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**Assessment of the influence of biophysical properties related to fuel conditions on fire severity using remote sensing techniques: a case study on a large fire in NW Spain**

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1 **Abstract**

2 This study analyzes the suitability of remote sensing data from different sources  
3 (Landsat 7 ETM+, MODIS and Meteosat) in evaluating the effect of fuel conditions on  
4 fire severity, using a megafire (11891 ha) that occurred in a Mediterranean pine forest  
5 ecosystem (NW Spain) between August 19<sup>th</sup> and 22<sup>nd</sup>, 2012. Fire severity was measured  
6 via the delta Normalized Burn Ratio index. Fuel conditions were evaluated through  
7 biophysical variables including: (i) the Visible Atmospherically Resistant Index and  
8 mean actual evapotranspiration, as proxies of potential live fuel amount; (ii) Land  
9 Surface Temperature and water deficit, as proxies of fuel moisture content.  
10 Relationships between fuel conditions and fire severity were evaluated using Random  
11 Forest models. Biophysical variables explained 40 % of the variance. The Visible  
12 Atmospherically Resistant Index was the most important predictor, being positively  
13 associated with fire severity. Evapotranspiration also positively influenced severity,  
14 although its importance was conditioned by the data source. Live fuel amount, rather  
15 than fuel moisture content, primarily affected fire severity. Nevertheless, an increment  
16 in water deficit and land surface temperature was generally associated with greater fire  
17 severity. This study highlights that fuel conditions largely determine fire severity,  
18 providing useful information for defining pre-fire actions aimed at reducing fire effects.

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20 **Keywords:** VARI index, evapotranspiration, Meteosat, MODIS, Landsat, fire effects

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## 27 **Introduction**

28 In the European Mediterranean region, fire is a major disturbance (Oliveira *et al.* 2012)  
29 with significant ecological and socio-economic impacts on forest ecosystems (Pausas *et*  
30 *al.* 2009). It is well established that a major determinant of the magnitude of the ecological  
31 impact and effects of wildfires is fire severity (Harris and Taylor 2017), as it can alter  
32 vegetation composition, structure and regeneration dynamics (Wang and Kembell 2003;  
33 González-De Vega *et al.* 2018), as well as contribute to increasing soil degradation  
34 (Heydari *et al.* 2017). Fire severity refers to the change between pre- and post-fire  
35 conditions (Key 2006; Meng *et al.* 2017; Fernández-García *et al.* 2018a), and is  
36 operationally represented as both aboveground and belowground consumption of organic  
37 matter (Keeley 2009). It has been commonly evaluated through field methods, (e.g., the  
38 Composite Burn Index – CBI – and the GeoCBI index); but also using remotely sensed  
39 spectral indices validated with field-measured metrics, as a timely and cost-effective  
40 alternative to field methods (Fang *et al.* 2018). Properties of fire regime, such as the  
41 severity and size of fires, are expected to increase in the future in the Mediterranean  
42 region, likely due to land use and climate change, and forest management policies  
43 (González-De Vega *et al.* 2016), which might lead to drastic shifts in fire activity and  
44 seasonality. Therefore, modelling potential fire severity and understanding its main  
45 drivers of control emerges as a priority for improving pre-fire forest management  
46 strategies (Estes *et al.* 2017; García-Llamas *et al.* 2019).

47 Among the environmental factors that influence fire severity, there is increasing evidence  
48 that fuel is a major controlling factor (Kraaij *et al.* 2018; García-Llamas *et al.* 2019). In  
49 forest ecosystems, fuel characteristics, such as fuel moisture and structure, may affect fire  
50 spread, progression and behaviour (Harris and Taylor 2017), which largely determines  
51 fire severity levels. Furthermore, fuel composition and loading influence heat flux during

52 combustion, which ultimately may condition the spatial patterns of fire severity (Fang *et al.*  
53 *al.* 2018). Nevertheless, how fuel characteristics are specifically related to fire severity is  
54 still not fully understood. Whereas studies by Lentile *et al.* (2006) and Lydersen *et al.*  
55 (2017) have shown clear relationships between fuels and fire severity, others, such as  
56 Bessie and Johnson (1995) and Estes *et al.* (2017), suggested that fuels have a less  
57 important role on fire severity compared to other environmental factors (e.g., weather  
58 conditions and topography).

59 Fuel characteristics, such as fuel amount or spatial structure, can be modified through  
60 management treatments (Lee *et al.* 2018). As a consequence, knowledge of the role  
61 played by fuel in fire severity is critical for prioritizing effective pre- and post-fire  
62 management strategies. Fire management strategies require, however, the development  
63 of reliable and accurate information that helps and supports decision-making processes  
64 (Chuvieco and Kasischke 2007).

65 Recent advances in remote sensing techniques have provided major opportunities to  
66 obtain valuable information for scientists and decision-makers related to fuel  
67 characteristics for fire severity modelling in a cost-effective way. For example, satellite  
68 remote sensing offers great potential for (i) mapping fuel models (Riaño *et al.* 2002; van  
69 Wagtendonk and Root 2003); (ii) estimating live fuel moisture content from vegetation  
70 indices (Myoung *et al.* 2018); and (iii) measuring potential biomass production, the  
71 balance between moisture availability, fuel dryness and vegetation drought-stress from  
72 remotely sensed evapotranspiration products (Kane *et al.* 2015; Fang *et al.* 2018).  
73 Information from remote sensing systems offers several advantages as it is spatially  
74 comprehensive and can be periodically updated (Chuvieco and Kasischke 2007), thus  
75 enabling the assessment of spatial and temporal variation in fuel characteristics and their  
76 effect on fire severity. For example, Landsat satellite has been widely used for monitoring

77 and modelling fuel characteristics, since it provides one of the longest moderate spatial  
78 resolution imagery collections (Banskota *et al.* 2014). Moderate Resolution Imaging  
79 Spectroradiometer (MODIS) vegetation products have also been commonly used in fire  
80 studies across the globe, due to their near-global spatial coverage and high temporal  
81 resolution (Uyeda *et al.* 2015; Fang *et al.* 2018). Additionally, characteristics of newer  
82 satellites, such as the high temporal resolution of Meteosat Second Generation (MSG;  
83 (Amraoui *et al.* 2013), are incurring interest in the fire research field. Nevertheless,  
84 despite its advantages, the operational use of remote sensing data in assessing the role of  
85 fuels in fire severity still presents some challenges associated with the current status of  
86 satellite sensor technology (Chuvieco and Kasischke 2007) and the availability of the  
87 spectral, spatial or temporal resolution required for operational performance (Meng and  
88 Zhao 2017).

89 In this study, we aim to examine the suitability of different remote sensing sources  
90 (Landsat 7 ETM+, MODIS and Meteosat) to evaluate how biophysical properties are  
91 related to fuel conditions and how they can predict fire severity. Further, we provide  
92 recommendations at management level for defining actions to reduce fire effects. As a  
93 case study, we used a megafire that occurred in 2012 in NW Spain, which affected 11891  
94 ha of a Mediterranean ecosystem dominated by *Pinus pinaster* Aiton.

95

## 96 **Methods**

97

### 98 ***Study site***

99 This study was conducted in the Sierra del Teleno mountain range (NW Spain; Fig. 1)  
100 where 11891 ha burned in August, 2012 (between 19<sup>th</sup> and 22<sup>nd</sup>). The orography is

101 heterogeneous with altitude ranging from 2188 to 840 m.a.s.l. and 10% average slope.  
102 Soils are acidic originated over siliceous lithology (i.e., quartzite, conglomerate,  
103 sandstone and slate) with low organic matter content (Fernández-García *et al.* 2018b).  
104 The climate in this area is Mediterranean. Mean annual temperature is 10 °C, with 2-3  
105 months of drought in summer and a mean annual precipitation rate of 650 to 900 mm  
106 (20 years averaged values covering period 1950-1999; Ninyerola *et al.* 2005). During  
107 the week preceding the fire and during the fire itself, there was a heatwave that  
108 increased the fire risk (Quintano *et al.* 2015). The Sierra del Teleno mountain range has  
109 frequently been affected by wildfires mainly associated to dry spring-summer lightning  
110 storms and anthropic causes (Santamaría 2015). Small fires have commonly burned the  
111 area during winter, spring and autumn, while large fires mainly occur during the  
112 summer season (July-September; Santamaría 2015). The area affected by the fire was  
113 dominated by a mature natural maritime pine (*Pinus pinaster* Ait.) forest, with a tree  
114 density in mature stands of 765 plants ha<sup>-1</sup>. The shrubby understory community is  
115 mostly dominated by *Erica australis* L. and *Pterospartum tridentatum* (L.) Willk.  
116 Maritime pine populations in this area are highly adapted to intense crown fires with  
117 more than 95% of mature trees bearing serotinous cones (Tapias *et al.* 2004).  
118 Nevertheless, short fire return intervals (the average fire free interval has been estimated  
119 at 15 years) might prevent *P. pinaster* from reaching reproductive maturity, thus  
120 undermining population resilience (Taboada *et al.* 2018). The fire under consideration  
121 was an extreme convective-crown-fire that completely destroyed the understory and  
122 consumed the majority of tree crowns (40% of the surface burned at high severity  
123 levels; Quintano *et al.* 2015). Such extreme fire severity characteristics justified the  
124 selection of this fire event as a case study.

125

126 ***Fire severity***

127 Fire severity data were estimated from two Landsat 7 ETM+ images obtained on  
128 September 20<sup>th</sup>, 2011 (pre-fire image) and September 20<sup>th</sup>, 2012 (post-fire image) from  
129 the United States Geological Survey (USGS) Earth Explorer server  
130 (<http://earthexplorer.usgs.gov/>). Image selection was conducted considering the  
131 availability of cloud-free images closest to the date of the fire, aiming to avoid  
132 phenological changes in the vegetation (Lecina-Díaz *et al.* 2014). We applied the  
133 FLAASH algorithm (Berk *et al.* 1999; Matthew *et al.* 2003) to conduct atmospheric  
134 correction of the images, which enabled us to obtain a Bottom of Atmosphere (BOA)  
135 reflectance product.  
136 Fire severity was calculated via the delta Normalized Burn Ratio (dNBR; Key and  
137 Benson 2006; Eq. 1), an index widely used for estimating fire severity in forest systems  
138 (Soverel *et al.* 2010; Whitman *et al.* 2018).

139  
140 
$$dNBR = \frac{NIR - SWIR}{NIR + SWIR} \quad (\text{Eq. 1})$$

141  
142 where the Near-Infrared (NIR) and the Short Wave Infrared (SWIR) bands used for  
143 calculation were the NIR (B4) and the SWIR-2 (B7) bands of Landsat 7 ETM +. dNBR  
144 values in unburned areas were normalized to zero by subtracting the average dNBR in  
145 unburned areas outside the fire from those within the fire perimeter to account for inter-  
146 annual phenological differences between pre- and post-fire images (Miller *et al.* 2009).  
147 dNBR values were validated using the CBI index, which was estimated three months  
148 after fire following the protocol described by Fernández-García *et al.* (2018a), which is  
149 a modification of the CBI protocol developed by Key and Benson (2006). CBI values  
150 ranged between 0 (unburned) and 3 (high severity) according to the burn severity scale



151 by Key and Benson (2006). They were obtained averaging the scores assigned to several  
 152 variables of five vertical strata, in 54 plots of 30 m x 30 m randomly distributed across  
 153 the study area. The correlation value between the spectral index and CBI was 0.88. See  
 154 Fernández-García *et al.* (2018a) for further details on the dNBR validation.  
 155 In this study, we used continuous dNBR values as the response variable in further  
 156 analysis. Nevertheless, for easier interpretation, we also show dNBR as classified fire  
 157 severity using breakpoints defined based on the CBI values: low severity,  $45.898 \geq$   
 158  $dNBR < 413.185$ ; moderate severity,  $413.185 \geq dNBR < 732.565$ ; high severity,  $\geq$   
 159  $732.565$ ; by Fernández-García *et al.* (2018b) (Fig. 1).

160

### 161 ***Biophysical properties related to fuel conditions***

162 The biophysical properties related to fuel conditions were characterized by including  
 163 metrics related to fuel loads and moisture content. We estimated the potential live fuel  
 164 amount on the basis of two variables: (i) the Visible Atmospherically Resistant Index  
 165 (VARI), and (ii) the mean actual evapotranspiration (AET). The VARI is an index  
 166 based on the red, green and blue visible bands (Eq. 2; Gitelson *et al.* 2002), which is  
 167 related to the live vegetation fraction and net primary production (Gitelson *et al.* 2002;  
 168 Maguigan *et al.* 2016). It was derived from a Landsat 7 ETM+ image (30 m spatial  
 169 resolution) obtained on September 20<sup>th</sup>, 2011 (the pre-fire image applied for calculating  
 170 fire severity; see section 2.2 for further details on image pre-processing).

$$171 \quad VARI = \frac{R_{green} - R_{red}}{R_{green} + R_{red} - R_{blue}} \quad (\text{Eq. 2})$$

172 where  $R_{\text{band}}$ ,  $\text{band}=\text{green, red and blue}$  is the BOA reflectance for each band, respectively.

173 AET is related to potential biomass production and thus, to fuel amount (Kane *et al.*  
 174 2015). It was calculated by averaging information acquired between June and August,  
 175 2012 from two different remote sensing data sources: (i) a MSG (Schmetz *et al.* 2002;

176 Romaguera *et al.* 2012) evapotranspiration product at 10-day intervals and 3 Km spatial  
177 resolution, provided by the EARS enterprise; (ii) the MOD16A2 global  
178 evapotranspiration product at 8-day intervals and 500 m spatial resolution from MODIS  
179 (<https://modis.gsfc.nasa.gov/data/dataproduct/mod16.php>; Hantson *et al.* 2015). We  
180 selected summer months because it is the season when large fires mainly occurred in the  
181 area (Santamaría 2015), and it is well established that a main factor of fire ignition and  
182 propagation is the presence of fuel ready for burning (Gouveia *et al.* 2012; Russo *et al.*  
183 2017), especially in crown convective fires.

184 Variables accounting for fuel moisture content included the Land Surface Temperature  
185 (LST) and water deficit, which were derived from the MODIS satellite. We estimated  
186 these variables for the week prior to the fire because both the high temperatures and the  
187 low relative humidity of the heatwave episode during the week preceding the fire likely  
188 exacerbated the effects of summer drought and, thus, fuel desiccation and flammability  
189 (van Mantgem *et al.* 2013). The LST, which is expected to increase in drier vegetation  
190 (Dasgupta *et al.* 2005), was computed by averaging daily information from the MODIS  
191 1 Km LST product. Water deficit, at 500 m spatial resolution, was estimated as the  
192 difference between PET and the AET (Kane *et al.* 2015). PET and AET were obtained  
193 from the MOD16A2 global evapotranspiration product at 8-day intervals.

194

### 195 ***Statistical analysis***

196 In order to explore the relationship between the response variable (fire severity) and the  
197 predictors (biophysical variables related to fuel conditions), we applied the Random  
198 Forest (RF) machine learning algorithm (Breiman 2001), using the ‘randomForest’  
199 package (Liaw and Wiener 2002) for R (R Core Team 2017) and a random sampling set  
200 of 1000 pixels (1 % of pixels from the image) to build the models.

201 To avoid multicollinearity problems among the predictors, we previously checked  
202 Pearson's bivariate correlations, the reached correlation values being lower than 0.60  
203 (Supplementary material, Table 1).  
204 The predictive power of RF was estimated through the internal out-of-bag error rates  
205 (Kane *et al.* 2015). Furthermore, in order to obtain stable results, the parameter of *n*tree  
206 (i.e., the number of trees to run) was set to 500 and the *m*try parameter (i.e., the number  
207 of input predictors tested at each split) was established through initial tuning  
208 experiments. The decrease in the accuracy (% IncMSE) criterion was used to determine  
209 the relative importance of predictors in the variance explained in models. RF models  
210 were run 50 times and the average was provided as the final result, aiming to obtain  
211 stable model outputs and to minimize stochastic errors. Additionally, we obtained  
212 partial dependence plots for each predictor.

213

## 214 **Results**

215 Random Forest models accounted for approximately 40% of the fire severity variance.  
216 Regarding the individual contribution of each predictor in explaining fire severity,  
217 biophysical properties associated with the potential amount of live fuel were relatively  
218 more important than those associated with fuel moisture content (Fig. 2). In detail, the  
219 VARI index emerged as the most important predictor influencing fire severity (Fig. 2).  
220 Overall, high values of the VARI index were related to an increment in fire severity levels,  
221 thus indicating higher fire severity in areas of great availability of live fuel (Fig. 3 a).  
222 Additionally, the importance of AET in Random Forest models changed between remote  
223 sensing data sources of different spatial resolution (Fig. 2). Particularly, AET obtained  
224 from MSG was the second most influential predictor explaining fire severity.  
225 Nevertheless, AET derived from MODIS had less influence on fire severity, even less

226 than biophysical properties related to fuel moisture content (i.e., water deficit) (Fig. 2).  
227 Regardless of the remote sensing data source, higher AET values were correlated with  
228 higher fire severity levels, but just towards a threshold (2.5 mm and 2.9 mm for AET from  
229 MSG and MODIS, respectively; Fig. 3 b, d). Increasing water deficit was generally  
230 associated with greater fire severity levels (Fig. 3 c). Furthermore, LST was weakly  
231 related to fire severity (Fig. 2) and exhibited a negative influence on fire severity (Fig. 3  
232 e).

233

## 234 **Discussion**

235

### 236 ***Influence of fuel on fire severity***

237 The results of this study confirm previous findings demonstrating the role of fuel  
238 conditions, obtained from different remote sensing data sources, as major  
239 controlling factors of fire severity patterns (Lentile *et al.* 2006; Gouveia *et al.*  
240 2012; Kraaij *et al.* 2018). Nevertheless, in Mediterranean pine forest dominated  
241 by *P. pinaster*, results showed that fuel characteristics were not equally related to  
242 fire severity. The amount of live fuel, measured through the VARI index,  
243 appeared to be the most important factor, positively affecting fire severity.  
244 Positive correlations between higher levels of fire severity and the presence of  
245 dense live vegetation loads has also been reported in other areas dominated by  
246 pine forests (Schoennagel *et al.* 2004; Arkle *et al.* 2012). In this context,  
247 chemical properties of *P. pinaster*, such as high resin content, together with the  
248 structural characteristics of needles, tend to increase live biomass flammability  
249 and the energy released during combustion (Calvo *et al.* 2003), therefore  
250 contributing to higher fire severity levels. Additionally, recurrent fires in some

251 zones of the study site have contributed to high post-fire regeneration stand  
252 densities (Calvo *et al.* 2013; Taboada *et al.* 2017), and resprouter shrub species  
253 [i.e., *Erica australis* L. and *Pterospartum tridentatum* (L.) Willk.] of high  
254 pyrogenicity (Calvo *et al.* 2008), which have been found to trigger high fire  
255 severity levels (García-Llamas *et al.* 2019).

256 The importance of live fuel on fire severity was also evinced by the overall  
257 positive effect of AET on fire severity, likely due to the association of this  
258 parameter with vegetation productivity and, thus, with mounts of live fuel (Kane  
259 *et al.* 2015). Nevertheless, the impact of AET on fire severity changed  
260 substantially depending on the remote sensing data source used for analyses.

261 AET obtained from MSG was the second most important predictor of fire  
262 severity, but the AET product from MODIS showed less importance than fuel  
263 moisture predictors (i.e., water deficit). The difference in spatial resolution  
264 between remote sensing derived AET products might justify this inconsistency  
265 in AET importance, thus indicating that the resolution might affect the  
266 predictability of fire severity models (Harris and Taylor 2017; Fang *et al.* 2018).

267 In this context, it is well known that different spatial processes could operate at  
268 different scales and, hence, conclusions at one scale might not be enforceable at  
269 another (Suárez-Seoane and Baudry 2002; Wu and Li 2009). Consequently,  
270 spatial resolution discrepancies between data sources may constrain the accuracy  
271 of models and lead to conflicting conclusions, thus limiting the development of  
272 remote sensing applications (Wu and Li 2009; García-Llamas *et al.* 2016). As a  
273 result, although the capacity of remote sensing techniques to provide information  
274 at multiple resolutions might be advantageous (Lentile *et al.* 2006), their utility  
275 for assessing the role of fuel on fire severity might be hampered by mismatches

276 between the resolution of the data source and the scale at which fuel  
277 characteristics and fire severity correlate.

278 High fire severity levels have proven to be largely determined by fuel moisture  
279 content (Ferguson *et al.* 2002). Our results indicated that high-severity fires were  
280 more likely under greater hydric stress conditions (i.e., higher water deficit and  
281 LST values). This result might be explained by the fact that dry conditions tend  
282 to favour the consumption of greater amounts of fuel, as well as higher levels of  
283 energy released during combustion (Dillon *et al.* 2011). Nevertheless, although  
284 summers in the Mediterranean Iberian Peninsula are typically dry enough to  
285 promote fuel desiccation that permits ignition, the abundance of live biomass  
286 loads for combustion, rather than fuel moisture, has been noted as the primary  
287 limiting factor of fire severity (Pausas and Paula 2009; Lecina-Diaz *et al.* 2014),  
288 as also observed in our study. One reason could be that dry conditions limit  
289 vegetation growth and, thus, fuel accumulation and continuity, leading to a  
290 decrease in the risk of crown fire spread (Alvarez *et al.* 2012) and fire severity.

291 Additionally, these results could also be related to scale issues, in a way that the  
292 spatial resolution of moisture predictors may not properly match the scale at  
293 which fire severity patterns and fuel moisture content characteristics correlate.

294

### 295 ***Management recommendations***

296 Our findings evinced how high live fuel accumulations may increase  
297 susceptibility to high-severity fire events in Mediterranean *P. pinaster* forest  
298 ecosystems. Under this assumption, pre-fire management strategies aiming at  
299 reducing high live fuel loads would be essential to reduce the likelihood of  
300 severe fires. Effective pre-fire fuel treatments should prioritize the reduction of

301 canopy bulk density through silvicultural treatments, aiming at hampering crown  
302 fire spread, and dismissing fire intensity, as well as convective heat transfer into  
303 the canopy, thus reducing fire severity (Lininger 2006). Additionally, creating  
304 open and sparse stands and retaining large trees, which reduce fuel continuity,  
305 would also be recommended, aiming to increase the resilience of the system  
306 (Agee and Skinner 2005). In this way, studies by Gallegos *et al.* (2003) and Kim  
307 *et al.* (2016) showed how a relatively open forest structure was correlated with a  
308 decrease in fire severity. Nevertheless, it is necessary to consider that fuel  
309 reduction treatments need to be balanced against the development of fire-prone  
310 understory vegetation. In this context, stand opening might enhance the  
311 development of fire-prone shrubby understory (Fernandes and Rigolot 2007) and  
312 the desiccation of live and dead fuels (Peterson *et al.* 2003), which would make  
313 periodic surface fuel treatments necessary.

314

### 315 **Conclusions**

316 The results of this study highlight that, in severe crown-convective fires in *P. pinaster*  
317 Mediterranean forest, the accumulation of live vegetation available to be burned plays a  
318 relatively more important role in determining high levels of fire severity than fuel  
319 moisture conditions. In addressing the role of fuel characteristics in fire severity, the  
320 VARI index from Landsat 7 ETM+ and the AET product from MSG might be valuable  
321 tools for determining the amount of live fuel susceptible to influencing fire severity.  
322 However, we further highlight the importance of a proper selection of the remote data  
323 sources at the operational spatial resolution which might affect the predictability of fire  
324 severity models. Our analysis provides information that can be helpful for  
325 environmental managers when defining strategies aimed at reducing severity and its

326 ecological effects during the pre- and post-fire decision-making process. These  
327 strategies should prioritize the reduction of live fuel accumulations and the  
328 enhancement of a more open canopy through the modification of forest stands and  
329 structure.

330

### 331 **Conflicts of interest**

332 The authors declare no conflicts of interest.

333

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548 **Figures**

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550 **Fig. 1** Location map of the study area (Sierra del Teleno, NW Spain) including a  
551 pre-fire vegetation map of the burned area produced using: a) an  
552 orthophotograph (year 2011) from the Spanish National Plan for Aerial  
553 Orthophotography  
554 (<http://centrodedescargas.cnig.es/CentroDescargas/index.jsp#>); b) the CORINE  
555 Land Cover data base available for 2012; and c) a fire severity map obtained  
556 using classified dNBR values derived from Landsat 7 ETM+ post-burned  
557 imagery (20<sup>th</sup> September 2012) with breakpoints defined based on the CBI  
558 values: low severity,  $45.898 \geq \text{dNBR} < 413.185$ ; moderate severity,  $413.185 \geq$   
559  $\text{dNBR} < 732.565$ ; high severity,  $\geq 732.565$  from Fernández-García *et al.*  
560 (2018b); b)

561 **Fig. 2** Relative importance, measured as % IncMSE, of variables from Random  
562 Forest models explaining fire severity. Abbreviations are Actual  
563 Evapotranspiration from Meteosat Second Generation satellite ( $\text{AET}_{\text{MSG}}$ ) and  
564 from MODIS satellite ( $\text{AET}_{\text{MODIS}}$ ); and Land Surface Temperature (LST).

565 **Fig. 3** Partial dependence plots showing the relationship between fire severity  
566 and each of the predictors included in Random Forest models: a) VARI index; b)  
567 Actual Evapotranspiration from Meteosat Second Generation satellite ( $\text{AET}_{\text{MSG}}$ );  
568 c) Water deficit; d) Actual Evapotranspiration from the MODIS satellite  
569 ( $\text{AET}_{\text{MODIS}}$ ); e) Land Surface Temperature (LST).

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For Review Only

574 **Fig. 1**

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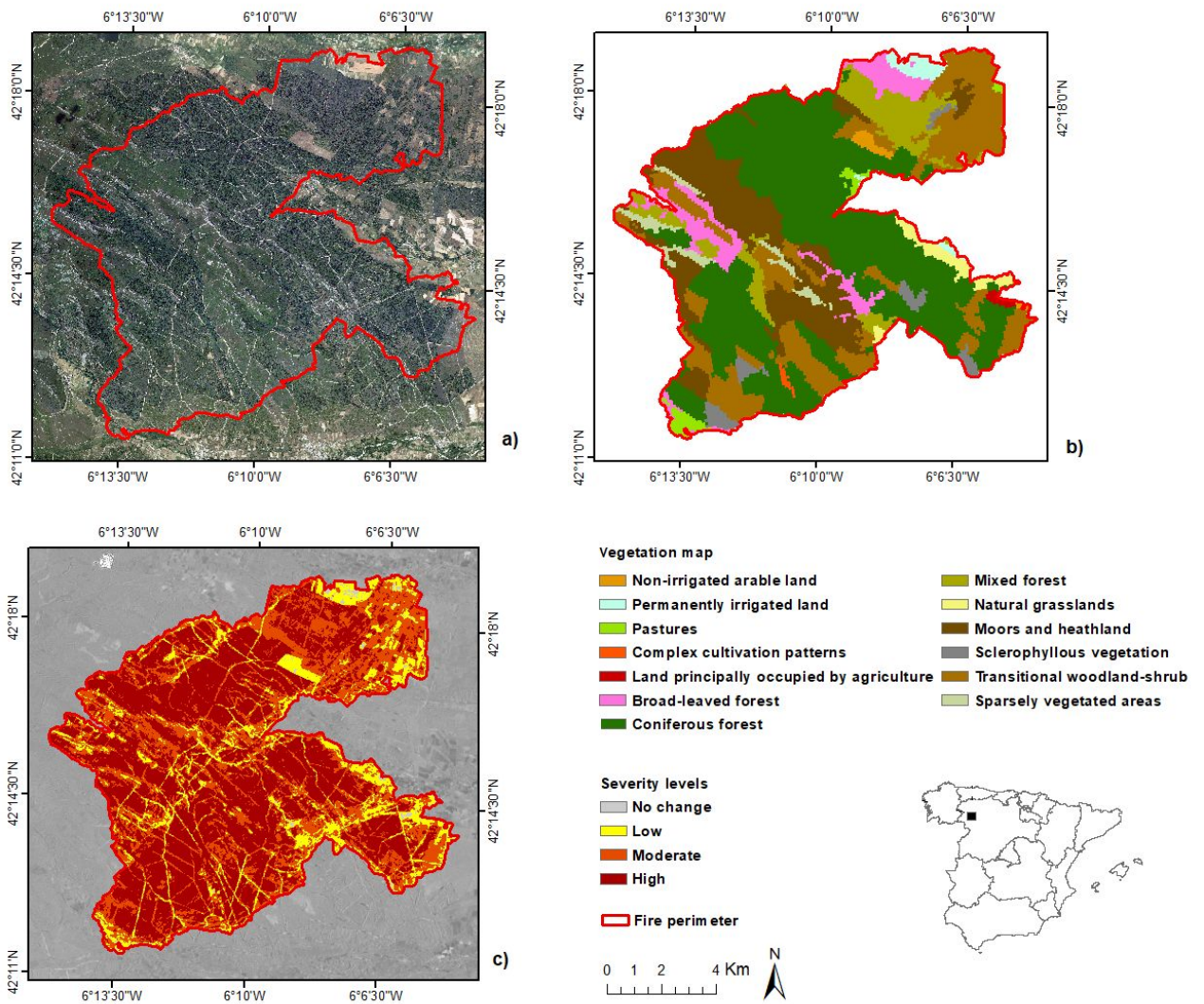
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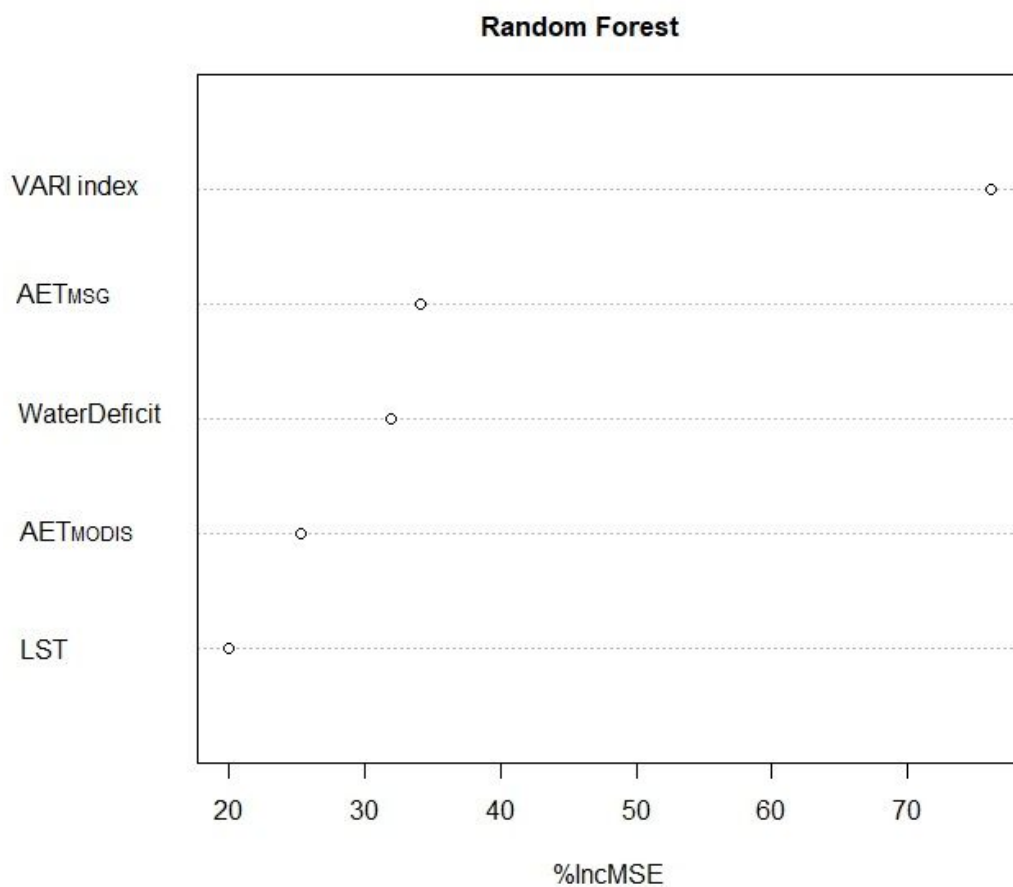
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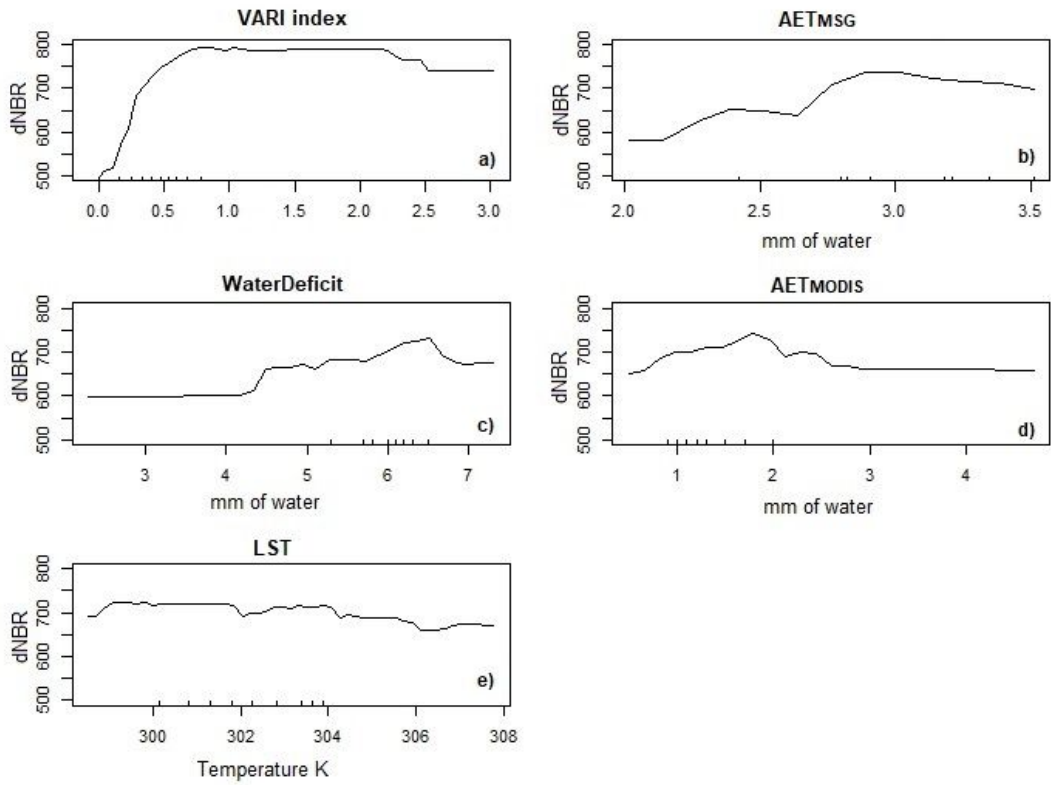
621 **Fig. 2**  
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646 **Fig. 3**  
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Potential live fuel amount had more influence on fire severity than fuel moisture content on pine forest ecosystems. The Visible Atmospherically Resistant Index, as a proxy of live fuel amount, showed the strongest association with fire severity. Remote sensing has high potential for determining fuel characteristics susceptible to influencing fire severity, although spatial resolution might constrain the utility of fire severity models.

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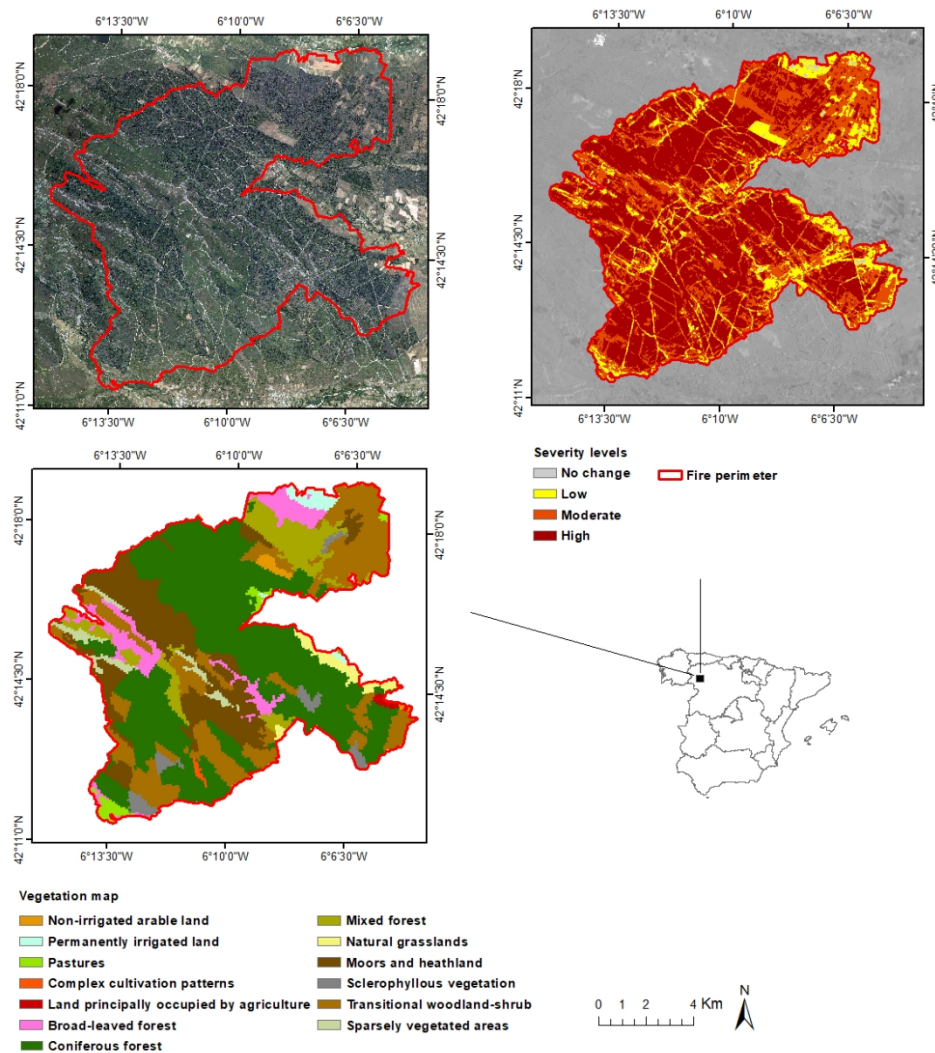


Fig. 1 Location map of the study area (Sierra del Teleno, NW Spain) including a pre-fire vegetation map of the burned area produced using: a) an orthophotograph (year 2011) from the Spanish National Plan for Aerial Orthophotography (<http://centrodedescargas.cnig.es/CentroDescargas/index.jsp#>); b) the CORINE Land Cover data base available for 2012; and c) a fire severity map obtained using classified dNBR values derived from Landsat 7 ETM+ post-burned imagery (20th September 2012) with breakpoints defined based on the CBI values: low severity,  $45.898 \geq \text{dNBR} < 413.185$ ; moderate severity,  $413.185 \geq \text{dNBR} < 732.565$ ; high severity,  $\geq 732.565$  from Fernández-García et al. (2018b); b)

312x344mm (96 x 96 DPI)



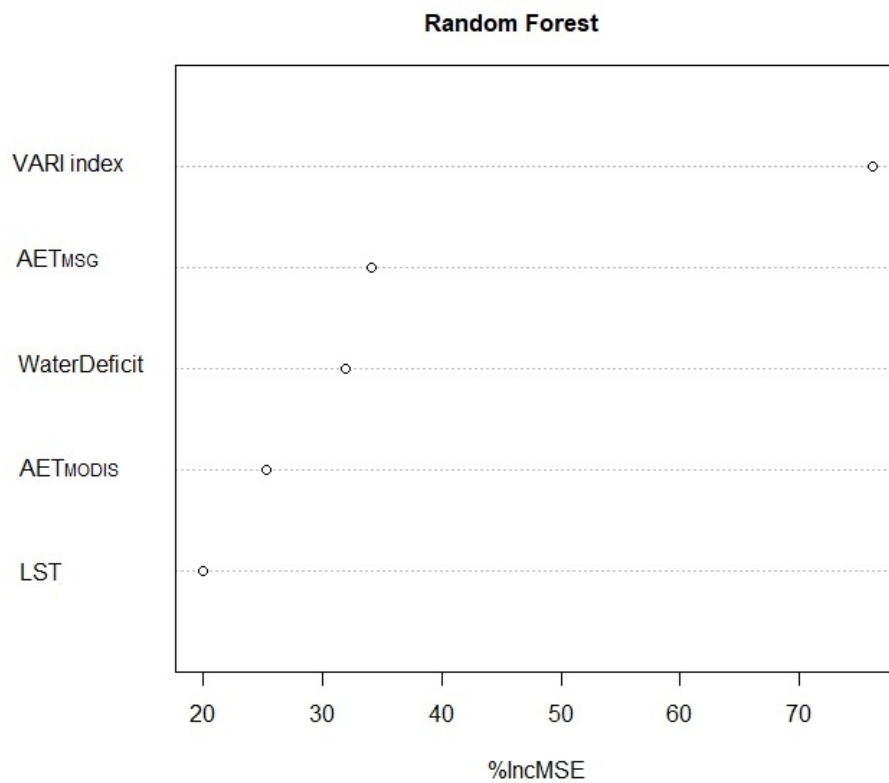


Fig. 2 Relative importance, measured as % IncMSE, of variables from Random Forest models explaining fire severity. Abbreviations are Actual Evapotranspiration from Meteosat Second Generation satellite (AETMSG) and from MODIS satellite (AETMODIS); and Land Surface Temperature (LST).

183x157mm (96 x 96 DPI)

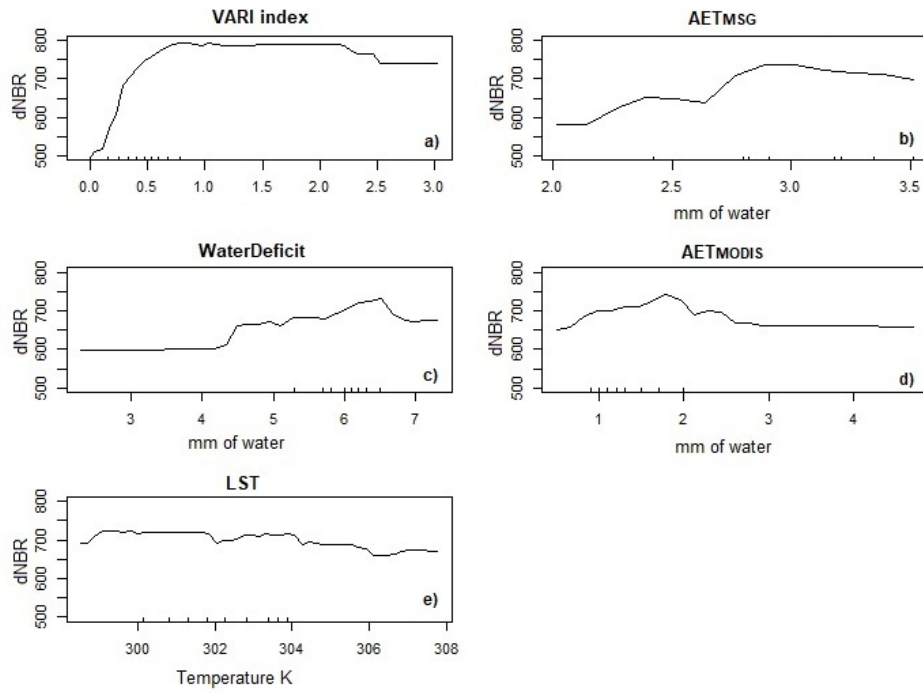


Fig. 3 Partial dependence plots showing the relationship between fire severity and each of the predictors included in Random Forest models: a) VARI index; b) Actual Evapotranspiration from Meteosat Second Generation satellite (AETMSG); c) Water deficit; d) Actual Evapotranspiration from from MODIS satellite (AETMODIS); e) Land Surface Temperature (LST).

194x139mm (96 x 96 DPI)

Table 1. Pearson's correlation coefficients ( $r$ ) between pairs of predictors (biophysical variables related to fuel conditions)

	VARI index	AET <sub>MODIS</sub>	AET <sub>MSG</sub>	Water deficit	LST
VARI index	1.00	0.00	-0.01	0.00	-0.11
AET <sub>MODIS</sub>	0.00	1.00	-0.60	0.53	-0.21
AET <sub>MSG</sub>	-0.01	-0.60	1.00	-0.61	0.35
Water deficit	0.00	0.53	-0.61	1.00	-0.43
LST	-0.11	-0.21	0.35	-0.43	1.00

AET<sub>MODIS</sub> (Actual Evapotranspiration obtained from the MOD16A2 global evapotranspiration product); AET<sub>MSG</sub> (Actual Evapotranspiration obtained from the Meteosat Second Generation).