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# Modelling human-fire interactions: combining alternative perspectives and approaches

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest

### *Author contribution statement*

SPH, AF, JM and JDAM contributed to the conception and design of this study. SPH and AF wrote the first draft of section 1; JM and CS drafted 2.1; JDAM and OP drafted 2.2; YK drafted 2.3; SPH and SR drafted 2.4; GR and TS drafted 2.5; KS and KY drafted 2.6; SPH drafted sections 3 and 4. AF coordinated and edited the manuscript and produced Fig. 7. JDAM and OP produced Fig. 8. and SPH and SR produced Fig. 9. All authors contributed to the final version of the manuscript.

### *Keywords*

Pyrogeography, climate and fire projections, Fire management, Fire policies, human-fire models, Agent-based models (ABMs), fire-enabled global vegetation model, firespread models

### *Abstract*

Word count: 285

Although it has long been recognised that human activities affect fire regimes, the interactions between humans and fire are complex and poorly understood. Many different approaches are used to study human-fire interactions, but in general they have arisen in different disciplinary contexts to address highly specific questions. Models of human-fire interactions range from conceptual local models to numerical global models. However, given that each type of model is highly selective about which aspects of human-fire interactions to include, the insights gained from these models are often limited and contradictory, making them a poor basis for developing fire-related policy and management practices. Here, we first review different approaches to modelling human-fire interactions and then discuss ways in which these different approaches could be synthesised to provide a more holistic approach to understanding human-fire interactions. We argue that the theory underpinning many types of models was developed using only limited amounts of data and that, in an increasingly data-rich world, it is important to re-examine model assumptions in a more systematic way. All of the models are designed to have practical outcomes but are necessarily simplifications of reality and as a result of differences in focus, scale and complexity, frequently yield radically different assessments of what might happen. We argue that it should be possible to combine the strengths and benefits of different types of model through enchainning the different models, for example from global down to local scales or vice versa. There are also opportunities for explicit coupling of different kinds of model, for example including agent-based representation of human actions in a global fire model. Finally, we stress the need for co-production of models to ensure that the resulting products serve the widest possible community.

### *Contribution to the field*

In the face of recent changes in wildfire regimes, there is an urgent need to understand human-fire interactions - how fire regimes will change in the future, how changes will impact human society and how these impacts could be mitigated. Many different approaches are used to study human-fire interactions, from conceptual local models to numerical global models, but generally they have arisen in different disciplinary contexts to address highly specific questions, and the insights gained are often limited and contradictory, making them a poor basis for developing fire-related policy and management practices. We review different approaches to modelling human-fire interactions and then discuss ways in which these different approaches could be synthesised to provide a more holistic approach to understanding these interactions. We argue that, in an increasingly data-rich world, it is important to re-examine model assumptions in a more systematic way. We also argue that it should be possible to combine the strengths and benefits of different types of model through coupling or enchainning different models, for example from global down to local scales or vice versa. Finally, we stress the need for co-production of models to ensure that the resulting products serve the widest possible community.

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# 1 **Modelling human-fire interactions: combining alternative perspectives and approaches**

2  
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31 models

## 32 33 34 **Abstract**

35  
36 Although it has long been recognised that human activities affect fire regimes, the interactions  
37 between humans and fire are complex, imperfectly understood, constantly evolving, and  
38 lacking any kind of integrative global framework. Many different approaches are used to study  
39 human-fire interactions, but in general they have arisen in different disciplinary contexts to  
40 address highly specific questions. Models of human-fire interactions range from conceptual  
41 local models to numerical global models. However, given that each type of model is highly  
42 selective about which aspects of human-fire interactions to include, the insights gained from  
43 these models are often limited and contradictory, which can make them a poor basis for  
44 developing fire-related policy and management practices. Here, we first review different  
45 approaches to modelling human-fire interactions and then discuss ways in which these different  
46 approaches could be synthesised to provide a more holistic approach to understanding human-  
47 fire interactions. We argue that the theory underpinning many types of models was developed  
48 using only limited amounts of data and that, in an increasingly data-rich world, it is important  
49 to re-examine model assumptions in a more systematic way. All of the models are designed to  
50 have practical outcomes but are necessarily simplifications of reality and as a result of

51 differences in focus, scale and complexity, frequently yield radically different assessments of  
52 what might happen. We argue that it should be possible to combine the strengths and benefits  
53 of different types of model through enchainning the different models, for example from global  
54 down to local scales or vice versa. There are also opportunities for explicit coupling of different  
55 kinds of model, for example including agent-based representation of human actions in a global  
56 fire model. Finally, we stress the need for co-production of models to ensure that the resulting  
57 products serve the widest possible community.

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59  
60  
61 **Word count:** 10651

## 62 63 64 **1. Introduction**

65  
66 Naturally occurring landscape fires, or wildfires, have been an integral component of the Earth  
67 System for 350-400 million years, since the development of vegetation on land (Scott, 2000;  
68 Bowman et al., 2009). Humans have used fire for domestic purposes for about one million  
69 years (e.g. Goren-Inbar et al., 2004; Karkanis et al., 2007; Berna et al., 2012) and fire has been  
70 used as a management tool to facilitate land clearance and pasture improvement at least since  
71 the Neolithic (Piperno, 1994; Arroyo-Kalin, 2012). Fire continues to be used today in  
72 subsistence activities and for maintaining cultural identity, where traditional fire knowledge  
73 governs burning (e.g. Mistry et al., 2005; Eriksen, 2007). It has been estimated that about 280  
74 million hectares of land, mostly in the tropics and subtropics, are used for swidden agriculture  
75 (Heinimann et al., 2017) — much of which is facilitated by the use of fire for land clearance.

76  
77 Fire is the most important cause of natural disturbance (Pausas et al., 2017), influencing  
78 vegetation patterns and biogeochemical cycles (Scott, 2000) and promoting biodiversity in fire-  
79 prone ecosystems (He et al., 2019). Fires also provide important ecosystem services, including  
80 helping to regulate the occurrence of catastrophic fires (Pausas and Keeley, 2019). However,  
81 alongside these benefits, there are considerable negative impacts from wildfires on human  
82 safety and health (e.g. Johnston et al., 2012; Liu et al., 2015; Yu et al., 2020), economic costs  
83 from fire management, disaster relief, property and forestry damage, tourism loss and health  
84 costs (Butry et al., 2001), severe impacts on forest recovery (Stevens-Rumann et al., 2018) and  
85 especially in ecosystems that are not well adapted to fire (Whitman et al., 2019; Kelly et al.,  
86 2020), and significant feedbacks from fires to climate (Liu et al., 2014; Harrison et al., 2018;  
87 Walker et al., 2019). Human-induced deforestation fires in tropical fire-resistant biomes also  
88 have noticeable and largely negative effects on biodiversity, human health and climate (e.g.  
89 Van der Werf et al., 2009; Reddington et al., 2014; Spracklen and Garcia-Carreras, 2015;  
90 Crippa et al., 2016; Exbrayat et al., 2017; Ellwanger et al., 2020), although this is most  
91 characteristic of the deforestation fires that are used to promote more intensive land-use  
92 practices rather than facilitating swidden agriculture (Murdiyarso and Adiningsih, 2007).

93 The frequency and severity of wildfires are heterogenous over space and time, influenced by  
94 interactions between climatic conditions, ignitions and available fuel (Moritz et al. 2005,  
95 Krawchuck et al. 2009, Harrison et al. 2010). It is becoming increasingly evident that  
96 anthropogenic climate warming promotes the conditions for wildfire, through extending the  
97 periods of fire weather, which occurs through a combination of high temperatures, low  
98 humidity and rainfall, and often high winds (Jolly et al., 2015; Jones et al., 2020). Future

99 climate projections indicate that there will be an increase in the likelihood of fire weather and  
100 this has been seen as another motivation for political action to limit climate change to below  
101 2°C (e.g. Burton et al., 2018; Turco et al., 2018). However, despite the increased prevalence of  
102 fire weather, satellite datasets show a decrease in burned area in recent years (Van Lierop et  
103 al., 2015; Doerr and Santín, 2016; Andela et al., 2017, Lizundia-Loiola et al. 2020a, Lizundia-  
104 Loiola et al. 2020b). This trend is not statistically significant at the global scale (Forkel et al.,  
105 2019a) but is important in certain regions, most noticeably in sub-Saharan Africa. The causes  
106 of this decline remain uncertain: Andela et al. (2017) argued that the decline was a reflection  
107 of human-induced land-use changes but more recent analyses suggest that changes in climate  
108 and natural vegetation cover also play a role, leading to both increased and decreased fire, and  
109 can offset the carbon losses from land-use change at a regional scale (Forkel et al., 2019a).  
110 Whatever the cause of the recent decline in burnt area, the implications for environmental  
111 policy and fire management are far different from those that would emerge from a  
112 consideration of fire weather trends alone.

113 Predictions of the future trajectory of wildfires are required in order to predict the consequences  
114 of these changes for the Earth System (e.g. Kloster et al., 2012; Kloster and Lasslop, 2017),  
115 and these models must necessarily include some consideration of the role of anthropogenic  
116 fires and the complex role of humans in fire management (Lavorel et al., 2007; Knorr et al.,  
117 2016; Rabin et al., 2017). Projections are also required of how changes in wildfires might  
118 impact human activities and, in turn, human activities might be modified in the light of these  
119 impacts and how political, economic, social or cultural factors might affect these responses.  
120 Models of human-fire relationships can also illuminate our understanding of the potential for  
121 human fire practices to have positive ecological outcomes, and of the role that fire plays in  
122 sustaining cultures and livelihoods.

123  
124 Many different types of models have been employed to examine human-fire interactions,  
125 ranging from informal or conceptual models to formal or mathematical models (Edmonds,  
126 2018), on scales ranging from local to global. These models have generally been developed  
127 and deployed to answer specific questions, and thus are rooted within disciplinary perspectives  
128 and understanding. Despite the recognition that integration of these different perspectives and  
129 approaches would be beneficial, and promote a better understanding of pyrogeography  
130 (Bowman et al., 2009), little progress has been made towards such an integration. This is a  
131 serious concern because, as the differences in the trends in fire weather versus burnt area amply  
132 illustrate, consideration of limited aspects of the climate-fire-human nexus could lead to  
133 radically different approaches to fire management and the development of policies for  
134 adaptation/mitigation actions. As in many areas of global change science, policy and  
135 management choices will need to reflect trade-offs between costs and benefits and this will  
136 require integrating the different perspectives gained by deploying multiple kinds of models.

137  
138 In this paper, we address the following questions: (i) what kinds of models are currently being  
139 used to address human-fire interactions? (ii) what can we learn from each of the different kinds  
140 of models?; and (iii) can we reconcile the different modelling perspectives and build more  
141 comprehensive fire-system models? To answer these questions, we first describe a number of  
142 different types of models that have been used to describe the interactions between humans and  
143 fire, encompassing both formal and informal models that operate at different spatial scales and  
144 emerge from different disciplinary or social perspectives. We describe what they are designed  
145 to do, their key characteristics, the assumptions that underpin them, how the models are  
146 currently implemented and their data requirements, and explicitly examine their current  
147 uncertainties and simplifications. We then explore commonalities between these models, if and

148 how different approaches can be reconciled or integrated, and if and when it is helpful to do  
149 so. Finally, we outline the major challenges and provide a basic roadmap for integrating  
150 insights from different types and scales of models. Through doing so, we propose a way  
151 forward for improving our understanding of human-fire interactions, providing a more solid  
152 foundation for predicting future fire regimes and a more comprehensive basis for building fire  
153 management plans and policies.

154  
155

## 156 **2. Approaches to modelling fire**

157

158 Interest in human-fire relationships spans many disciplines, each asking very different types of  
159 questions, grounded in different philosophical approaches and drawing on a different  
160 knowledge base. The tools used to address these questions, and specifically the informal or  
161 formal models developed within different research domains, can therefore be expected to be  
162 different from one another. Here, as a basis for exploring commonalities across models, we  
163 describe some of the types of models that are currently being used to examine human-fire  
164 interactions. These models differ in the spatial and temporal scale at which they operate, and  
165 the resolution and complexity that bio-physical processes and humans are represented (Figure  
166 1). We structure this discussion moving from the most people-centric models (place-based  
167 models of fire knowledge, agent based models, economic models), which are differentiated to  
168 some extent by the spatial scale at which they are developed and used, to the physics-based  
169 models that incorporate human-fire interactions to some extent (wildfire spread models, global  
170 fire models). In the last subsection, we look at how policies are developed and implemented in  
171 the context of modelling human-fire interactions.

172

### 173 **2.1 People-centric models**

174

#### 175 **2.1.1 Place-based models of fire knowledge**

176

177 Place-based models of fire knowledge represent the relationships between people, fire and the  
178 landscape in a local context in verbal, visual, written, or numerical form. Humans may be  
179 represented in such models as (i) users of fire for specific subsistence activities such as farming  
180 or pastoralism, (ii) fire managers, controlling fire in the landscape, often within non-  
181 governmental or governmental institutions, or (iii) holistic fire users, embedded within social-  
182 ecological systems in which fire is understood to have agency. Place-based models of fire  
183 knowledge can be used to understand historical and current patterns of fire use, the status of  
184 fire knowledge, the influence of social, environmental, economic and political factors on fire  
185 use, fire cosmologies and fire governance.

186

187 The methodologies by which place-based models of fire knowledge are constructed and  
188 documented vary in the extent of involvement by local people in the research process. At one  
189 end of the spectrum, there are models constructed by researchers without involving local  
190 people, where the human influence on fire regimes is inferred from collated datasets. For  
191 example, Van Wilgen et al. (2004) combined a 45-year spatial dataset of fire occurrence in the  
192 Kruger National Park with climate data and information about management policies in different  
193 time periods to model the fire-return time and variability resulting from different management  
194 approaches. Models may be constructed by researchers using data about local people through  
195 ethnographic observation, interviews, questionnaires or participatory research methodologies.  
196 For example, Sorrenson (2004) used data from interviews with swidden farmers in the

197 Brazilian Amazon to develop a model linking the calendar week when farmers chose to burn  
198 an area to the length of the preceding fallow period. Where local people are involved, the  
199 research process attempts to elicit the mental models that fire users and other stakeholders have  
200 of their external reality and their place within it (Jones et al., 2011). Models co-produced by  
201 researchers with local people may involve amalgamation of models constructed by individuals  
202 or involve a group modelling process.

203

204 Modelling processes also vary greatly in the extent to which they are structured around model  
205 production and the particular form of model envisaged. To model fire use in Bolivia, for  
206 example, Devisscher et al. (2016) followed a structured process of fuzzy cognitive mapping,  
207 involving focus group discussions to identify model variables and quantify the strength of  
208 relationships between them. Conceptual models may emerge post-hoc, drawing upon data from  
209 several sources. Monzón-Alvarado and Keys (2014), for example, used insights from research  
210 interviews and participatory mapping with swidden farmers in Mexico to develop a qualitative  
211 model of the cascading effects of early rains on agricultural burn outcomes across ecological,  
212 economic and cultural domains.

213

214 There are many participatory modelling techniques that explicitly aim to co-produce a model  
215 with local people, many of which produce qualitative models (Voinov et al., 2018). A number  
216 of these techniques have been used to develop place-based models of fire knowledge. Seasonal  
217 calendars, for example, have been constructed to understand different fire practices in the  
218 context of annual ecological and social cycles (e.g. Rodríguez et al., 2011; McKemey et al.,  
219 2020). Rich pictures, artistic impressions that can include pictures, text, and symbols  
220 representing particular situations or issues from the viewpoint(s) of the person or people who  
221 create them (Bell et al., 2016), have been used to develop shared understanding of fire  
222 management between Indigenous community members and representatives of governmental  
223 and non-governmental organisations (Bilbao et al. 2019, Figure 2). Causal loop diagrams, that  
224 depict causal or correlative relationships between different variables in a system (Lane, 2000),  
225 have been used to model responses of swidden agriculture to climate and social change in  
226 Panama (Li and Ford, 2019) and the role of fire use in land cover change in Indonesia  
227 (Medrilzam et al., 2014). Quantitative or semi-quantitative approaches have also been used to  
228 co-produce models. In fuzzy cognitive mapping, participants construct a diagram showing the  
229 direction and strength of relationships between variables, where the variables are defined by  
230 the participants (Özesmi and Özesmi, 2004). This methodology has been used, for example, to  
231 model fire use and wildfire risk in Bolivia (Devisscher et al., 2019). Constructing Bayesian  
232 belief networks, participants relate elements with discrete possible states to one another in a  
233 hierarchy, such that the state of elements higher up the hierarchy probabilistically influences  
234 the state of those lower down (Düspohl et al., 2012). This approach has been used to understand  
235 adaptive fire management in conservation areas in Australia (Smith et al., 2007). Different  
236 methodologies are appropriate in different social contexts. Barber and Jackson (2015), for  
237 example, argue that, to Aboriginal Australians, visual and relational modelling approaches  
238 make better intuitive sense than quantitative approaches, because these societies have both  
239 strong traditions of using artwork to represent relationships between people and the wider  
240 cosmological landscape and also keep track of elaborate kinship systems.

241

242 Some forms of local knowledge, and some socio-ecological entities, relationships and  
243 processes, cannot be represented using participatory research frameworks. The biophysical  
244 elements of socio-ecological systems are generally more easily represented than socially-  
245 constructed elements (Crane, 2010; Jones et al., 2011). Models may also not account for the  
246 multiple ways in which people understand causality simultaneously: offered explanations for



247 using fire might be proximate, functional, ontogenetic, evolutionary, or all four simultaneously  
248 (see Bliege et al. commentary in Scherjon et al. 2015, p. 315). Participatory modelling  
249 processes are affected by the power relations inherent in any local context, and between  
250 researchers and local people (Cooke and Kothari, 2001). Trust is important, particularly in  
251 cases where fire use has been delegitimised by the state and local fire users may therefore be  
252 wary of discussing the issue. The generalisation and simplification involved in model creation  
253 may impede consensus when people in a community have different understandings and  
254 practices. It is important to understand whether participating individuals have the right to share  
255 collective knowledge or speak on behalf of a group (Davis and Wagner, 2003).

256  
257 Constructing place-based models of fire knowledge can benefit local fire users. While  
258 modelling codifies what is already known, it can also be a creative process of knowledge  
259 making (Barber and Jackson, 2015). Workshops to elicit understandings of fire and socio-  
260 ecological change among the Pemón in Venezuela, for example, exposed conflicting  
261 perspectives among elders and young people and allowed communities to develop new shared  
262 understandings (Rodríguez et al., 2018). Formalising knowledge and practices in model form  
263 can also give local people credibility and visibility. In the case of the Pemón, articulation of  
264 local knowledge in this way promoted dialogue with resource managers, shifting official  
265 narratives away from fire suppression towards management (Bilbao et al., 2019). However,  
266 there is considerable debate about whether rules derived from locally-specific knowledge can  
267 be applied in other places or at broader scales. When rules derived from Aboriginal fire  
268 knowledge were applied to institutional fire management in Australia, for example, they were  
269 criticised as prescriptive and ecologically detrimental (Wohling, 2009). Using place-based  
270 models of fire knowledge outside of their context also carries ethical implications because local  
271 people may not understand, and may therefore not be able to give informed consent to, the way  
272 their knowledge, in model form, is used.

273  
274  
275  
276

### 2.1.2 Agent-based models

277  
278 Agent-based models (ABMs) belong to a class of computational models that represent  
279 individual, heterogeneous, and often interacting, entities using sets of computational rules or  
280 relationships (e.g., Grimm et al., 2005; Bithell et al., 2008). The individual entities or agents in  
281 an ABM represent individual humans or groups of humans (i.e., institutions) and their activities  
282 in the social and physical worlds (Figure 3). Agents have the ability to make decisions about  
283 future actions based on their state, the state of other agents, and/or the state of the simulated  
284 environment (O’Sullivan et al., 2012). Decision-making is represented using explicit rules or  
285 decision-trees. Actions that result from specific decisions may modify the state of the decision-  
286 making agent, other agents, or the environment.

287  
288 ABMs provide considerable flexibility in the representation of decision making. For example,  
289 they can represent decision-making (i) with multiple alternative rules or strategies; (ii) that are  
290 imperfectly rational, for example because of incomplete availability of information; (iii) that  
291 pursue non-economically advantageous goals, for example because of cultural norms; or (iv)  
292 are adaptive through time, simulating learning processes. Furthermore, different decision-  
293 making rules can be used for different members of a heterogeneous agent population. This  
294 flexibility has promoted the use of ABMs in studies of socio-ecological systems, in which  
295 interactions between agents and individual and environmental heterogeneity are understood to

296 be essential features (Levin et al., 2013). For example, ABMs have been used widely to  
297 examine land use and cover (e.g., Parker et al., 2003; Groeneveld et al., 2017), with specific  
298 consideration of land management systems including agriculture, (e.g., Huber et al., 2018),  
299 rangelands (Walker and Janssen, 2002) and forests (e.g., Rammer and Seidl, 2015). Most of  
300 these studies have been conducted at the human landscape-scale (i.e., 100–10,000 km<sup>2</sup>), and  
301 combine qualitative and quantitative data to structure and parameterise the models. Brändle et  
302 al. (2015), for example, examined processes of land abandonment and re-forestation in the Visp  
303 area of the Central Valais of Switzerland, developing an agent decision-making typology via a  
304 farm household survey in conjunction with the national agricultural census.

305  
306 In the context of fire, an ABM offers the potential to represent the decision-making in  
307 anthropogenic fire use and management as a process explicitly. However, so far, they have  
308 only been deployed to investigate the management and use of fire in land systems at a  
309 landscape-scale in the global north (e.g. Spain, USA; Wainwright and Millington, 2010; Hulse  
310 et al., 2016; Spies et al., 2017). Although these studies demonstrate the utility of ABMs for  
311 examining landscape-scale processes and locally-relevant policies and management strategies,  
312 the transferability of fire ABMs to other locations or their application beyond the landscape  
313 scale has yet to be demonstrated. Agent-based approaches to represent human behaviour have  
314 been used, however, to examine land-systems at a continental scale through defining Agent  
315 Functional Types (AFTs) (Brown et al., 2019). AFTs build on theoretically-informed  
316 typologies to create generalisations about human–environment interactions through two  
317 essential human characteristics: roles (e.g., forester, farmer) and behaviours (e.g., imitation,  
318 conservatism). They therefore allow representation not only of direct human impacts on the  
319 environment, but also behaviourally-mediated responses people might make to consequent  
320 environmental change.

321  
322 The advantages that ABMs provide for representing heterogeneous individual agents and their  
323 interactions have high data costs for both model parameterisation and evaluation. Data  
324 concerning the beliefs, values and/or objectives that shape human decision-making, for  
325 example, are needed to construct ABMs (Smajgl et al., 2011; Robinson et al., 2007) but are  
326 difficult to collect even at local scales. Most land-system ABMs have been placed-based and  
327 landscape-scale because the empirical data required to construct and use these models are  
328 difficult to obtain at broader scales (Verburg, 2019). Furthermore, the inherent complexity of  
329 dynamics resulting from multiple interacting, heterogeneous individuals can make identifying  
330 the causes of emergent patterns and outcomes challenging. It can be difficult to establish which  
331 features are common to the system of study and which are contingent on particular boundary  
332 conditions or structures in a case study (Millington et al., 2012; Manson et al., 2020). In the  
333 face of limited data for parameterisation and the high degrees of freedom in model structure,  
334 there may be considerable subjectivity involved in ABM development (Lee et al., 2015) and  
335 robust empirical verification or validation of a model is challenging (Schulze et al., 2017). As  
336 with all models, the quality of representation is dependent on the quality of data and theory  
337 available; in the case of ABMs for agency of individual humans these can be both lacking and  
338 contested.

339  
340 The adoption of more general assumptions, such as the use of AFTs, may facilitate the  
341 application of ABMs to understand human-fire interactions at a global scale. However, this  
342 will require a substantial improvement in the availability of data on human activities in relation  
343 to fire. Information about fire use in the context of agriculture, hunting and pastoralism is  
344 widespread in the literature, but fragmented across numerous academic disciplines including  
345 anthropology, sociology, development studies, ecology, and agronomy (Coughlan and Petty

346 2012). Synthesising such data into a global dataset to provide the empirical basis for improved  
347 modelling of anthropogenic fire is an important research priority. However, such synthesis  
348 could be used with tools such as cluster analysis to define AFT roles (Malek et al., 2019); this  
349 would be equivalent to gathering primary data e.g. through social surveys for using ABMs at  
350 finer spatial scales (Smajgl et al., 2011). Determining the global spatial distribution and  
351 variation of AFTs defined through a series of small-scale case studies represents a further  
352 challenge, but could be solved through comparison with secondary data sets and previous  
353 attempts to map land use and land use intensity at the global scale (e.g. Haberl et al., 2007;  
354 Malek and Verburg, 2020).

355  
356 Representation of the policy development process (see Section 2.3) is a major challenge in  
357 computational modelling of socio-ecological systems (Brown et al., 2019). Whilst agent-based  
358 modelling of policy outcomes and their (un-)intended consequences is comparatively  
359 widespread, few models include an explicit representation of the policymaking process  
360 itself (Castro et al., 2020). Policy is generally represented, at the regional to global scale, as a  
361 weighting towards a given outcome or ecosystem service provision within land user  
362 calculations (e.g. Holzhauer et al., 2018). One important shortcoming of this approach for  
363 wildfire models is the inability to account for abrupt policy changes in response to catastrophic  
364 fire regime shocks. Even when representing policy simply through input parameters,  
365 combining consideration of local, national, and global policy influences with land user  
366 preferences in a model could lead to highly complex emergent phenomena, with consequences  
367 for model interpretation and utility (Caillault et al., 2013).

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### 2.1.3 Economic models of wildfire

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372 Economic analysis examines the human drivers of wildfire occurrence, its effects on economic  
373 activity, and quantifies wildfire costs and benefits in terms of changes in human welfare (Figure  
374 4). Economic models of wildfire are largely empirical and aim to establish relationships  
375 between variables describing human behaviour and wildfire, estimate marginal effects, or  
376 monetise impacts. Modelling can be at the micro-level of individual agents including persons  
377 and firms, or at the aggregate macro-level of jurisdictions, states or countries.

378 Wildfire can be the intended outcome of the behaviour of economic agents, where its timing  
379 and frequency is determined to optimise an objective function (Yoder, 2004; Varma, 2003;  
380 Prestemon and Butry, 2005; Purnomo et al., 2017). Economic models can be used to assess the  
381 efficiency of wildfire use, the extent to which its occurrence aligns with its socially desirable  
382 level. Many wildfire costs are not borne by the agents enjoying the benefits, and compensation  
383 mechanisms are not in place. These external costs are ignored by fire users, leading to  
384 overutilization of wildfire. At the same time, failure to acknowledge external benefits can lead  
385 to oversupply of suppression and under-provision of wildfire. Wildfires can occur as a result  
386 of seemingly unrelated economic activity and distorted incentives (Warziniack et al., 2019;  
387 Champ et al., 2020; Kountouris, 2020). Economic models characterise the wildfire-human  
388 interaction, highlight the presence of external costs and study agents' incentives, to assist in  
389 the development of effective wildfire policy.

390  
391 Econometric models of wildfire combine variables on natural and human systems. Models may  
392 use time series data, samples of a population at a given time (cross-sections) or repeated  
393 sampling of the population through time (panel) data. Wildfire occurrence and burned area  
394 information typically come from earth observation or international, national and local incident

395 databases. There are multiple sources of economic variables. Macroeconomic models to assess  
396 the relationship between wildfire and the aggregate economy usually employ data on national  
397 or subnational income, employment, land use, or other economy-wide metrics (Wibbenmeyer  
398 et al 2019; Liao and Kousky, 2020; Boustan et al., 2020). Microeconomic models examining  
399 the relationship between individual agent behaviour and wildfire use consumer, household,  
400 firm or farm level survey, census and administrative data, and contrast the behaviour of units  
401 that do, or do not experience wildfire and its consequences.

402  
403 Models assessing either wildfire impacts on economic outcomes or economic impacts on  
404 wildfires typically control for factors affecting both human behaviour and wildfire. Unobserved  
405 confounders simultaneously determining wildfire and economic outcomes introduce biases in  
406 the estimation of causal relationships. Researchers utilize variation in space and time for  
407 estimation (Jayachandran, 2009; Moeltner et al., 2013). Biases due to individual (agent or  
408 jurisdiction) specific, time-invariant unobserved characteristics can be addressed through  
409 differencing or fixed effects estimators, which utilize the time dimension to remove both  
410 observed and unobserved constant-over-time characteristics, and employ within variation to  
411 estimate coefficients of interest (Michetti and Pinar, 2018; Bayham and Yoder, 2020).

412  
413 Endogeneity concerns remain from individual-specific time-varying unobserved variables,  
414 while panel data are not always available. Assessing the effect of wildfire smoke on health and  
415 behaviour, for example, is challenging as agents can self-select their degree of exposure. To  
416 address this type of problem, researchers leverage plausibly exogenous variation in agents'  
417 exposure (Angrist et al., 1996). Zivin et al. (2019), for example, used variation in wind direction  
418 to compare examination performance in schools located upwind and downwind of a wildfire.

419  
420 Estimates of the economic value of wildfire impacts can be used for developing wildfire  
421 management policy, and for comparing different mitigation and adaptation interventions in a  
422 cost-benefit analysis framework. A good or service is considered to have economic value to  
423 the extent it contributes to human welfare. Economic valuation techniques are used to estimate  
424 the change in human welfare resulting from experiencing wildfire or its aftermath, and translate  
425 this into monetary units. Valuation assumes substitutability: consumers are willing to sacrifice  
426 income to avoid the negative consequences of wildfire, or are willing to accept compensation  
427 for wildfire damages. The economic value of some impacts can be inferred directly using  
428 market prices and estimations of the cost of replacing lost infrastructure and production (Butry  
429 et al., 2001; Richardson et al., 2012; Stephenson et al., 2013). It is harder to capture the total  
430 economic value of wildfire, however, either because there are no markets and prices for some  
431 ecosystem goods and services, or because observed prices are inaccurate signals of the true  
432 marginal social costs and benefits (Freeman et al. 2014). Ignoring the value of non-marketed  
433 goods and services, and pricing distortions, reduces the estimated cost of wildfire leading to its  
434 overuse.

435  
436 The non-marketed impacts of wildfire can be monetised using revealed and stated preference  
437 valuation methods (Freeman et al., 2014). Revealed preference methods use information from  
438 transactions in related markets to infer the value of an ecosystem good or service. The travel  
439 cost method is used to monetise the loss in recreational value from wildfire by modelling  
440 demand for recreation activities as a function of burned areas (Nobel et al., 2020) or wildfire  
441 risk (Hesseln et al., 2003). Hedonic pricing approaches typically use data from property market  
442 transactions to infer the influence of wildfire risk (Donovan et al., 2007; McCoy and Walsh,  
443 2018) or the proximity to burned area (Stetler et al., 2010) on property prices. Stated preference  
444 valuation asks consumers to participate in hypothetical markets and declare their preference

445 for a non-marketed good or service. In contingent valuation studies consumers state whether  
446 they are willing to pay (accept) some price to avoid (as compensation for incurring) the effects  
447 or risk of wildfire (Loomis et al., 2005; Loomis et al. 2009; Molina et al., 2019). In choice  
448 experiments, consumers make a series of choices among hypothetical good profiles comprising  
449 a series of attributes at different levels. When one of the attributes is monetary, the willingness  
450 to pay for each characteristic can be estimated (Remoundou et al., 2012; Campbell and  
451 Anderson, 2019; Mueller et al., 2019; Alló and Loureiro, 2020) Both stated preference  
452 approaches directly model consumer's utility to explain stated choices. Whereas revealed  
453 preference methods only capture the effect of wildfire on use values (recreation, amenity etc),  
454 stated preference approaches also capture non-use values (existence, bequest etc). However,  
455 values estimated from stated preference studies could over- or underestimate the true costs and  
456 benefits of wildfire since they are hypothetical by design and, although careful design of the  
457 hypothetical market may go some way to reducing the biases (Carson and Groves, 2007;  
458 Vossler et al., 2012), the validity and usefulness of stated preference value estimates for policy  
459 making is highly debated (Hanemann, 1994; Diamond and Hausman, 1994; Hausman, 2012;  
460 Carson, 2012).

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## 463 **2.2 Physics-centric models**

464

### 465 **2.2.1 Wildfire spread models**

466

467 Spread models predict the position and intensity of the wildfire as a function of time and explain  
468 how it will evolve over a given landscape. They are widely used as tools for wildfire  
469 preparedness (e.g. for prescribed burn planning, fuel management, evaluating threats to values-  
470 at-risk, ecological applications, and training tools) and for operational firefighting (supporting  
471 incident management). They have also been used for post-wildfire investigations into  
472 suppression effectiveness and forensic support (Pearce, 2009). In contrast to the other types of  
473 models described here, wildfire spread models do not seek to address the two-way interactions  
474 between humans and fire explicitly. The outputs of wildfire spread models are also being  
475 integrated with fire evacuation models such as EXODUS (Veerawamy et al., 2018) and open  
476 source platforms (Ronchi et al. 2019).

477

478 It was understood more than half a century ago that the principle of energy conservation could  
479 provide the basis for simulating the rate at which a fire front spreads across a landscape  
480 (Rothermel, 1972; Weber, 1991). In fire spread models, the spread of fire from one grid cell to  
481 the next may be based on the physical conservation of energy principle. Physics-based fire  
482 models include models of fuel-flame-plume interactions, such as Wildland Fire Dynamics  
483 Simulator (WFDS) (Mell et al., 2009). These models include physical processes such as fluid  
484 dynamics, combustion, heat transfer, pyrolysis, microphysics and turbulence, which are  
485 generally resolved at a high spatial resolution (cm-scale). Other physically-based models are  
486 concerned with plume-atmosphere interactions, which usually involve coupling relatively  
487 simple fire models within a high resolution mesoscale atmospheric model such as the Weather  
488 Research and Forecasting model (WRF-FIRE) (Mandel et al., 2011).

489

490 Physics-based models are computationally demanding and are not able to simulate fire spread  
491 in real-time (Figure 5). Semi-empirical fire spread models were developed in response to  
492 operational needs to simulate the spread of fire across landscapes in real-time, or ideally faster  
493 than real-time. Such fire spread or fire growth models use spatial data on fuel characteristics  
494 (e.g. vegetation type, loading, moisture content), topography (elevation, slope, aspect), and  
495 weather (temperature, relative humidity, wind speed, wind direction). Model outputs (e.g. fire  
496 perimeter, fuel consumption) are determined by empirical fire behaviour sub-models, termed  
497 fuel models – a suite of empirically-derived fuel-specific equations that describe the  
498 relationship between the fuel, topography and weather inputs, and the fire rate-of-spread and/or  
499 intensity. The spatially-explicit simulation of a fire spread across a landscape uses Huygens’  
500 physical principle of elliptical wave propagation (Richards, 1990; Finney, 1998). Examples of  
501 semi-empirical fire spread models include the Fire Area Simulator (FARSITE: Finney 1998)  
502 and Prometheus (Tymstra et al., 2010). FARSITE was developed by the U.S. Forest Service  
503 (USFS) as a National System for predicting wildland fire behaviour and spread in areas of the  
504 United States and is widely used by federal/state land management agencies as an operational  
505 tool for planning land management fires, responding to escaped fires, and responding to  
506 wildfire incidents. FARSITE’s empirical fuel models rely upon the surface fire predictions of  
507 Rothermel (1972), whose equations were derived from a series of small-scale laboratory burns  
508 based on homogeneous dead fuel beds. In contrast, the Prometheus model uses empirical fuel  
509 models representing 16 fuel types typical of Canadian ecosystems based on measurements of  
510 landscape-scale fires (Tymstra et al., 2010). Prometheus is mainly used to provide a decision-  
511 support tool to aid fire managers planning prescribed fires, and in responding to escaped fires  
512 which necessitate the need to fight fire on the landscape (Suffling et al., 2008), but has also  
513 been used to examine landscape fire risk (Stralberg et al., 2018; Parisien et al., 2005). Other  
514 examples of semi-empirical fire spread models include Phoenix (Tolhurst et al., 2008) and  
515 SPARK (Miller et al., 2015) developed for Australian bushfires (Neale and May, 2018).

516

517 As well as providing information on spatially-explicit fire perimeters, most of the semi-  
518 empirical models will also provide information on fireline intensity ( $\text{kW m}^{-1}$ ), flame length  
519 (m), rate of spread ( $\text{m min}^{-1}$ ), heat release density ( $\text{kJ m}^{-2}$ ), reaction intensity ( $\text{kW m}^{-2}$ ), along  
520 with information about such behaviours as crown fire activity (e.g. FARSITE). Depending on  
521 their use, fire spread models may include a number of additional physical or parameterised  
522 sub-models. Some examples include the parameterisation of embers-driven spotting behaviour  
523 (Finney, 1998) and emissions modules that may be used for subsequent modelling of smoke  
524 plume dispersion (Volkova et al., 2018).

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### 2.2.2 Global fire models

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Global fire models are mathematical representations of processes that determine the occurrence and extent of fire, including ignition, spread, fuel combustion, vegetation mortality and natural suppression (Hantson et al., 2016). Global fire models are designed to interface with dynamic global vegetation models (DGVMs) to explicitly model the impact of fire on ecosystems and large-scale vegetation distribution. However, since DGVMs are increasingly included in the land-surface component of climate or earth system models, fire-enabled global vegetation models are also used to make predictions of how changes in fire regime impact pyrogenic emissions, biogeochemical cycles and ultimately climate.

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The vegetation model in which the fire model is embedded provides information about the vegetation, generally in terms of the proportions of different plant functional types present, and this in turn determines the amount of both live and dead fuel loads. Climate affects both vegetation growth and the probability of fire. Temperature and precipitation determine what plant types can grow and their productivity, for example, and hence determine fuel availability; they also determine the rate at which fuel dries out and therefore whether it is susceptible to burn. Wind speed, fuel continuity and the atmospheric vapour pressure deficit are important factors determining the rate at which a fire spreads and hence how large an area is burnt.

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The most fundamental assumption underpinning the representation of fire in global vegetation-fire models is that processes can be represented mathematically and are universal in space and time. Spatial or temporal patterns in the expression of these processes should arise explicitly from the patterns in the controls on these processes. Thus, for example, a lightning strike will trigger an ignition if it produces a long continuing current sufficient to reach a given temperature threshold. Spatial differences in the number and energy of cloud-to-ground lightning strikes then determine how many lightning ignitions will take place in a given region. Similarly, an ignition will cause a fire only if the fuel bed is sufficiently dry; spatial differences in the occurrence of fire after ignition are then determined by climate factors that affect fuel dryness in a given location.

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The implementation of universal processes modulated by spatial or temporal differences in their controls is not always straightforward. In practice, many global vegetation-fire models use simplifications (parameterisations) of complex processes or represent these processes through empirical relationships. For example, fuel drying rates are determined not only by the atmospheric vapour pressure deficit and wind speed but also by the size and arrangement of the fuel (fuel packing). The influence of fuel packing on drying is represented through empirical relationships that relate packing to the size of the fuel, which in turn is related to the rate of drying and fire spread. Simplifications may also be introduced because of inadequacies in the available input data. For example, until recently the only global lightning data set available provided information about the total number of lightning strikes (Cecil et al., 2014), requiring assumptions about the partitioning between cloud-to-cloud and cloud-to-ground strikes and about the energetic efficiency of cloud-to-ground strikes (Latham and Schlieter, 1989). In the absence of other information, it is usually assumed that these relationships are constant in space and time (see e.g. Thonicke et al., 2010).

573 Further simplifications are introduced (see Hantson et al., 2016; Rabin et al., 2017) because  
574 global vegetation-fire models are designed to operate at a coarse resolution (0.5° x 0.5° or  
575 coarser). This has three consequences. Firstly, the input data are specified at this resolution  
576 which means the model is run using average conditions. For example, the influence of wind  
577 speed on fire spread does not take account of variable wind gustiness or of pyrogenically  
578 induced winds. Secondly, models do not predict the precise location of a fire, but rather the  
579 proportion of a grid cell that is affected. Finally, there are no interaction between grid cells:  
580 fires do not spread from grid cell to grid cell.

581  
582 Although most global fire-vegetation models include some consideration of the role of humans  
583 in fire regimes (Rabin et al., 2017), this is the area which is treated most simplistically in the  
584 current generation of models. Humans are considered as a source of ignitions in many models  
585 (Figure 6). The number of ignitions is generally specified as a function of population density,  
586 increasing up to a threshold value where there are no additional ignitions with increasing  
587 population. Both the strength of the relationship between population density and number of  
588 ignitions and the threshold value are empirically tuned and vary between models. Some models  
589 employ different relationships between population density and number of ignitions depending  
590 on human economic systems (e.g. LPJ-LMfire: Pfeiffer et al., 2013), although again the values  
591 are empirically tuned. Humans may also be considered as a source of landscape modification  
592 (Figure 6), both promoting (e.g. agricultural fires, deforestation fires) and suppressing (e.g.  
593 through landscape fragmentation) fire. However, the failure to identify a universal process  
594 susceptible to mathematical formulation and modification through changes in easily obtained  
595 inputs means that these treatments are not fully prognostic. For example, deforestation fires are  
596 currently simulated using observed patterns of deforestation as an input. This allows the  
597 ecological, biogeochemical and climatic consequences of recent deforestation to be quantified,  
598 but the model has no predictive power because it does not incorporate process understanding  
599 about the causes (and therefore the possible future occurrence) of deforestation. Similarly,  
600 although most models exclude fire in cropland areas and thus account for the contribution of  
601 agricultural expansion to landscape fragmentation, models which include fire as an agricultural  
602 management tool are not fully prognostic, relying on data derived from remote sensing for  
603 burned cropland fraction (Rabin et al., 2018) or for empirical (non-process-based)  
604 parameterization of crop fires (Li et al., 2013).

605  
606 Global vegetation-fire models are useful tools for investigating the impact of changes in  
607 climate on fire regimes and feedbacks to climate. In a world increasingly affected by changes  
608 in land use and land management, it is imperative to incorporate more realistic treatments of  
609 human-fire interactions (Andela et al., 2017; Teckentrup et al., 2019; Forkel et al., 2019a,  
610 Hantson et al., 2020). Improved understanding of the processes involved, identification of  
611 which drivers could be specified from global data sources, and the creation of appropriate  
612 driving data sets are key to implementing human-fire interactions in global models in a realistic  
613 way.

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## 617 **2.3 Fire and Policy**

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619 Policies are a set of ideas or guidelines for the actions undertaken by many types of organisation  
620 including governments, non-governmental organisations (NGOs) and businesses. Fire policies  
621 may draw on the information provided by the various fire models described in the preceding  
622 sections and – through their impact on human behaviour and vegetation – change the input



623 data for these models. Thus, when thinking about modelling human-fire interactions, it is  
624 helpful to consider how policies are developed and implemented (Figure 7).

625

626 Policies are usually developed in response to a problem. However, the problem of fire can be  
627 framed very differently: for example, ecologists may focus on maintaining biodiversity by  
628 managing the size and timing of fires in line with the needs of an ecosystem or species of  
629 interest, whereas town councils will focus on preventing damage to people and infrastructure.  
630 In response to the 2015 Paris Climate Agreement, managing land use to reduce carbon  
631 emissions or increase sequestration has become an increasingly powerful driver for many fire-  
632 related policies (Eloy et al., 2019). However, land use management decisions necessarily  
633 involve trade-offs between the aspirations of different groups of people (Mace et al., 2018).  
634 Thus although policies to reduce emissions from deforestation and forest degradation and  
635 enhance carbon stocks (REDD+) are promoted as win-win solutions, their implementation  
636 could lead to significant carbon-biodiversity trade-offs in fire-prone old-growth grassland  
637 ecosystems and reverse progress made in decentralising forest management to local  
638 communities (Phelps et al., 2010; Phelps et al., 2012).

639

640 Policy formulation is a messy and unpredictable process (Cairney, 2015) that involves  
641 weighing up and negotiating trade-offs, that are essentially about power, relationships,  
642 responsibility and accountability (Nunan et al., 2018). In many cases, policy is determined  
643 more by politics than evidence. In Australia, for example, the compulsory purchase of land by  
644 government recommended by the Victoria Bushfire Royal Commission on the catastrophic  
645 fires of 2009 (Teague et al., 2010) was not adopted because of its political unpopularity  
646 (Bowman et al., 2011). Similarly, an investigation into a fire in which five fire-fighters died in  
647 Spain terminated discussion of the limitations of fire control (González-Hidalgo et al., 2014).  
648 The adoption of evidence-based policy may also be limited because the underpinning bodies  
649 of evidence, whether local or global, are rarely neutral. Fire experiments, which informed both  
650 colonial and post-colonial fire policy in West Africa, were designed to test the belief that the  
651 savanna was the product of generations of anthropogenic burning (Laris and Wardell, 2006), a  
652 view that has been widely contested both by social scientists (Amanor, 2002; Leach and  
653 Scoones, 2015) and by ecologists (West et al., 2000; Bond and Zaloumis, 2016). Knowledge-  
654 production is fundamentally political in nature, as is evident in the privileging of remote  
655 sensing and quantitative analyses over traditional ecological knowledge in supporting fire  
656 suppression policies (Sletto, 2008; Leach and Scoones, 2015).

657

658 Fire-related policies broadly fall into two categories, state-enforced regulations and market-  
659 based mechanisms, though the boundaries between them are increasingly blurred (Sikor et al.,  
660 2008; Lambin et al., 2014). Regulatory policies include land use zoning associated with rules  
661 about whether and when fires can be set. Market-based mechanisms, such as commodity  
662 roundtables (e.g. the Roundtable on Sustainable Palm Oil) may be implemented by the private  
663 sector but enforced by NGOs. Payments for Environmental Services schemes, like REDD+,  
664 may involve both governments and NGOs in implementation and enforcement (Lambin et al.,  
665 2014). The different approaches can co-exist. Carmenta et al. (2017), for example, report that  
666 severe peat fires in Sumatra led to the development of a variety of fire management  
667 interventions across scales, sectors and stakeholders, ranging from new regulations to technical  
668 innovations, developments in fire monitoring and the provision of incentives to communities  
669 for fire-free practices.

670

671 Once policies are formulated, there is an assumption that they will be implemented (Figure 7).  
672 In reality, there is often a large policy-implementation gap. This may arise because responsible

673 authorities lack the capacity or resources to enforce new rules. It can also be the result of poor  
674 policy development processes which have not effectively addressed the trade-offs experienced  
675 by some stakeholders. The fire exclusion policy adopted in Bale National Park in Ethiopia, for  
676 example, forced local communities to stop small-patch burning practices and resort to illicit  
677 fires, often set late in the dry season when ignition is more likely, to maintain the grazing  
678 landscape, with the inadvertent result that the size of fires in the park has increased (Johansson  
679 et al., 2019). In contrast, wide acceptance allows Indigenous Tagbanua farmers in the  
680 Philippines to practise traditional fire-based swidden farming despite the practice being  
681 criminalised for decades by both state and non-state actors (Dressler et al., 2020). Political  
682 interests may also undermine policy intentions. In Tanzania, for example, community forest  
683 and fire management initiatives must defend collectively owned lands from the hunting fires  
684 set by more powerful and politically well-connected stakeholders who hold hunting  
685 concessions (Khatun et al., 2017). Understanding the diverse motivations for fire use is  
686 essential if interventions are to succeed (Carmenta et al., 2017). In the case of Sumatran peat  
687 fires, for example, no single stakeholder group is primarily responsible for fire-setting and there  
688 are many nuanced motivations for setting fires (Carmenta et al., 2017). Co-production of fire  
689 policies through the involvement of local stakeholders (Laris and Wardell, 2006; Monzón-  
690 Alvarado et al., 2014; Humphrey et al., 2020) and the recognition of traditional knowledge in  
691 the environmental policy making process (Rodríguez et al., 2018; Bilbao et al., 2019;  
692 Devisscher et al., 2019; Mistry et al., 2019) may be important ways to narrow the policy-  
693 implementation gap. When policies are evaluated (and possibly adapted) there is a need to  
694 disaggregate across societal groups, with particular attention paid to the voices of often  
695 marginalised stakeholders, such as the poorest, Indigenous peoples and women (Schreckenber  
696 et al., 2018).

### 699 **3. Issues and Commonalities**

701 The models discussed here originate from diverse disciplines, were developed for different  
702 purposes and address different questions, include different types of processes, and operate on  
703 different time and space scales, resolution and complexity (Figure 1). Nevertheless, they share  
704 some common features.

706 Each type of model has a theoretical basis for the representation of the relationship between  
707 humans, the biological, physical, and in some cases, spiritual, attributes of the environment,  
708 and fire. The underlying theory may be incomplete, the theoretical basis of some individual  
709 models developed within each class of models may even be wrong, but there is an assumption  
710 that the models should embody causal relationships. Data analysis or machine-learning  
711 approaches have been used to derive empirical relationships or parameterisations for economic  
712 models (Papakosta et al., 2017; Storm et al., 2020) and global fire models (Forkel et al., 2017;  
713 Stralberg et al., 2018; Forkel et al., 2019b), and may even be useful for the development of  
714 typologies (e.g. Delgado et al., 2018), but these are not unsupervised analyses and the types of  
715 data are selected based on the underlying theory involved.

717 Each type of model is a simplification of the complexities of the real world. Even place-based  
718 models of fire knowledge represent a partial view, because participants are selected or self-  
719 select, because people understand and relate to fire in multiple ways which may not always be  
720 elicited in the process of model construction, or because some social constructs are difficult to  
721 represent. Practical considerations also lead to simplification, whether this is the limited  
722 computer power available for global-scale fire modelling which precludes ultra-high resolution

723 in order to simulate individual fires (see e.g. Toivanen et al., 2019) or the limited data  
724 availability that necessitates substituting travel costs to monetise loss of recreational value in  
725 economic modelling (e.g. Hesseln et al., 2003; Nobel et al., 2020). Simplification may be  
726 driven by considerations of the relative importance of specific processes at a given time or  
727 space scale, informed by theory, or by lack of appropriate data. Lack of quantitative data on  
728 the timing and extent of human burning and fire suppression in agricultural areas, for example,  
729 underpins the widespread use of population density as a surrogate measure. However, all of  
730 the types of model require extensive data inputs, and in many cases data limitations are the  
731 strongest constraint on model development.

732  
733 The models differ in potential for co-production by scientists and stakeholders that use or  
734 manage fire or are directly impacted by wildfires. In some cases, stakeholder knowledge is  
735 incorporated by scientists into a pre-determined model structure. This is the case, for example  
736 where stated preference approaches are used in economic modelling (e.g. Loomis et al., 2005),  
737 or interview and social survey data feeds into an agent-based model (e.g. Spies et al., 2017).  
738 Stakeholders may also participate more directly, potentially playing a part in defining the  
739 structure of the model. Place-based models of fire knowledge have been most amenable to such  
740 participatory modelling approaches (e.g. Bilbao et al., 2019). Generally, co-production is more  
741 likely and feasible where models operate at smaller spatial scales, and can incorporate  
742 information from individuals or communities, and where power differentials between  
743 stakeholders are less extreme.

744 Each type of model is oriented towards and designed to lead to practical outcomes. Place-based  
745 models of fire knowledge, for example, can be used to engineer dialogues between different  
746 groups of stakeholders or help promote cultural identity. ABMs can be used to develop locally  
747 relevant policies for landscape management, while economic models can be used to ensure that  
748 the hidden costs and benefits of wildfire are factored into the development of effective fire  
749 management policies. Global fire models provide a way to predict changes in fire regimes and  
750 fire impacts in response to future climate and land-use scenarios. However, different types of  
751 models may yield different recommendations for fire policy and management because of their  
752 very different foci and scales. The need to develop more holistic fire-related policies and  
753 practices provides a good motivation for combining the strengths and benefits of different types  
754 of models.

755  
756 Some differences between the models may be more apparent than real. There is an apparent  
757 tension for example between the assumption made by global fire models that processes are  
758 universal and the place-centred focus of place-based models of fire knowledge . This translates  
759 into the perception that policies and practices based on local knowledge cannot be usefully  
760 applied elsewhere. However, global fire models also assume that universal processes such as  
761 ignition, fire spread and extinction are governed by factors that vary spatially, such as climate  
762 or vegetation properties or land use, thus giving rise to different fire regimes (Hantson et al.,  
763 2016). The use of agent typologies (e.g. Lauk and Erb, 2016) makes a similar assumption - that  
764 there are universal activities or types of behaviour, although the mix of different agent types  
765 may change through time or across space as do climate and vegetation properties.

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#### 4. Moving forward: key challenges and a roadmap for model use and integration

771 The major challenge for developing better models of human-fire interaction is lack of data that  
772 can be used to develop heuristic, globally-applicable schemes in a modelling framework.  
773 Collecting field data at a local level is time-consuming. The synthesis of data from multiple  
774 local studies into a global data set could provide one route to obtaining sufficient data to  
775 parameterise models, whether these are ABMs, economic models or fire-enabled vegetation  
776 models, but the quality of such a synthesis depends to some extent on whether the same  
777 information has been collected and whether the same data-collection methods have been  
778 applied (Costafreda-Aumedes et al., 2017). Many place-based models of fire knowledge are  
779 not framed in the quantitative way required for use by global fire models, for example. There  
780 is also an issue about representativeness. In the physical sciences, there are standard methods  
781 that are used to judge what is the minimum data set required to provide global metrics (see e.g.  
782 Mann et al., 2008). Such an assessment is likely to be more difficult given the diversity of  
783 human socio-economic and cultural systems and the heterogeneity of their influences on fire.  
784 Furthermore, research on human use and management of fire is fragmented across many  
785 disciplines and heterogenous in the methods use and data produced. However, this situation is  
786 not uncommon in studies of socio-ecological systems and meta-study methods to synthesise  
787 diverse case-studies have been developed (Magliocca et al., 2015; van Vliet et al., 2016). Large  
788 scale syntheses using such methods are ongoing (e.g. Perkins et al 2021; Smith and Mistry,  
789 2021), with the aim of improving systematic understanding of human use and management of  
790 fire, which in turn will be useful in developing improved human-fire models.

791  
792 The scaling-up of models that function at a local scale to the global scale is also a major  
793 challenge. Models of fire spread, for example, explicitly deal with the influence of topography,  
794 whereas global fire-enabled vegetation models ignore topographic influences. To some extent,  
795 this is because of the computational cost that working at sufficiently high resolution would  
796 entail but it also reflects decisions about the importance of specific factors at different scales,  
797 and whether these processes can be represented probabilistically rather than deterministically.

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799  
800 To some extent, scaling up can be seen as a process of simplification. For example, scaling  
801 ABMs to the global scale could involve defining a limited number of Agency Functional Types  
802 (AFTs) based on theoretical typologies derived for example from local fire studies. This would  
803 be parallel to the use of Plant Functional Types (PFTs) in most of the current generation of  
804 dynamic global vegetation models (and indeed in most land-surface models). This parallel is  
805 informative about the potential traps involved in such simplification. The original idea behind  
806 the use of PFTs to represent plant functional diversity involved classifying plants in terms of  
807 adaptations to climate (Prentice et al., 1992; Harrison et al., 2010), drawing inspiration from  
808 the seminal work of Raunkiær (1909). PFTs defined in this way do not necessarily represent  
809 plant functional diversity with respect to other traits, for example they do not distinguish  
810 between fire-adapted, fire-tolerant and fire-intolerant species (Pausas et al., 2004; Brando et  
811 al., 2012; Clarke et al., 2013). Furthermore, recent empirical (Diaz et al., 2015) and theoretical  
812 (Wang et al., 2017, Smith and Keenan, 2020; Wang et al., 2021) developments suggest that  
813 there are alternative ways to treat plant diversity, including simulating the adaptive traits  
814 directly (e.g. Scheiter et al., 2013; Fyllas et al., 2014; Berzaghi et al., 2020) or as emergent  
815 properties of the system (Wang et al., 2017; Franklin et al., 2020; Harrison et al., 2021). Thus,  
816 in the creation of simplified representations of human-fire interactions, it will be important to  
817 consider both the purpose of the model which will use these relationships and to test the  
818 theoretical basis for such representations rigorously. Furthermore, in so far as the development  
819 of typologies of fire users assumes there are universal rules governing how specific fire-user  
820 types behave across time and space, or that certain fire practices are associated with certain

821 environmental conditions, there is a danger of adopting outdated concepts including  
822 environmental determinism or societal evolution through linear stages of economic  
823 development, with corresponding land management practices, from primitive to modern  
824 (Coughlan, 2015; Coughlan and Petty, 2013).

825  
826 Despite these challenges, there are ways to move forward. Climate projections are made using  
827 scenarios of changes in anthropogenic emissions and land use developed using alternative  
828 assumptions about human activities in the future, for example a continued dependence on fossil  
829 fuels or the widespread adoption of deliberate strategies to reduce emissions (O'Neill et al.,  
830 2017; Riahi et al., 2017). Global fire-enabled vegetation models can use these climate  
831 projections to examine the consequences of climate changes for future fire regimes, but they  
832 could also use the underlying scenarios about human activities to modulate the treatment of  
833 human ignitions and/or suppression.

834  
835 Notwithstanding the highly political nature of much policy-formulation, the potential for  
836 different types of models to lead to radically different outcomes for policy and management  
837 means that some form of model integration is vital. The primary step is the development of  
838 ways to use outputs from one model to inform other models. For example, global vegetation-  
839 fire models could be used to make projections of the probability of climate-induced changes in  
840 fire regimes. These projections could be used in the context of economic models to determine  
841 the costs and benefits of fire management or fire reduction at a regional scale. Agent-based  
842 models could then be used to establish whether specific mitigation actions are likely to be taken  
843 up in these regions. The predicted changes in human behaviour could then be used to construct  
844 new scenarios for incorporation into global vegetation-fire models simulations. The enchaining  
845 of models in this way is already integral to impact modelling, for example in the framework of  
846 the ISIMIP project (Rosenzweig et al., 2017). The challenge is either to develop consistent  
847 terminology and standardised protocols that allow outputs from one model to feed into another  
848 model or to provide appropriate tools that translate these outputs into appropriate formats.

849  
850 Another step in using multiple kinds of models to address human-fire interactions could focus  
851 on the implicit coupling of global and regional models. Global climate simulations, for  
852 example, are used to provide the boundary conditions for regional climate models which  
853 because of their higher resolution can be used to project the influence of local features, such as  
854 large lakes, on regional climate (e.g. Diallo et al., 2018). Higher-resolution regional models  
855 can also reduce the need for parameterisation of individual processes (Giorgi, 2019), but since  
856 they operate on a limited spatial domain they can do so without excessive computational costs.  
857 Similar approaches could be adopted with fire modelling, either to link similar types of models  
858 across scales (e.g. fire spread models and global vegetation-fire models) or to derive  
859 probabilistic representations of human-fire interactions derived from local studies into global-  
860 scale models. Improved coupling between regional and global scales would facilitate  
861 addressing fire policy questions since wildfires are not typically confined to a single  
862 jurisdiction. Fire management has a global dimension, as illustrated by climate change  
863 mitigation concerns and transboundary pollution associated with forest fires in the tropics  
864 (Khatun et al., 2017). Scale is a challenge for natural resource governance, since ecological  
865 and social/administrative processes rarely occur on the same spatial or temporal scale (Nunan  
866 et al., 2018) and politics and power often determines the scale at which decisions are made  
867 (Zulu, 2009). Effective multi-level governance requires both vertical coordination between  
868 actors at different levels and horizontal cooperation, e.g. between different sectors (Nunan et  
869 al., 2018).

870

871 It is difficult to envisage creating a single model that addresses all the different questions and  
872 scales currently addressed by different types of human-fire models. Nevertheless, there are  
873 obvious avenues for integration. The use of local conceptual or place-based models of fire  
874 knowledge and of global fire-use typologies to develop agent classifications for use in global  
875 ABMs seems a fruitful avenue to explore. ABM can be readily combined with economic  
876 models (e.g. Bert et al., 2015), and building economic constraints into land- and fire-use  
877 decision-making would be useful. There is also an important gap in linking place-based models  
878 of fire knowledge with ABM. Given that landscape-scale ABMs have already drawn on  
879 interviews, surveys and workshops with fire managers in developed-world contexts (e.g.  
880 Millington et al., 2008; Spies et al., 2017), there is no reason why models could not be derived  
881 from data generated in similar ways with indigenous fire practitioners. Pursuing such model  
882 integration to understand human-fire interactions in developing world landscapes will be  
883 important for improving fire management and ensuring sustainability under changing socio-  
884 economic and climate conditions.

885  
886 There is potential for global ABM predictions to be incorporated in fire-enabled global  
887 vegetation models: given that some global models already allow relationships between  
888 population density and number of ignitions to vary depending on changes in human economic  
889 systems through time (e.g. Pfeiffer et al., 2013), this could be extended to include other human-  
890 fire interactions, such as suppression. Including humans as agents within a fire-enabled global  
891 vegetation model would also lay the groundwork for incorporating feedbacks between  
892 changing fire regimes and changing human activities (Figure 8). For example, under a loose  
893 model coupling, the ABM would provide static inputs to the fire-enabled global vegetation  
894 model, for example by replacing anthropogenic ignitions from population density with an  
895 ABM output. Under a tighter-coupling (Figure 8), the ABM would be run alongside the fire-  
896 enabled global vegetation model, allowing cross-system feedbacks to be captured though at the  
897 expense of significant additional model complexity. In a loose coupling, the ABM's ecological  
898 inputs such as land cover and NPP would come from secondary data, whilst under a tighter  
899 model coupling, these could come from the dynamic outputs of the fire-enabled global  
900 vegetation model (Antle et al., 2001). Designing rigorous methods of evaluating these coupled  
901 human-fire models, as is already done for fire-enabled vegetation models (Hantson et al.,  
902 2020), will require careful consideration.

903  
904 The enchaining of models is not unidirectional. While it may be useful to think how insights  
905 gained at local scales or models that consider a single component of the human-fire system  
906 can contribute to improving global fire models, there could also be a useful flow of  
907 information from global models to other kinds of fire modelling. When modelling closely  
908 coupled human-natural systems, it is common to explore the uncertainty associated with  
909 policy decisions, socioeconomic trends, and technological development by exploring discrete  
910 scenarios for the future. These scenarios, or storylines, can be used to set up simulations from  
911 one kind of model that can then be fed into other kinds of models, in order to evaluate various  
912 aspects of the changing Earth system. The Inter-Sectoral Impacts Model Intercomparison  
913 Project (ISIMIP), for example, uses scenario-based trajectories from climate, economic, and  
914 land-use models as inputs to models that simulate the impacts of climate change on sectors  
915 including agriculture, human health, fisheries, and many others (Frieler et al., 2017). The  
916 outputs from global fire models could be used in a similar way. For example, global fire  
917 models driven by different scenarios of climate change could provide information about  
918 potential changes in fire frequency, burned area and fire intensity. These outputs could then  
919 be used in economic modelling, as the environmental constraints for ABM modelling at a

920 regional or local scale, or as what-if scenarios for local fire modelling. This can be illustrated  
921 by considering simulations of the response of burned area to changes in climate and land use  
922 under the SSP2-RCP4.5 scenario made with the CESM2-WACCM coupled climate model  
923 (Danabasoglu et al., 2020). By the middle of the 21st century (2040-2049), the model  
924 predicts a decrease in burnt area in western Africa although there is a substantial increase in  
925 burnt area in a limited area of north-central Africa (Figure 9a). In contrast, the model predicts  
926 a generalised increase in burnt area along the southern margin of Amazonia (Figure 9b). The  
927 projections of decreased burnt area in western Africa suggest that rigorous fire suppression  
928 policies may not be required as part of conservation measures to protect forested areas. On  
929 the other hand, the projected increase in burnt area in South America would have major  
930 economic and policy implications. These kind of scenario maps could also form the basis for  
931 exploring how local populations could adapt their current use of fire.

932 Above all, the process of coupling different types of model will be a learning exercise, in part  
933 because it challenges narrow discipline-bound assumptions and in part because it provides  
934 the opportunity to assess the strengths and weaknesses of different approaches to  
935 understanding human-fire interactions (Antle et al., 2001; Voinov and Shugart, 2013).  
936 Coupling different types of models should facilitate detailed representation of individual  
937 elements of human-environment systems and also exploration of the links and feedbacks  
938 between those elements. However, there are technical, conceptual and semantic challenges in  
939 model coupling (Janssen et al., 2011), and these challenges are linked to important issues of  
940 model uncertainty and assessment (Millington et al., 2017). Semantic integration of models  
941 requires ensuring language, understanding, and perspectives on the entities and processes  
942 being modelled are shared between modellers from different disciplinary backgrounds.  
943 Conceptual integration requires ensuring alignment and consistency of concepts and units as  
944 information is passed between models, likely requiring conversion of units but also  
945 potentially concepts. Assessing the types and magnitudes of uncertainty introduced through  
946 model coupling will be an ongoing issue, although tools are available to assist in its  
947 management (e.g. Bastin et al. 2013). Coupling models of human activity with biophysical  
948 models to improve our understanding of fire regimes can benefit from the previous  
949 experience to couple models rooted in different scientific disciplines (e.g., Janssen et al.,  
950 2011; Voinov and Shugart, 2013, Calvin and Bond-Lamberty, 2018). Ultimately, model  
951 coupling should provide a stronger foundation for making predictions about future fire  
952 regimes and how these are influenced and will influence human actions. It will also provide a  
953 basis for the co-production of fire-related policies that take account of the aspirations of all  
954 sectors of society, thus promoting environmental justice

## **Conflict of Interest**

*The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.*

## **Author Contributions**

SPH, AF, JM and JDAM contributed to the conception and design of this study. SPH and AF wrote the first draft of section 1; JM and CS drafted 2.1.1; JDAM and OP drafted 2.1.2; YK drafted 2.1.3; GR and TS drafted 2.2.1, SPH and SR drafted 2.2.2; KS and KY drafted 2.3; SPH drafted sections 3 and 4. JDAM and AF produced Fig. 1; JDAM and OP produced Fig. 8.; and SPH and SR produced Fig. 9. AF coordinated and edited the manuscript, and all authors contributed to the final version.

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## Figure Captions

Figure 1 Graphical illustration of the relationships between scale (spatial and temporal) and comprehensiveness (number of components in a model), with bio-physical resolution and complexity, and with the resolution and complexity of the representation of humans and human activities, for different fire models.

Figure 2 Rich picture exploring fire management in the Canaima National Park, Venezuela, made by Indigenous participants of a climate change workshop in 2017 (Source: Jay Mistry).

Figure 3 Elements of a possible agent-based model at the landscape-scale. Agents make decisions about future actions based on their state (including their goals and available resources), their interactions with other agents, constraints or incentives due to laws, policies and markets. and/or their perceived state of the simulated environment. As in the real world, agents often have a limited sphere of influence over the environment (e.g. which they own and/or manage).

Figure 4 External costs of wildfires. Note: The horizontal axis measures wildfire incidents or area burned. The vertical axis measures costs and benefits in £. The marginal benefit line shows the additional benefit from one extra wildfire. Marginal Social and Marginal Private cost lines show the additional private and social costs from an extra wildfire.  $F_S$  and  $F_P$  represent the social and private optimal wildfire occurrence. Area E shows the external costs from oversupplying wildfires.



Figure 5. Typical time and space scales for different types of operational firespread models  
Figure by Ronchi et al., 2019, CC BY.

Figure 6. Simplified representation of the structure of a global fire model. The orange boxes represent natural processes and the blue boxes human activities that impact fire starts, spread or duration, exclusion and/or suppression. The grey arrows show pathways taken by individual global fire models where arrows to a specific box show that this process is included explicitly. GPP: gross primary production; RH: relative humidity; PD: population density; GDP: gross domestic product; PFT: plant functional type. The Nesterov Index is one example of a fire danger index where ignition probability is calculated as a function of climate. The Rothermel equation is a quasi-empirical expression for the rate of fire spread based on the conservation of energy.

Figure 7. Simplified policy cycle: Far from being a technocratic exercise, politics is embedded in the cycle, from the framing of the problem to determining which evidence to use, weighing up trade-offs between different policy options, ensuring resources and buy-in for policy implementation and undertaking and reacting to evaluation.

Figure 8 Options for integrating an agent-based model of anthropogenic fire impacts into a fire-enabled global vegetation model or Earth System Model (ESM). The table shows examples of socio-ecological feedbacks that could be captured by tight model coupling.

Figure 9. Simulated burned area by the middle of the 21st century (2040-2049) in response to the SSP2-RCP4.5 scenario made with the CESM2-WACCM coupled climate model, A: for northern Africa, and B: for South America.

Figure 1.JPEG

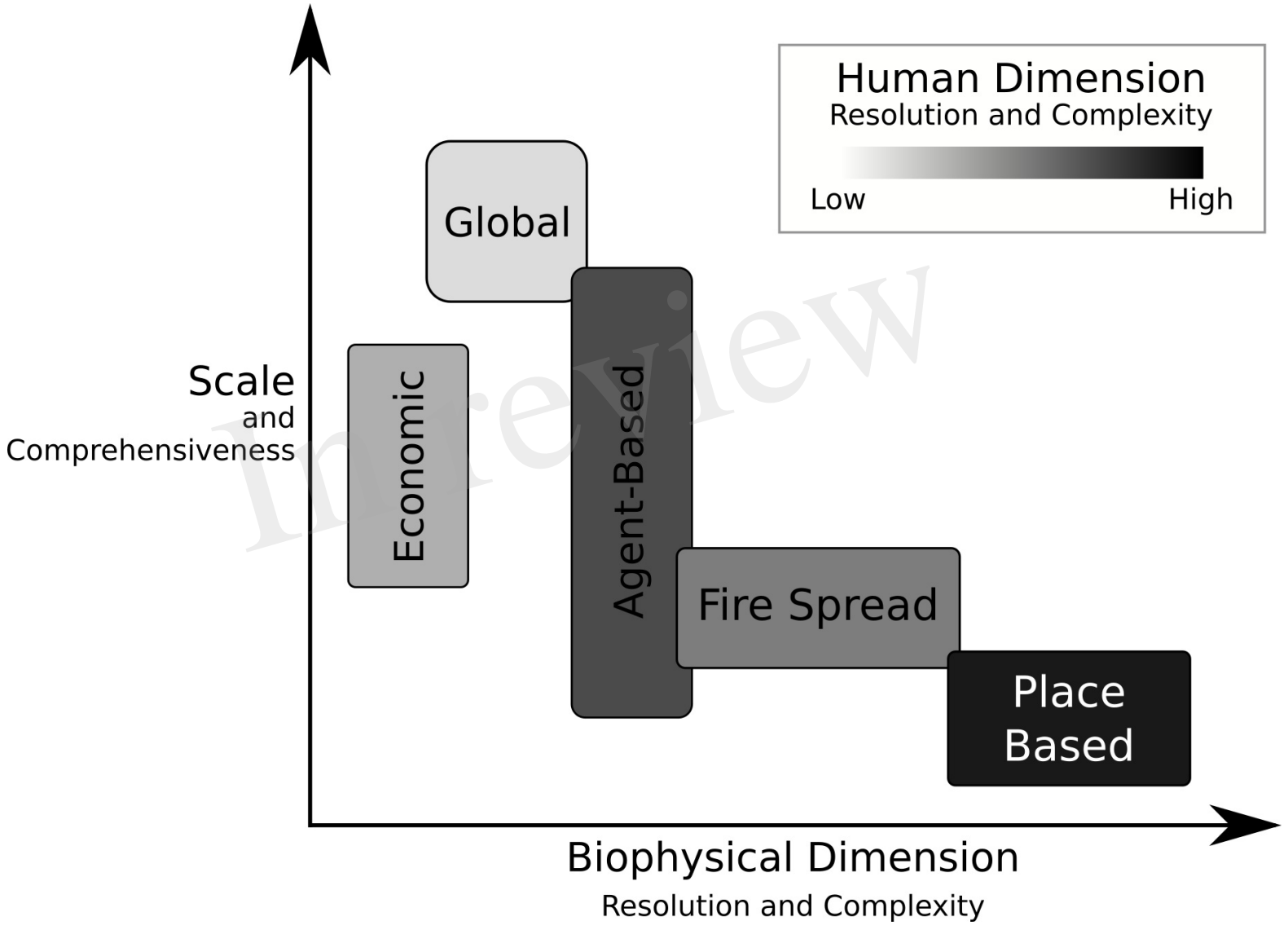


Figure 2.JPEG

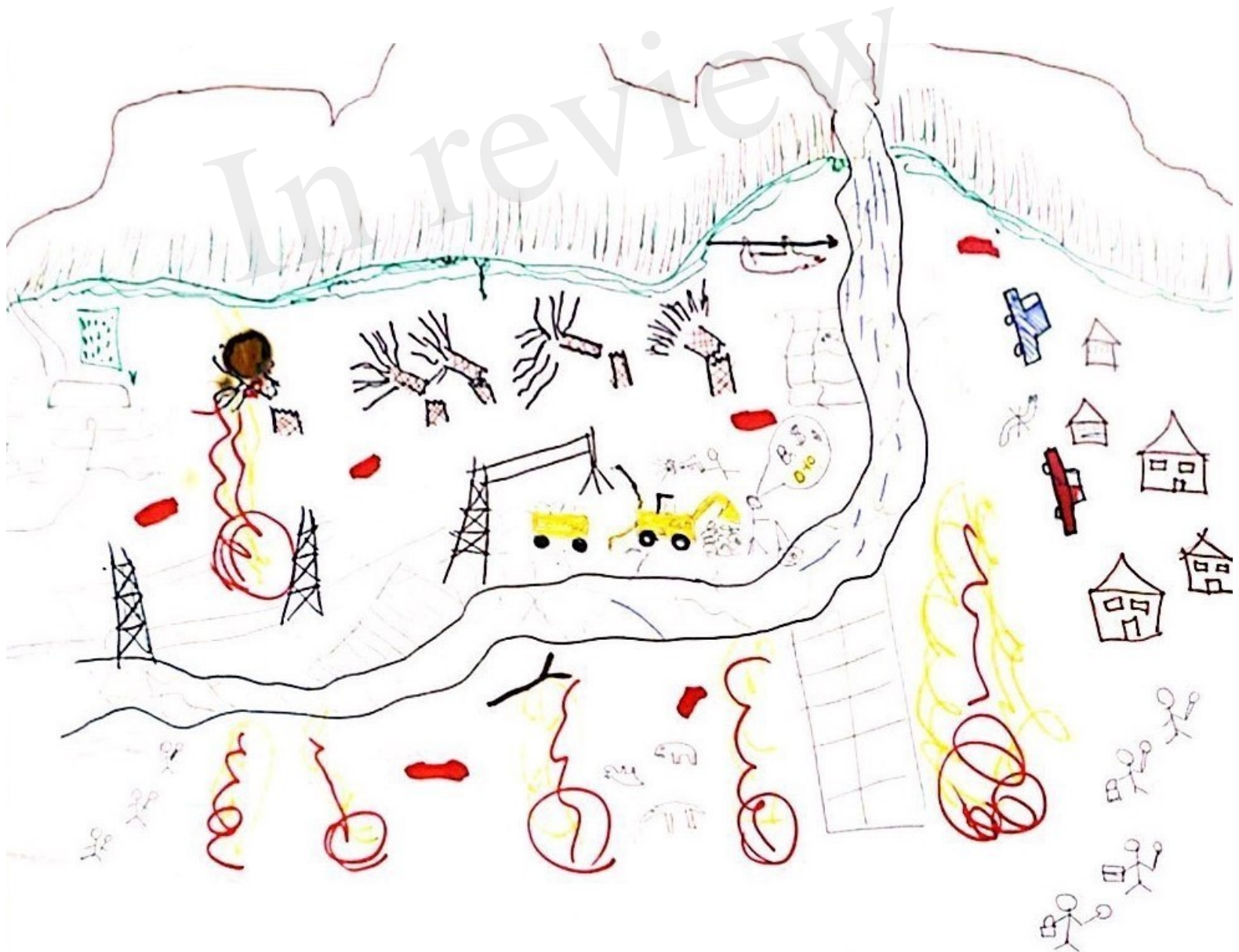


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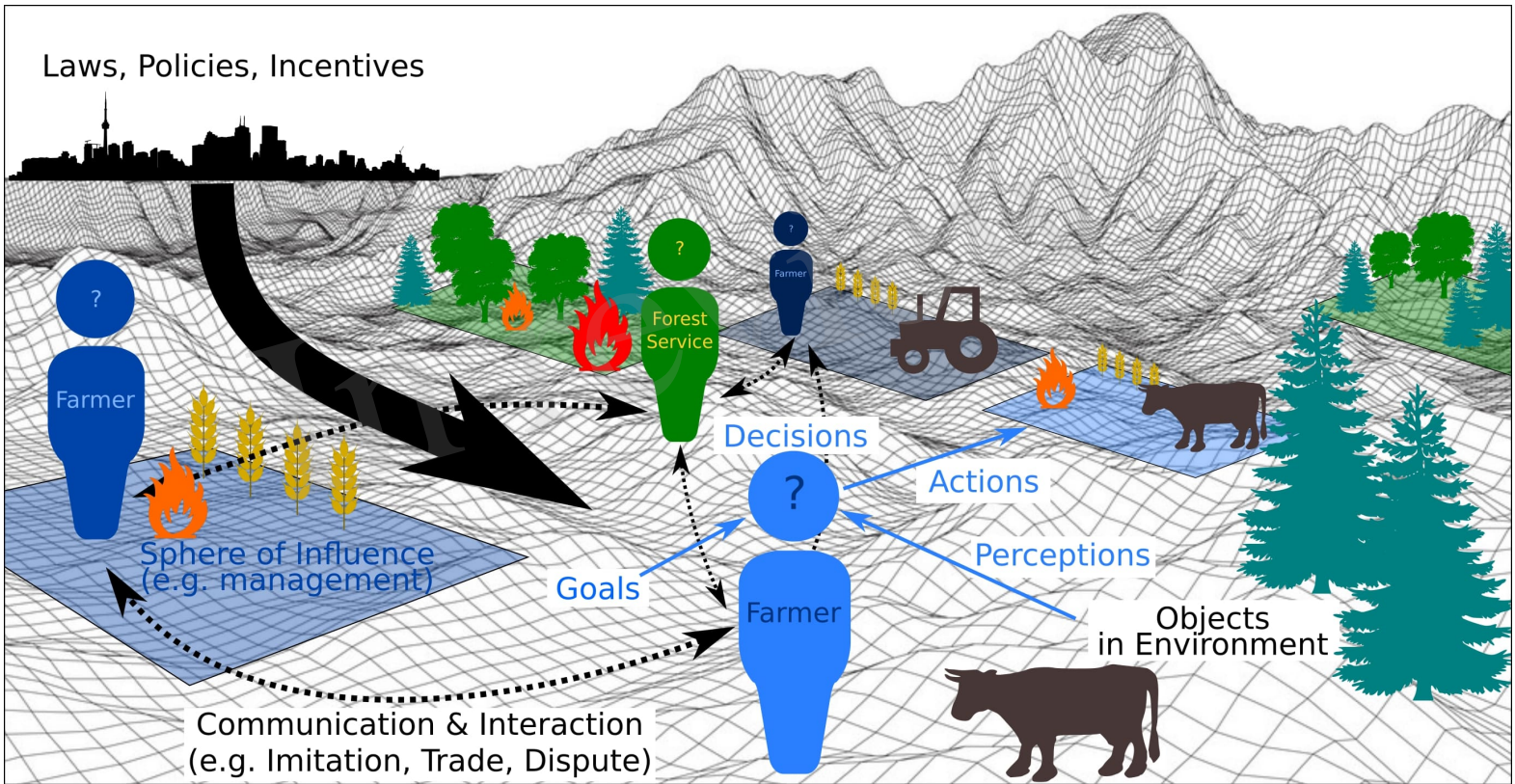


Figure 4.JPEG

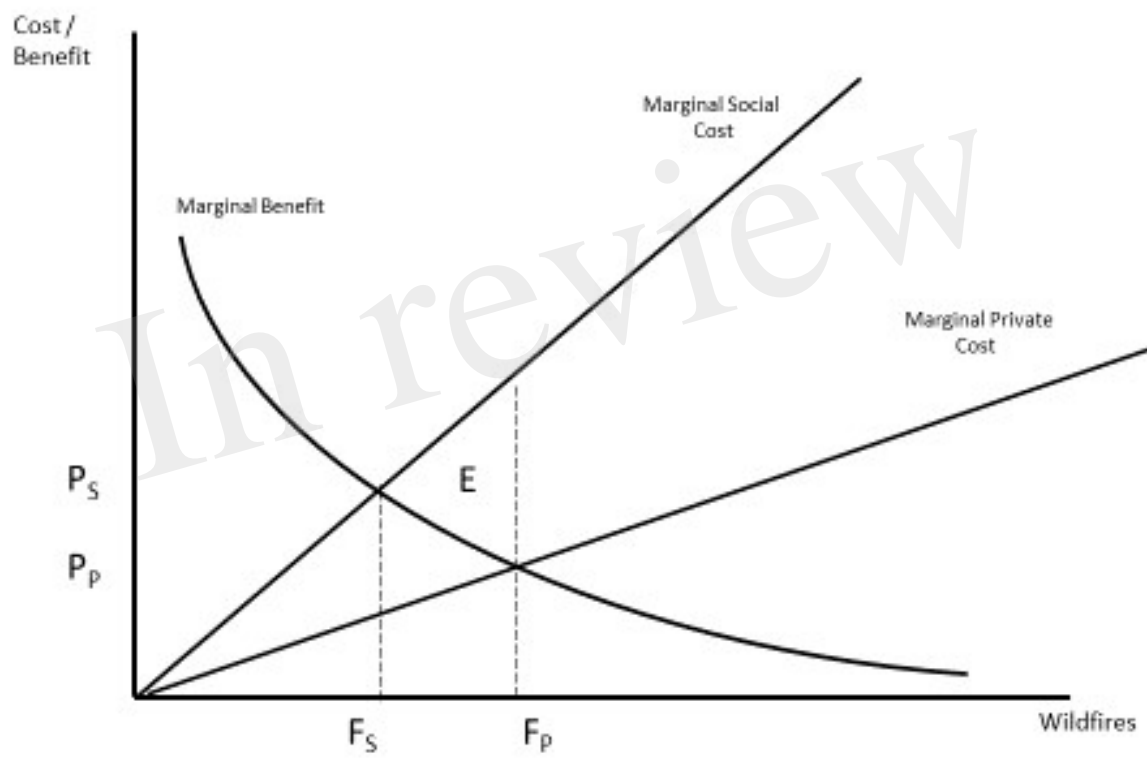


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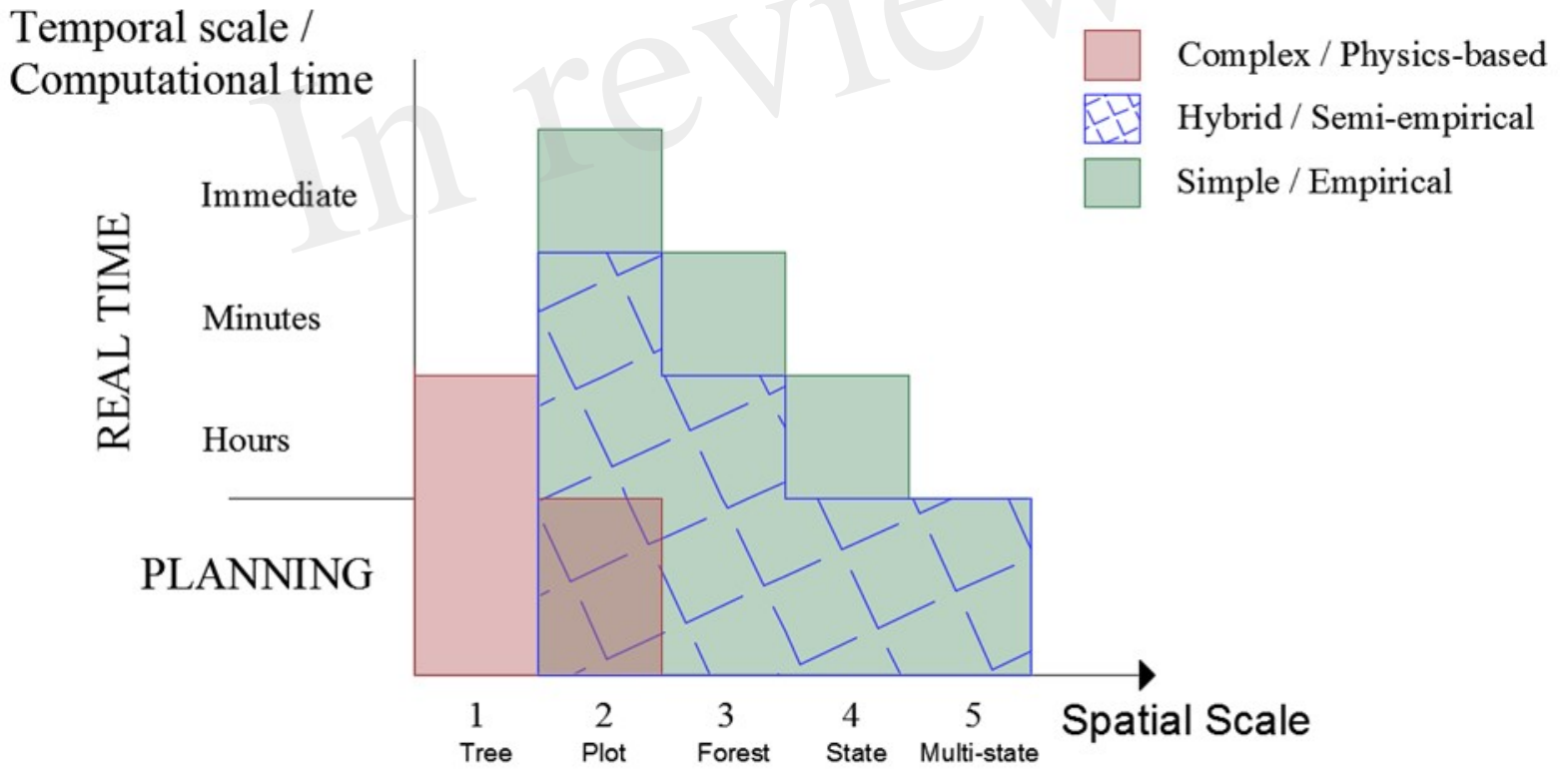




Figure 6.JPEG

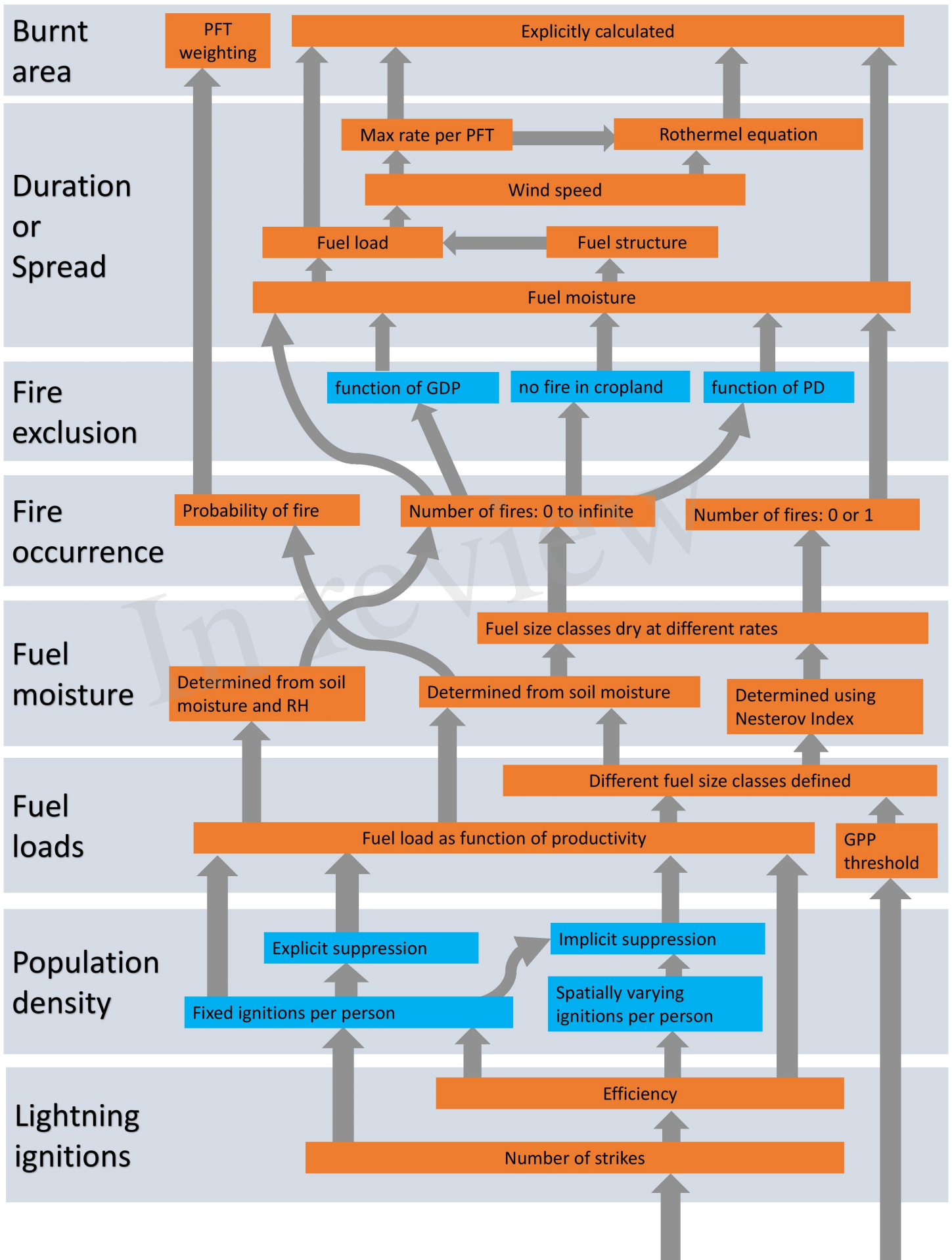


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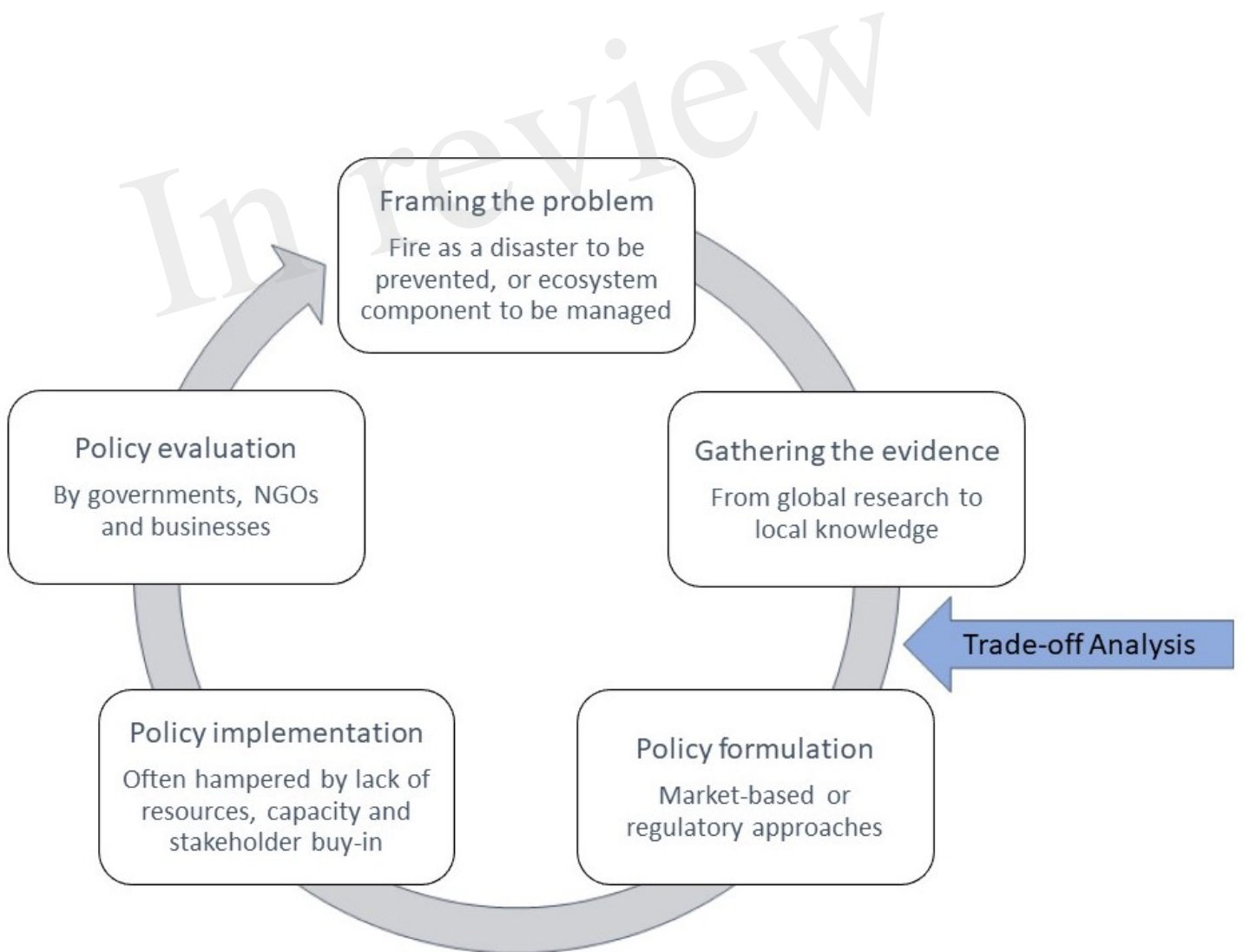




Figure 8.JPEG

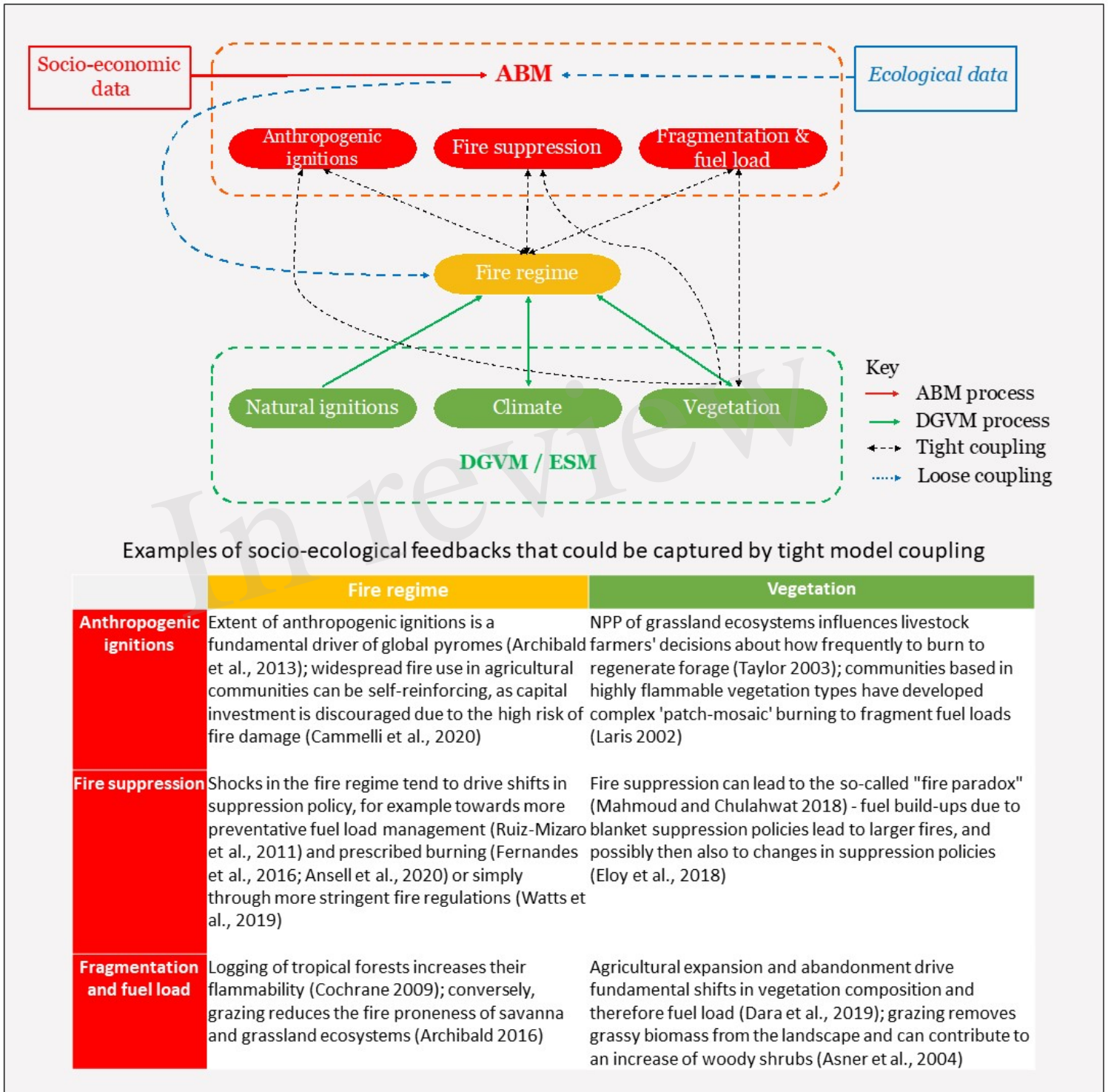


Figure 9.JPGG

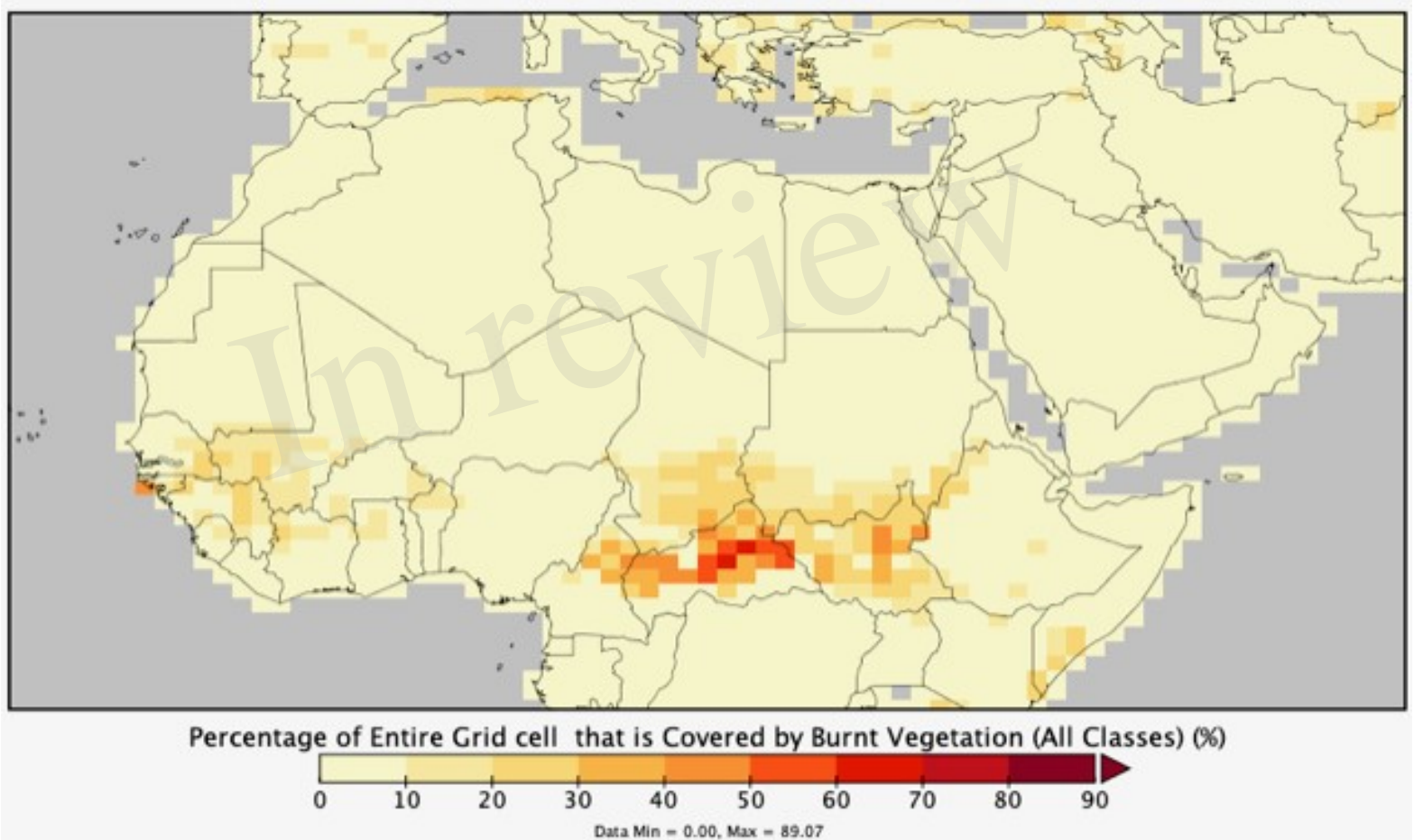


Figure 10.JPEG

