed to have the same properties and thus to be the same
227 size. Reg-FIRM uses a simplified form of the Rothermel (1972) equations to calculate rate of spread; these
228 effectively depend only on wind speed, fuel moisture (as approximated by near-surface soil moisture), and PFT-
229 dependent fuel bulk density. Fire duration is determined stochastically from an exponential distribution with a mean
230 of 24 hours, to account for the fact that less frequent large fires account for a disproportionate amount of the total
231 area burned. The RoS equations are used to estimate the burned surface by approximating the shape of the fire as an
232 ellipse, as suggested by van Wagner (1969).

233 The fire module in the Canadian Terrestrial Ecosystem Model (CTEM: Arora & Boer, 2005; Melton and Arora,
234 2015), uses a variant on the Reg-FIRM scheme where the pre-defined FDI approach is replaced by an explicit
235 calculation of susceptibility, which is the product of the probabilities associated with fuel, moisture, and ignition
236 constraints on fire (Table 1). Ignitions are either caused by lightning, the incidence of which varies spatially, or
237 anthropogenic. Anthropogenic ignition is constant in CTEMv1 (Arora & Boer, 2005) but varies with population
238 density in CTEMv2 (Melton and Arora, 2015). As in Reg-FIRM, fire duration is determined in such a way as to
239 incorporate the disproportionate area burned by long-lasting fires, but CTEM does this deterministically rather than
240 stochastically. CTEM includes fire suppression via a “fire extinguishing” probability to account for suppression by
241 natural and man-made barriers, as well as deliberate human suppression of fires. The fire model development in
242 CLM (Kloster et al. 2010, and Li et al., 2012; 2013) is based on the CTEM work but introduced anthropogenic
243 ignitions and suppression on fire occurrence as functions of population density. Li et al. (2013) set anthropogenic
244 ignitions and suppression also as functions gross domestic production (GDP), and introduced human suppression on
245 fire spread.

246 The SPread and InTensity of FIRE (SPITFIRE) model (Table 1) (Thonicke et al., 2010) is a RoS-based fire model
247 developed within the Lund-Potsdam-Jena (LPJ) DGVM. It is a further development of the Reg-FIRM approach, but
248 SPITFIRE uses the complete set of physical representations to calculate both rate of spread and fire intensity.
249 However, maximum fire duration is limited to four hours. Anthropogenic ignitions are a function of population
250 density as in REGFirm, although the function is regionally tuned in SPITFIRE. Fire is excluded from agricultural
251 areas but SPITFIRE effectively includes human fire suppression on other lands because human ignitions first
252 increase and then decrease with increasing population density. The SPITFIRE model has been implemented with
253 modifications in other DGVM’s, including ORCHIDEE (Yue et al., 2014), JSBACH (Lasslop et al., 2014), LPJ-
254 GUESS (Lehsten et al., 2009), and CLM-ED (Fisher et al., 2014).

255 Some fire models based on SPITFIRE, such as the Land surface Processes and eXchanges model (LPX) (Prentice et
256 al., 2011; Kelley et al., 2014) and the Lausanne-Mainz fire model (LMfire) (Pfeiffer et al., 2013), have introduced
257 further changes to the ignitions scheme. Natural ignition rates in both models are derived from a monthly lightning



258 climatology, as in SPITFIRE, but LPX preferentially allocates lightning to days with precipitation (which precludes
259 burning) such that only a realistic number of days have ignition events. Similarly to LPX, LMfire limits lightning
260 strikes to rain days, and also estimates interannual variability in lightning ignitions by scaling a lightning climatology
261 using long-term time-series of convective available potential energy (CAPE) produced by atmosphere models.
262 LMfire further reduces lightning ignitions based on the fraction of land already burnt, since lightning tends to strike
263 repeatedly in the same parts of the landscape while being rare in others. LPX and LMfire also modified the treatment
264 of anthropogenic burning relative to the original SPITFIRE. LMfire specified that the number of anthropogenic
265 ignitions differs amongst livelihoods by distinguishing human populations into three basic categories: hunter-
266 gatherers, pastoralists, and farmers. Each of these populations has different behaviour with respect to burning based
267 on assumptions regarding land management goals. LPX, on the other hand, does not include human ignitions on the
268 grounds that the supposed positive relationship of population density to fire activity is an artefact, as discussed
269 above. Finally, LMfire accounts for the constraint on fire spread imposed by fragmentation of the burnable landscape
270 by human land use (as well as topography) while individual fires are allowed to burn across multiple days, and fires
271 occurring simultaneously within the same grid cell can effectively coalesce as they grow larger. Like LMfire, the
272 HESFIRE model (Le Page et al., 2015) also focuses on the constraints on fire spread – using landscape
273 fragmentation (due to human activities, topography, or past fire events) to determine the probability of extinction of a
274 fire that is ignited.

275 Schemes to simulate anthropogenic fire associated explicitly with land-use change have also been developed. Kloster
276 et al. (2010) include burning associated with land-use change by assuming that some fraction of cleared biomass is
277 burned. This fraction depends on the probability of fire as mediated by moisture, such that the combusted fraction is
278 low in wet regions (e.g. northern Europe) and high in dry regions (e.g. central Africa). Li et al. (2013) proposed an
279 alternative scheme to model fires caused by deforestation in the tropical closed forests, in which fires depended on
280 deforestation rate and weather/climate conditions, and were allowed to spread beyond land-type conversion regions
281 when weather/climate conditions are favourable. When the scheme was used in their global fire model, fires due to
282 human and lightning ignitions described in Li et al. (2012) were not used in the tropical closed forests. Li et al.
283 (2013) also include cropland management fires, prescribing seasonal timing based on satellite observations but
284 allowing the amount of burning to depend on the amount of post-harvest waste, population density, and gross
285 domestic product, and fires in peatlands, depending on a prescribed area fraction of peatland distribution, climate and
286 area fraction of soil exposed to air.

287

288 3.3 Modelling the impact of fire on vegetation and emissions

289 The impact of fire on vegetation operates through combustion of available fuel, plant mortality, and triggering of
290 post-fire regeneration. There is more similarity in the treatment of fire impacts between models than many other
291 aspects of fire.



292 Glob-FIRM assumes that all the aboveground litter/biomass is burnt, while subsequent models assume that only a
293 fraction of the available fuel is burnt. In CTEM, the completeness of combustion varies by fuel class and PFT (Arora
294 and Boer, 2005) while models such as MC-FIRE and SPITFIRE include a dynamic scheme for completeness of
295 combustion which depends on fire characteristics and the moisture content of each fuel class (Thonicke et al., 2010;
296 Lenihan et al., 1998).

297 Post-fire vegetation mortality is generally represented in a relatively simple way in fire-enabled DGVMs (Table 2).
298 Glob-FIRM, CTEM, Reg-FIRM, and the models described by Li et al. (2012) and Kloster et al. (2010) use PFT-
299 specific parameters for fractional mortality. MC-FIRE has a more explicit treatment of mortality, in which fire
300 intensity and residence time influence tree mortality from ground fires via crown scorching and cambial damage.
301 Canopy height relative to flame height (which is a function of fire intensity) determines the extent of crown
302 scorching. Bark thickness, which scales with tree diameter, protects against damage to the trunk, such that thicker-
303 barked trees have more chance of surviving a fire of a given residence time. LPJ-SPITFIRE uses a similar approach
304 except that bark thickness scales with tree diameter, which, together with canopy height depends on woody biomass.
305 LMfire includes a simple representation of size cohorts within each PFT, with the bark thickness scalar being defined
306 explicitly for each size cohort. In contrast, gap-based vegetation-fire models such as LPJ-GUESS-
307 SPITFIRE/SIMFIRE (Lehsten et al. 2009; Knorr et al. 2016) and ED-SPITFIRE (Fisher et al. 2015), explicitly
308 simulate size cohorts within patches characterised by differential fire-disturbance histories. LPX-Mv1 (Kelley et al.,
309 2014) incorporates an adaptive bark thickness scheme, in which a range of bark thicknesses is defined for each PFT.
310 Since thinner-barked trees are more likely to be killed by fire, the distribution of bark thickness within a population
311 changes in response to fire frequency and intensity.

312 LPX-Mv1 (Kelley et al., 2014) is the only model to date to incorporate an explicit fire-triggered regeneration
313 process, through creating resprouting variants of the temperate broad-leaved and tropical broad-leaved tree PFTs.
314 Resprouting trees are penalised by having low recruitment rates into gaps caused by fire and other disturbances.
315 However, resprouting is only one part of the syndrome of vegetation responses to fire which include e.g. obligate
316 seeding, serotiny, and clonal reproduction (e.g. Pausas and Keeley, 2014).

317

318 4. Objective and organization of FireMIP

319 Existing fire models have very different levels of complexity, both with respect to different aspects of the fire regime
320 within a single model and with respect to different families of models. It is not clear what level of complexity is
321 appropriate to simulate fire regimes globally. Given the increasing use of fire-enabled DGVMs to project the impacts
322 of future climate changes on fire regimes and estimate fire-related climate feedbacks (e.g. Knorr et al., 2016; Kelley
323 and Harrison, 2014; Kloster et al., 2012; Pechony and Shindell, 2010), it is important to address this question.

324 Coordinated experiments using identical forcings allow comparisons focusing on differences in performance driven
325 by structural differences between models. The baseline FireMIP simulation will use prescribed climate, CO₂,



326 lightning, population density, and land use forcings from 1700 through 2013. Examination of the simulated
327 vegetation and fire during the 20th century will allow differences between models to be quantified, and any
328 systematic differences between types of models or with model complexity to be identified.

329 However, a single experiment of this type is unlikely to be sufficient to diagnose which processes cause the
330 differences between models. Various approaches can be used for this purpose, including sensitivity experiments and
331 parameter-substitution techniques. Similarly, the effect of model complexity can be examined by switching off
332 specific processes. In FireMIP, experiments will be performed to study the impact of lightning, pre-industrial burned
333 area, CO₂, nitrogen, and fire itself, between different models.

334 Many model intercomparison projects have shown that model predictions may show reasonably good agreement for
335 the recent period but then diverge strongly when forced with a projected future climate scenario (e.g. Flato et al.,
336 2013; Freidlingstein et al., 2014; Harrison et al., 2015). “Out-of-sample” evaluation is one way of identifying
337 whether good performance under modern conditions is due to the concatenation of process tuning. Within FireMIP,
338 we will use simulations of fire regimes for different climate conditions in the past (i.e., outside the observational era
339 used for parameterisation and/or parameter tuning) as a further way of evaluating model performance and the causes
340 of model-model differences.

341

342 5. Benchmarking and evaluation in FireMIP

343 Evaluation is integral to the development of models. Most studies describing vegetation-model development provide
344 some assessment of the model’s predictive ability by comparison with observations (e.g. Sitch et al., 2003;
345 Woodward and Lomas, 2004; Prentice et al., 2007). However, these comparisons often focus on the novel aspects of
346 the model and are largely based on qualitative measures of agreement such as map comparison (e.g. Gerten et al.,
347 2004; Arora and Boer, 2005; Prentice et al., 2011; Thonicke et al., 2010). However, they often do not track
348 improvements or degradations in overall model performance caused by these new developments.

349 The concept of model benchmarking, promoted by the International Land Model Benchmarking Project (ILAMB:
350 <http://www.ilamb.org>), is based on the idea of a comprehensive evaluation of multiple aspects of model performance
351 against a standard set of targets using quantitative metrics. Model benchmarking has multiple functions, including (a)
352 showing whether processes are represented correctly, (b) discriminating between models and determining which
353 perform better for specific processes, and (c) making sure that improvements in one part of a model do not
354 compromise performance in another (Randerson et al., 2009; Luo et al., 2012; Kelley et al., 2013). Since fire affects
355 many inter-related aspects of ecosystem dynamics and the Earth system, with many interactions being non-linear, the
356 latter is particularly important for fire modelling.

357 Kelley et al. (2013) have proposed the most comprehensive vegetation-model benchmarking system to date. This
358 system provides a quantitative evaluation of multiple simulated vegetation properties, including primary production,



359 seasonal net ecosystem production, vegetation cover, composition and height, fire regime; and runoff. The
360 benchmarks are derived from remotely sensed gridded datasets with global coverage, and site-based observations
361 with sufficient coverage to sample a range of biomes on each continent. Data sets derived using a modelling
362 approach that involves calculation of vegetation properties from the same driving variables as the models to be
363 benchmarked are explicitly excluded. The target datasets in the Kelley et al. (2013) scheme allow comparisons of
364 annual average conditions, seasonal and inter-annual variability. They also allow the impact of spatial and temporal
365 biases in means and variability to be separately assessed. Specifically designed metrics quantify model performance
366 for each process, and are compared to scores based on the temporal or spatial mean value of the observations and to
367 both a “mean” and “random” model produced by bootstrap resampling of the observations.

368 The Kelley et al. (2013) scheme provides the starting point for model evaluation and benchmarking in FireMIP, but
369 does not address key aspects of the coupled vegetation-fire system including the amount of above-ground biomass
370 and/or carbon, fuel load and fuel type, soil and/or fuel moisture, the number of fire starts, fire intensity, the amount
371 of biomass consumed in individual fires, and fire-related emissions. Global datasets of some of these properties are
372 now available, including above-ground biomass both derived from vegetation optical depth (Liu et al., 2015) and
373 ICESAT-GLAS LiDAR data (Saatchi et al., 2011), the European Space Agency Climate Change Initiative Soil
374 Moisture product (Dorigo et al., 2010), the Global Fire Assimilation System biomass burning fuel consumption
375 product, fire radiative power, and biomass-burning emissions (Kaiser et al., 2012), and fuel consumption (van
376 Leeuwen et al., 2014). These will be incorporated into the FireMIP benchmarking scheme. The goal is to provide a
377 sufficient and robust benchmarking scheme for evaluation of fire while ensuring that other aspects of the vegetation
378 model can also be evaluated.

379 The selection of target data sets, in particular how to deal with differences between products and uncertainties, is an
380 important issue in benchmarking. There are, for example, multiple burnt area products (e.g. GFED4, L3JRC,
381 MCD45, and ESA MERIS: see Table 3). In addition to the fact that all of these products systematically
382 underestimate burnt area because of difficulties in detecting small fires (Randerson et al., 2012), they differ from one
383 another. Although all four products show a similar spatial pattern with more burnt area in the tropical savannas and
384 less in temperate and boreal regions, L3JRC and MCD45 have a higher total burnt area than MERIS or GFED4
385 (Table 3). Differences between products are lower (though still substantial) in the tropical savannas than elsewhere;
386 extra-tropical regions are the major source of uncertainty between products (Fig. 3a). The same is true for interannual
387 variability (Fig. 3b), where differences between products are higher in regions where total burnt area is low. Most
388 products show an increase in burnt area between 2001 and 2007 in extra-tropical regions, but there are disagreements
389 even for the sign of regional changes (Fig. 3c). These types of uncertainties, which are also characteristic of other
390 data sets, need to be taken into account in model benchmarking—either by focusing on regions or features which are
391 robust across multiple products or by explicitly incorporating data uncertainties in the benchmark scores (see e.g.
392 Hargreaves et al., 2013).

393 Process analyses can provide an alternative approach to model evaluation. The idea here is to identify relationships
394 between key aspects of a system and potential drivers, based on analysis of observations, and then to determine



395 whether the model reproduces these relationships (see e.g. Lasslop et al., 2014; Li et al., 2014). It is important to use
396 techniques that isolate the independent role of each potential driving variable because relationships between assumed
397 drivers are not necessarily causally related to the response. Bistinas et al (2014) showed, for example, that burnt area
398 increases as net primary productivity (NPP) increases and decreases as fuel moisture increases. Given that increasing
399 precipitation increases both NPP and fuel moisture this results in a peak in fire at intermediate levels of NPP and
400 precipitation. Population density is also strongly influenced by NPP (i.e. the capacity of the land to provide
401 ecosystem services) and thus the apparent unimodal relationship between burnt area and population density (see e.g.
402 Aldersley et al., 2011) is an artefact of the relationship between population density and NPP. However, when
403 appropriate techniques are used to isolate causal relationships, the ability to reproduce these relationships establishes
404 that the model is simulating the correct response for the right reason. Thus, process-evaluation goes a step beyond
405 benchmarking and assesses the realism of model behaviour rather than simply model response, a very necessary step
406 in establishing confidence in the ability of a model to perform well under substantially different conditions from
407 present.

408 One goal of FireMIP is to develop modelling capacity to predict the trajectory of fire-regime changes in response to
409 projected future climate and land-use changes. It has been repeatedly shown that vegetation and carbon-cycle models
410 that reproduce modern conditions equally well produce very different responses to future climate change (e.g. Sitch
411 et al., 2008; Friedlingstein et al., 2014). The interval for which we have direct observations is short and does not
412 encompass the range of climate variability expected for the next century. Benchmarking using modern observations
413 does not provide an assessment of whether model performance is likely to be realistic under radically different
414 climate conditions. The climate-modelling community use records of the pre-observational era to assess how well
415 models simulate climates significantly different from the present (Braconnot et al., 2012; Flato et al., 2013; Harrison
416 et al., 2014; Schmidt et al., 2014; Harrison et al., 2015). FireMIP will extend this approach to the evaluation of fire-
417 enabled vegetation models, building on the work of Brücher et al. (2014). Many data sources provide information
418 about past fire regimes. Charcoal records from lake and mire sediments provide information about local changes in
419 fire regimes through time (Power et al., 2010) and have been used to document spatially coherent changes in biomass
420 burnt (Daniau et al., 2012; Marlon et al., 2008; Marlon et al., 2013). Hemispherically-integrated records of
421 vegetation and fire changes can be obtained from records of trace gases (e.g. carbon monoxide), and markers of
422 terrestrial productivity and biomass burning (e.g. carbonyl sulphide, ammonium ion, black carbon, levoglucosan,
423 vanillic acid) in polar ice cores (e.g. Wang et al., 2010; Kawamura et al., 2012; Wang et al., 2012; Asaf et al., 2013;
424 Petrenko et al., 2013; Zennaro et al., 2014). Both hemispherically-integrated and spatially-explicit records of past
425 changes in fire will be used for model evaluation in FireMIP.

426

427 6. The next steps

428 There has been enormous progress in global fire modelling over the past 10–15 years. Knowledge about the drivers
429 of fire has improved, and understanding of fire feedbacks to climate and the response of vegetation is improving.



430 Global fire models have developed from simulating burnt area only to representing all of the key aspects of the fire
431 regime. However, there are large and to some extent arbitrary differences in the representation of key processes in
432 process-based fire models and little is known about the consequences for model performance. While the
433 development of fire models has been towards increasing complexity, it is still not clear whether a global fire model
434 *needs* to represent ignition, spread, and extinction explicitly or whether it would be sufficient to just represent the
435 emergent properties of these processes (burnt area, or fire size, season, intensity, and fire number) in models with
436 fewer uncertain parameters. The answer to this question may depend on whether the goal is to characterize the role
437 of fire in the climate system or to understand the interaction between fire and vegetation. Burnt area and biomass are
438 the key outputs needed to quantify fire frequency and carbon, aerosol and reactive trace gas emissions and changes in
439 albedo required by climate and/or atmospheric chemistry models. Empirical models may be adequate to estimate
440 such changes. Other aspects of the fire regime are important factors with respect to the vegetation response to fire
441 and thus may require a more explicit simulation of e.g. fire intensity and crown fires. By systematically evaluating
442 models that use different approaches and have different levels of complexity in the treatment of processes in
443 FireMIP, we hope to acquire new insights to guide future model development.

444

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768 **Tables**

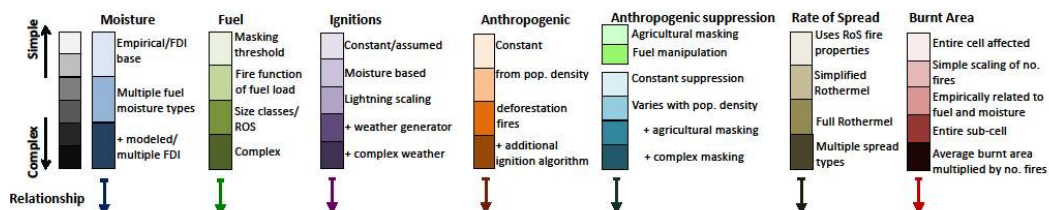
769 Table 1: Representation of fire processes in fire-enabled DGVM. The intensity of the colour represents the
770 complexity of the description of the process. Shades of grey describe the complexity of the model as a whole: light
771 grey being the simplest; black being the most complex. Blue represents the complexity of description of moisture
772 control on fire susceptibility ranging from: simple statistical relationships/ fire danger indices (FDIs) of fuel as a
773 whole (light blue); description of moisture in multiple fuel size classes; fully modelled or specifically chosen FDIs
774 for specific fuel moisture (dark blue). Green represents the complexity of fuel controlled fire susceptibility: simple
775 masking at a specified fuel threshold (light green); fuel structure effects on ignition probability and rate of spread;
776 and complex modelling of fuel bulk density (dark green). Purple shows complexity of natural ignition schemes: no
777 specified/ assumed ignitions (white); constant ignition source (light purple); simple relationship with fuel moisture;
778 prescribed ignitions - normally through lightning climatology inputs; prescribed lightning with additional scaling for
779 e.g. latitude dependent cloud-ground lightning (CG); daily distributed lightning via a weather generator; and with
780 additional complex ignition simulation (dark purple). Orange represents anthropogenic ignitions: none (white);
781 constant background ignition source (light orange); human population density varying ignitions based on a 'human
782 ignition potential' (HIP) and/or gross domestic product (GDP); inclusion of additional, complex human ignition
783 schemes such as pre-historic human behaviour (dark orange). Cyan and lime green represent inclusion of human
784 ignitions suppression and agriculture: none (white); constant suppression (light cyan); increasing suppression with
785 population (medium cyan); simple agricultural masking of fire (light lime green); fuel load manipulation from
786 agriculture (lime green); a mix of agricultural and ignition suppression (dark cyan). Italicize text under 'human
787 ignitions' and 'human suppression' denote models where the combined influence of human ignitions and suppression
788 result in a unimodal description of fire relative to population density. Brown shows complexity of the calculation of
789 fire sizes, typically through a rate of spread model (RoS): None (white); simplified RoS model to obtain fire
790 properties (light brown); simplified RoS to model individual fires; full Rothermel RoS; multiple RoS models (dark
791 brown). Red show complexity of the calculation of the overall burnt area: the entire cell is affected by fire (light red);
792 constant scaling of the number of fires to burnt area depending on vegetation type; scaling based on moisture and
793 fuel type; entirety of a subcell affected; and scaling of number of fires by fire size calculated by RoS model. Arrows
794 demonstrate the exchange of components between models. Arrows start in the model containing the original process
795 description.

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Model	Fuel Moisture	Fuel Load	Fire starts from lightning Ignitions	Anthropogenic Ignitions	Anthropogenic Suppression	Rate of Spread (ROS)	Burnt Area
CASA/GFED	None. Fire translated to burnt area from satellite fire counts.						Proportional to no. of fires, with more burnt area to fire in sparse vegetation (van der Werf, 2003)
GLOBFIRM	Moisture of extinction, above which fire does not occur (Thonicke et al. 2001) Increased fire occurrence with decrease moisture (Thonicke et al. 2001)	Discontinuity fuel load threshold, below which fire does not occur (Thonicke et al. 2001) Reduced fuel from grazing (Krinner et al. 2005)			Suppression from Reduced fuel from grazing (Krinner et al. 2005)		Increases exponentially with annual (Thonicke et al. 2001) or monthly (Krinner et al. 2005) summed fire occurrence.
SIMFIRE	Maximum possible burnt area as a function of FDI (Knorr et al. 2014)	Maximum possible fire as a function of APAR as proxy for fuel load (Knorr et al. 2014)			Increases exponentially with population (Knorr et al. 2014; Knorr et al. 2015)		Multiplication of maximum fire functions for fuel, moisture & suppression (Knorr et al. 2014).
P&S	Function of VPD (proxy for ambient atmospheric conditions) (Pechony & Shindell, 2009)	Fire scaled by vegetation density based on LAI (Pechony & Shindell, 2009)	Observed lightning flash count, scaled for cloud-to-ground (CG) ratio (Pechony & Shindell, 2009)		Increases with population (Pechony & Shindell, 2009)		
Rate of Spread Models							
MC-FIRE	Calculated from fuel size classes and live fuel component (Lenihan et al. 1998) Effects fire start (Lenihan et al. 1998) and RoS (Rothermel 1972)	Size ratios effects RoS (Rothermel 1972)	Fire only occur when 1000hr hour fuel content drops below threshold and rate of spread is above a threshold (Lenihan et al. 1998)		Capped burnt area for low intensity or slow spread rate fires in populated areas (Rogers et al. 2011)	Fire behaviour scaled by fuel load and moisture based Fire Danger Index (FDI) based rate of spread for ground (Rothermel 1972; Lenihan et al. 1998) and crown (Van Wanger, 1993) fires	Entire grid cell affected by fire during fire occurrence (Lenihan et al. 1998)
CTEM	Represented by soil moisture (Arara & Boer 2005; Melton & Arara 2015)	Linear increase fire occurrence between discontinuity and saturated fuel thresholds (Arara & Boer 2005)	Probability of fire occurrence a multiple of probabilities from fuel, moisture & ignitions (Arara & Boer 2005). Latitude dependant CG scaling for lightning (Kloster et al. 2012)	Deforestation fire (Kloster et al. 2012)	No. of days fire burnt suppressed at higher population density (Melton & Arara 2015)	No FDI (Arara & Boer 2005) Affected by differing fuel types (Arara & Boer 2005)	Maximum of 1 fire per sub-grid cell unit. Overall burnt area in grid cell is multiplication of probability of fire by number of units by average fire size per unit (Arara & Boer 2005; Melton & Arara 2015)
Li et al.	Represented by soil moisture & relative humidity (Li et al. 2012)		Ignitions & limitation from fuel and moisture (Li et al., 2012)	Deforestation & degradation fires in tropical closed forests (Li et al. 2013)	Suppression increases with GDP (Li et al. 2013)		
REGFIRM	Fire occurrence from moisture based FDI (Venesky et al. 2002)		Number of fires instead of probability of fire (Venesky et al. 2002)	"Human ignition potential" (HIP) (Venesky et al. 2002)		Variable wind speed affects rate of spread and fire oval shape (Venesky et al. 2002)	Number of fire multiplied by average area burnt per fire (Venesky et al. 2002)
SPIRFIRE/LPX/Lmfire			CG distributed between wet and dry lightning (Prentice et al. 2011) "Storm days" (Kelley et al. 2014) Inter-annual lightning from atmospheric conditions (Pfeiffer et al. 2013)	HIP varying with socio-economic development (Thonicke et al. 2010) Different human-fire relation for hunter-gatherers, pastoralists and farmers (Pfeiffer et al. 2013)	Cropland fire masking (Thonicke et al. 2010) Additional ignition suppression term (Thonicke et al. 2010) Explicit cropland fragmentation algorithm (Pfeiffer et al. 2013)	Multi-day fires (Pfeiffer et al. 2013) Different RoS for different vegetation type (Pfeiffer et al. 2013) Terrain impediment to spread (Pfeiffer et al. 2013) Reduced rate of spread at high wind speeds (Lasslop et al. 2014)	



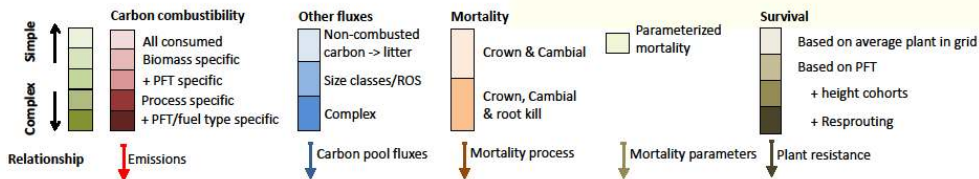


799 Table 2: Representation of the impacts of fire in fire-enabled DGVMs. Intensity of colour indicates the complexity of
800 the description of the component. Green indicates complexity of the representation of fire impacts. Red describes the
801 complexity of the description of atmospheric fluxes from fire: flux is equivalent to all consumed biomass (light red);
802 consumption based on biomass specific combustion parameters; inclusion of PFT combustion parameters; process
803 based; biomass/PFT parameterized process-based (dark red). Blue represents the complexity of carbon fluxes to
804 other carbon pools: no additional fluxes (white); non-combusted dead carbon flux (light blue); carbon fluxes based
805 on fire spread properties; fire-adapted vegetation carbon retention (dark blue). Orange represents complexity of
806 simulated mortality processes: parameterized mortality (yellow); mortality from crown and cambial damage (light
807 orange); additional root damage mortality (dark orange). Brown represents complexity of plant adaptation to fire
808 when mortality processes are included: mortality based on a grid cell's 'average plant' properties of fire resistant
809 traits (light brown); PFT based average traits; inclusion and height cohorts; inclusion of dynamic/complex adaptations
810 such as resprouting (RS)(dark brown). Arrows demonstrate the exchange of components between models, starting in
811 the model containing the original description.

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Model (main citation)	Carbon Emission	Other carbon feedbacks	Plant mortality type	Plant resistance
CASA/GFED	Combustibility dependent on fuel type (leaf, stem and root, dead) and life-form (wood or grass) (Potter & Klooster, 1999)	Killed but not consumed plant material enters litter pool. (Potter & Klooster, 1999)	Fraction of woody plants killed dependent on % woody to grass cover. In high wood cover, most trees are killed. Low tree and high grass cover, few trees are killed. (Potter & Klooster, 1999) All above-ground grass biomass killed; 90% belowground grass biomass survive (Potter & Klooster, 1999)	
GLOBFIRM	All aboveground litter & living biomass consumed and released to atmosphere (Sitch et al. 2003)	Includes 'Black carbon' (i.e. inert carbon for 1,000s years). (Krimmer et al. 2005)	PFT based mortality parameter (Thonicke et al. 2001)	
Rate of Spread Models				
MC-FIRE	All canopy carbon is released to atmosphere during crown fires (Lenihan et al. 1998) Scorched canopy leafmass from high ground fires released to atmosphere (Lenihan et al. 1998) Atmospheric release of consumed dead biomass is calculated from fuel amount and fuel moisture (Lenihan et al. 1998)	Scorched woodmass enters litter pool. (Lenihan et al. 1998)	Crown scorch mortality based on 'lethal scorch height' of fire and canopy height (Peterson & Ryan, 2009) Cambial mortality based on fire residence time and plant bark thickness (Lenihan et al. 1998) Root damage (Lenihan et al. 1998)	Complete mortality in crown fires (Lenihan et al. 1998) Crown/Cambial damage mortality from ground fire follow Peterson & Ryan (1986). All vegetation represented by average crown height and bark thickness, based on simple allometric equations (Lenihan et al. 1998) 'Depth of lethal heating' for roots based on Steward et al. 1990
CTEM	PFT based combustion parameters for different woody components (Arora & Boar 2005)		PFT specific parameters relating carbon consumption to plant mortality (Arora & Boar 2005) or PFT-specific mortality factor (Li et al. 2012)	
REGFIRM				
SPITFIRE/ LPX/Lnfire	Fuel load combustion split into PFTs (Thonicke et al. 2010).	Carbon retained by surviving resprouting PFTs (Kelley et al. 2014)		Scorch height and bark thickness calculated per PFT, using PFT-specific allometric parameters (Thonicke et al. 2010). Within PFT height cohorts affect bark thickness and height-based survival (Pfeiffer et al. 2013) Within PFT bark thickness competition (Kelley et al. 2014) Resprouting PFTs that resprout from reduced above-ground biomass rather than killed (Kelley et al. 2014)





814 Table 3: Overview of the burnt area (BA) products used for the intercomparison and their characteristics.

	GFED4	L3JRC	MCD45A1	ESA MERIS
Temporal Resolution	Daily (2001 - present)	Burn date (day)	Burn date (day)	Twice weekly
Spatial Resolution	0.25°	1km	500m	300m
Period covered	1997-present	2001-2006	2001-present	2006-2008
Mean BA (Mha)	346.8	398.9	360.4	368.3
Reference	Giglio et al. (2013)	Tansey et al. (2008)	Roy et al. (2008)	Alonso-Canas and Chuvieco (2015)

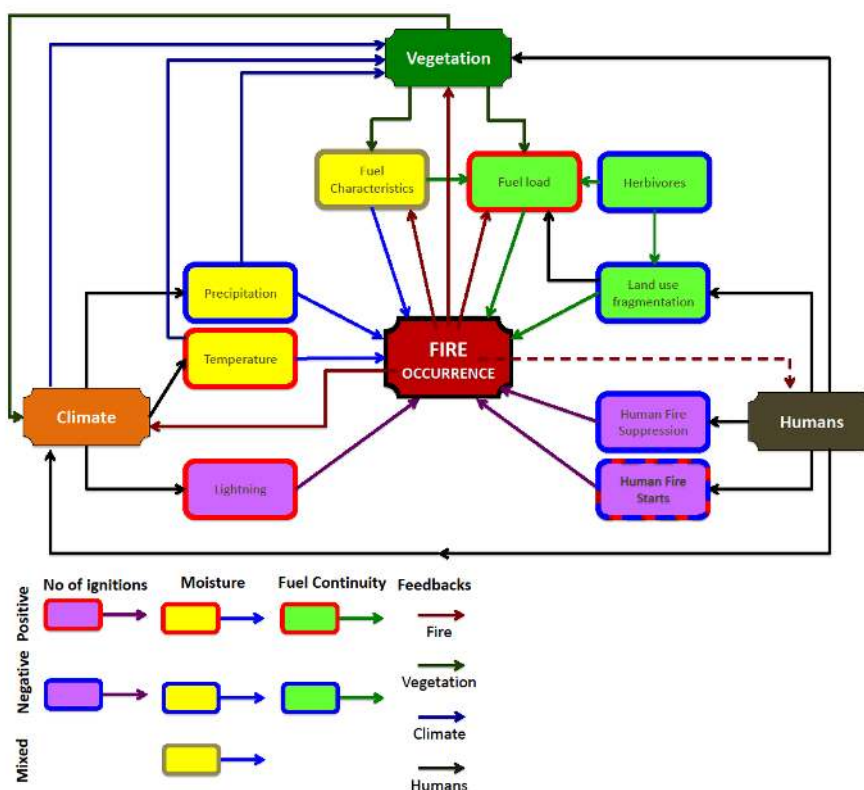
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817 **Figures**

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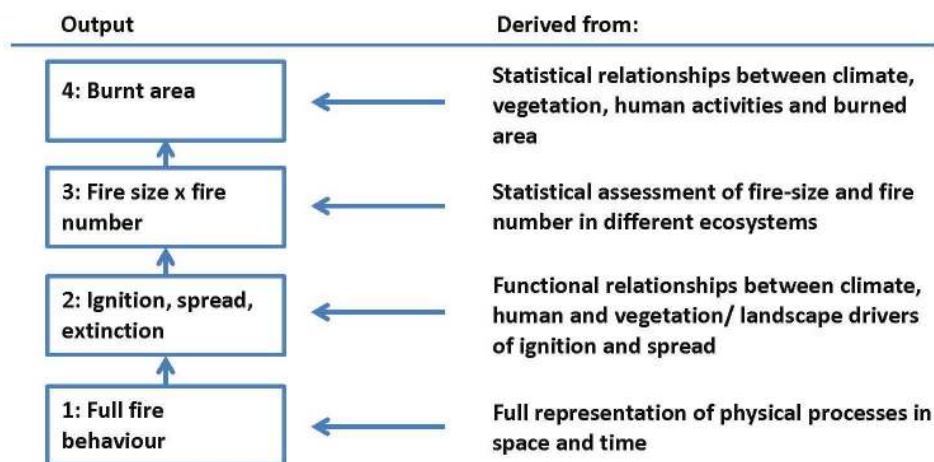
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821 Fig. 1: Summary of the interactions between the controls on fire occurrence on coarse scales. Green boxes show
 822 controls influencing fuel; blue influencing moisture; and purple influencing ignitions. Red box indicates positive
 823 influence on fire; blue a negative influence, and brown a mixed response. Brown arrows indicate interactions
 824 between people and other controls; dark green between vegetation and other controls; and dark blue from climate.
 825 Red arrows show feedback from fire.

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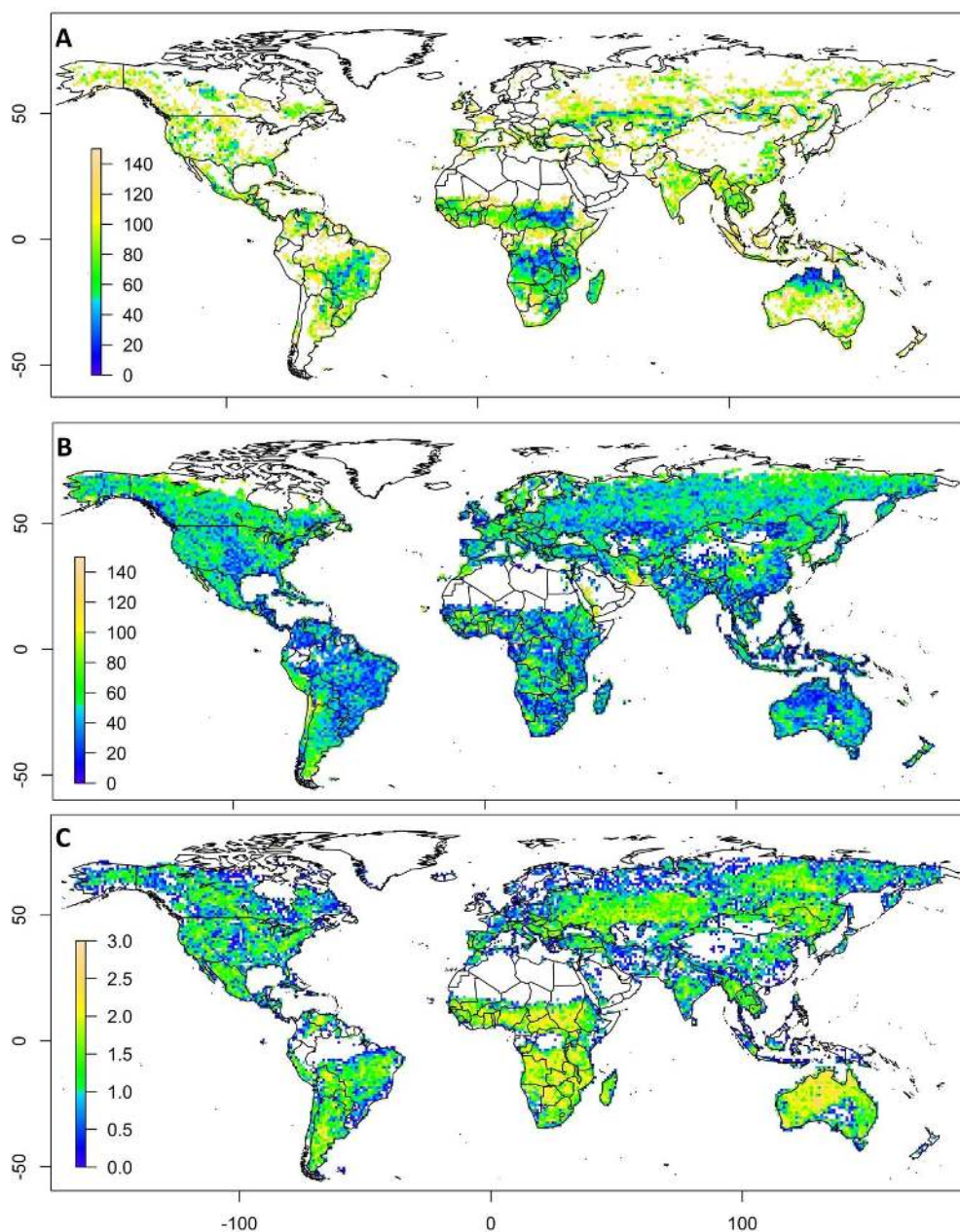
829 Fig. 2: Summarising the levels of model complexity required to derive different aspects of global fire regimes.
830 Outputs from models functioning at level 1 can be used to derive higher-level outputs, but it is not possible to work
831 backwards (i.e. empirical relationships between burnt area and environmental drivers will not allow for assessment
832 of changes in fire number and fire size). Currently there are fire routines in global DGVMs that represent all of these
833 levels of complexity (see Table 1), and it remains to be decided how much detail is required.

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838 Fig. 3: Coefficient of variation (%) characterizing a) inter-product variability in mean burnt area; b) the inter product
839 variability of the interannual variability in burned area; and c) the interproduct variability of the slope of temporal
840 trends (2001-2007). Plots a) and b) are based on all four burnt area products (GFED4, MCD45, L3JRC, ESA
841 MERIS) whereas plot c) is based on three products and does not include the MERIS data because it is currently only
842 available for 3 years, see Table 3.