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Bottom-Up Variables Govern Large-Fire Size in Portugal

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ABSTRACT

Large fires and their impacts are a growing concern as changes in climate and land use proceed. The study of large-fire controls remains incipient in comparison with other components of the fire regime. Improved understanding of large-fire size drivers can disclose fire–landscape relationships and inform more sustainable and effective fire management. We used boosted regression tree modeling to identify the variables influent on large-fire size (100–23,219 ha, $n = 609$) in Portugal (1998–2008) and quantify their relative importance, globally and across the fire-size range. Potential explanatory variables included metrics pertaining to fire weather and antecedent rainfall, burned area composition, fuel connectivity, pyrodiversity (from fire recurrence patterns), topography, and land development. Large fires seldom occurred in the absence of severe fire weather. The fire-size model accounted for 70% of the deviance and included 12 independent variables, of which

six absorbed 91% of the explanation. Bottom-up influences on fire size, essentially fuel-related, largely outweighed climate–weather influences, with respective importance of 85 and 15%. Fire size was essentially indifferent to land-cover composition, including forest type, and increased with high fuel connectivity and low pyrodiversity. Relevant synergies between variables were found, either positive or negative, for example, high pyrodiversity buffered the effects of extreme weather on fire size. The relative role of fire-size drivers did not vary substantially with fire size, but fires larger than 500 ha were increasingly controlled by fuel-related variables. The extent of an individual large fire is mainly a function of factors that land-use planning and forest and fuel management can tackle.

Key words: extreme fires; fire management; fire regime; fire weather; land management; landscape structure; Mediterranean Basin; pyrodiversity.

Author contributions PMF conceived the study, performed research, and wrote the paper. TMH, NG, CL, and AMGB analyzed data and contributed to writing.

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INTRODUCTION

Disturbance by fire is ubiquitous in Earth's terrestrial biomes wherever ignition sources, biomass (fuel), and suitable climate–weather conditions combine (Krawchuk and Moritz 2011). Fire size is a fundamental spatial attribute of the fire regime, given its importance to ecosystem function and structure and landscape diversity (Turner 2010). Fire size conveys potential damage (Strauss and others 1989) and, generically, is positively corre-

lated with overall burned area and fire intensity (Gill and Allan 2008; Archibald and others 2013). The ecological implications of fire size, immediate and delayed, are exerted directly through area-related effects, and indirectly through fire severity (Turner and others 1997). Fire size distribution is extremely unequal, with few fires becoming large, but those that do contribute to a large fraction of the total burned area (Strauss and others 1989). Fires at least 100 ha in southern Europe represent just 1.1% of the number of fires but account for 64.9% of the burned extent.[1] Maximum fire size varies globally over five orders of magnitude (10^2–10^6 ha) (Gill and Allan 2008; Archibald and others 2013). Nevertheless, the size of any given fire is difficult to predict due to the stochasticity involved (Falk and others 2007).

Fire behavior and severity are determined by the joint influences of fuel, topography, and weather conditions (Sullivan 2009; Fernandes and others 2010; Viedma and others 2015). Fuel structure and load vary at small scales producing a wide range of fire behavior characteristics such as spread rate, fireline intensity, and crown-fire likelihood (Fernandes 2009). Substantial fuel differences between vegetation types can result in preferential burning (Nunes and others 2005) and affect fire size (Liu and Wimberly 2015) and area burned (Parisien and others 2011). Because fire spread is a contagious process (McKenzie and others 2011), large fire development is contingent on fuel continuity over a large enough area (Gill and Allan 2008). More generally, the spatial organization, shape, and size of fuel patches are important to fire spread, which is apparent in simulation experiments (Ryu and others 2007; Parks and others 2012). Fire-landscape feedbacks generate fuel patch mosaics whereby the degree of heterogeneity, or pyrodiversity (Faivre and others 2011), is a legacy of past fires and regulates future fires (Peterson 2002; McKenzie and others 2011). Fine-grain mosaics, that is, high pyrodiversity on a small spatial scale, can change fire size distribution toward smaller fires (Minnich and Chou 1997; Bird and others 2012). However, such an effect may be indiscernible (Keeley and Zedler 2009) because it is contingent on fire weather severity and fuel structure and recovery (Price and Bradstock 2010; Collins and others 2009). Conversely, large fires

that simplify the landscape set the stage for even larger fires (Lloret and others 2002; Loepfe and others 2010).

Topography influences fire spread directly through slope steepness (Sullivan 2009). Indirect effects can be more relevant, and are expressed through contrasting vegetation types, fuel amounts, fuel moisture, and wind modification (Holden and others 2009; Parks and others 2011). Overall, topographic effects on fire spread are complex and highly variable (Hawbaker and others 2013).

Variability in fire-spread rate in a given fuel or vegetation type is mainly explained by atmospheric conditions, namely wind speed and the primary determinants of fine dead fuel moisture content—relative humidity and air temperature (Sullivan 2009; Anderson and others 2015). Antecedent and seasonal precipitation affect the moisture content of slow-drying fuels (Wotton 2009), hence their availability to burn (Fernandes and Loureiro 2013) and contribution to fire activity (Dennison and others 2008). At annual to multiannual scales, climatic patterns affect plant productivity, influencing fire spread in fuel-limited systems (Bird and others 2012; O'Donnell and others 2014).

The extent to which the various environmental factors control fire activity varies depending on fire regime attribute, ecosystem, and spatial and temporal scales (Heyerdahl and others 2001; Falk and others 2007; Parisien and Moritz 2009; Parks and others 2012; Parisien and others 2011, 2014; Liu and Wimberly 2015). Although bottom-up controls (fuels and topography) operate locally, coarser top-down controls (climate–weather, landform, land use) are dominant across large areas (Heyerdahl and others 2001; Falk and others 2007; Parks and others 2012). At intermediate scales, fires are subjected to complex and variable interactions between bottom-up and top-down controls (McKenzie and others 2011). Such interactions are theorized to elicit nonlinear growth responses across the spatial scale gradient, with changes in the prevailing fire-spread control (Peters and others 2004). This expectation is empirically supported by findings of environmental thresholds for rapid increases in fire size (Slocum and others 2010; O'Donnell and others 2014; Fang and others 2015). Finally, human-caused ignitions and fire suppression also shape the fire regime (Guyette and others 2002; Syphard and others 2007; Hawbaker and others 2013), weakening or even overriding biophysical influences (Heyerdahl and others 2001) and introducing further analytical complexity.

The response of fire activity to fire weather in the Mediterranean has been enhanced by fuel build-up

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[1] Computed from EFFIS—European Forest Fire Information System data supplied by the Joint Research Centre of the European Commission (http://forest.jrc.ec.europa.eu/effis/) for the 1990–2011 period.

ensuing contemporary socioeconomic and land-use changes (Pausas and Keeley 2014; Fernandes and others 2014). Fire–weather relationships in southern Europe have focused on burned area, number of fires and, more rarely, large-fire number or fraction (for example, Urbieta and others 2015). Large fires in the region typically coincide with severe fire weather (San-Miguel-Ayanz and others 2013), with fire size responding to drought level (Loepfe and others 2014). Some studies highlighted climate and ecoregion as drivers of large fires (Vázquez and others 2002; Verdú and others 2012), whereas others addressed the role of fuel connectivity (Lloret and others 2002; Loepfe and others 2010; Curt and others 2013) and fuel-weather synergies (Fernandes and others 2012; Koutsias and others 2012). In Europe, simultaneous consideration of top-down and bottom-up controls to model fire size is restricted to a study in a central Spain mountain range (Viedma and others 2009). In fact, understanding the spatial components of the fire regime as governed by environmental and anthropogenic factors is still elementary for most ecosystems on Earth (Bowman and others 2013), precluding formulation of more effective and sustainable land and fire management policies and strategies.

Southwestern Mediterranean landscapes are prone to high-intensity crown fires (Archibald and others 2013). Portugal accounted, respectively, for 35 and 47% of the number and area burned by large (≥ 100 ha) fires in southwestern Europe in the 1998–2008 period. In this context, our objectives were (i) to identify which factors drive the size of large fires in Portugal and quantify their relative influences, focusing on the top-down/bottom-up dichotomy, and (ii) analyze to what extent the dominant controls change across the observed fire size range. We considered a comprehensive set of potential explanatory variables, covering the effects of top-down (climate–weather) and bottom-up (fuels, topography, human-made features affecting fire suppression) influences. The Portuguese landscape is markedly heterogeneous due to complexity in topography and land-use and land-cover patterns, especially in the north and center of the country where most fire activity takes place (Pôças and others 2011). Bottom-up factors were thus expected to prevail as fire size drivers.

METHODS

Our study area was conterminous Portugal, 89,089 km². We identified and located each large fire (≥ 100 ha, 1998–2008) and determined its start and end dates by crossing fire perimeter records from the national digital fire atlas (Pereira and Santos 2003) with the Portuguese rural fire database, both available at http://www.icnf.pt/portal/florestas/dfci/inc/. A fire perimeter does not always correspond to a single fire, because distinct fires can merge to form one continuous patch. The analysis was restricted to individual fires, thus we identified and discarded burnt patches resulting from multiple fires.

Fire Weather

We used the daily Canadian fire weather index (FWI) system codes (Wotton 2009), calculated from noon weather observations, to describe fire weather conditions (maximum and mean values) for the days during which each fire spread. Data were obtained from the Portuguese Sea and Atmosphere Institute network of 80 weather stations, choosing the nearest station based on the shortest linear distance from the approximate center of the fire. We used the Initial Spread Index (ISI) to account for direct (wind speed) and indirect (dead fine fuel moisture content) atmospheric influences on fire-spread potential; the Buildup Index (BUI) to express available fuel as a function of dryness; and their combination into the fire weather index (FWI) to classify fire danger from potential fireline intensity as in Palheiro and others (2006).

Fire-danger rating stations may not fully reflect the influence of wind on fire-spread rate, because of distance and local factors. Thus, we calculated fire circularity (CIR) as a wind speed surrogate, obtained from principal component analysis of fire perimeter vertices following Barros and others (2012, 2013). CIR is the percentage of variance explained by the first principal component describing fire perimeter vertices, ranging from 50% for a circle to 100% for a straight line.

Antecedent precipitation can affect fine fuel continuity and loading and live fuel moisture content, which are expected to influence fire size. Weather stations data were used to calculate cumulative precipitation for the previous autumn (Rain_Oct–Dec), winter (Rain_Jan–Mar), autumn–winter (Rain_Oct–Mar), winter–spring (Rain_Jan–Jun), and autumn–spring (Rain_Oct–June) periods.

Fuel

Fuel Composition and Connectivity

Forest landscapes in Portugal are essentially composed of pine and eucalypt plantations and

Mediterranean evergreen oak woodland, with shrubland of variable composition prevailing in most mountainous areas. The 1990 land-cover map of Portugal (COS'90, http://62.48.187.114/COS/) on a 1:25,000 scale was the starting point to classify land cover. The legend was initially generalized in 23 classes: evergreen oaks (*Quercus suber* L., *Q. rotundifolia* Lam.), deciduous oaks plus sweet chestnut (*Q. robur* L., *Q. pyrenaica* Willd., *Q. faginea* Lam., *Castanea sativa* Mill.), eucalypt (*Eucalyptus globulus* Labill.), other hardwoods, maritime pine (*Pinus pinaster* Aiton), other conifers (mostly *P. pinea* L.), all possible mixed stands combinations, shrublands–grasslands, arable lands, and permanent crops. For each fire perimeter, we summarized areas (ha and %) within the 23 land-cover classes into 11 vegetation types, respectively, the nine forest types in Table 2, shrubland–grassland, and agriculture.

Within the analyzed fire perimeters, we assumed that major land-cover changes and forest to shrubland transitions were fire-driven (for example, Guiomar and others 2015). To update land-cover data for each fire year, we used bi-temporal maps, by overlaying the 1990 and 2007 land-cover maps (level 2, http://www.igeo.pt/nivel/cos2007n2.zip). The shrubland class was assigned to patches burned in previous years and classified as shrubland in 2007. This reduces the error associated with the effect of past disturbances on land cover and is more sensible than assuming no change or irreversible change in land cover. CORINE Land Cover data were used to assess the general robustness of these assumptions: polygons corresponding to land-cover class changes between 2006 and 2006 were selected and their intersection with the same-period burnt area was extracted. Nationally and in northern and central Portugal (where fire activity is higher), fire, respectively, affected 65.7 and 71.4% of the polygons that had changed, and 92.4 and 99.2% changed from forest to shrubland within burned areas.

Fuel connectivity was described by effective mesh size (Jaeger 2000), which conveys the likelihood that any two locations in the landscape are connected. Effective mesh size can be read as the average size of the area that a randomly located fire will burn in a fuel type without encountering a barrier or other fuel type. We adopted the modification of Moser and others (2007) to eliminate the bias intrinsic to boundaries:

$$\text{eMS}_j = \frac{1}{A_j} \sum_{i=1}^{n} a_{ij} \cdot \text{ac}_{ij} \qquad (1)$$

where eMS_j is the cross boundary effective mesh size of reporting unit j, A_j = area of the reporting unit j, n = number of patches, a_{ij} = size of the patch i within j, ac_{ij} = total area of the complete patch to which patch i belongs, within j. A included the fire area plus a surrounding buffer equal in size (Nunes and others 2005). Calculation of eMS was individualized for the primary land-cover classes, respectively, forest (eMSfor), shrubland–grassland (eMSshrub), and agriculture (eMSagr).

Pyrodiversity

Fire recurrence is an invisible property of the fire mosaic, as it captures the variability in fire frequency, and correlates with the visible fire mosaic, that is, time since fire (Faivre and others 2011). From the digital fire atlas (1975–2008), we determined fire recurrence as the number of times each 25×25 m^2 pixel burnt; cells unburned since 1975 were assigned zero. A country-level fire recurrence map was generated for each year of the study period (1998–2008). We used fire recurrence in lieu of fire frequency or fire return interval because these seldom could be determined for the area of a particular fire, given incomplete overlap with previously (since 1975) recorded fires. Patch metrics (McGarigal and others 2002) were computed for the landscape of each fire to describe pyrodiversity as the spatial structure of fire recurrence, using Patch Analyst and ArcView (Rempel and others 1999). The set of variables comprised mean fire recurrence (MFR) and 12 metrics of density, size, variability, edge, shape, and diversity, listed as Supplementary Online Material (Table S1).

Topography

Several surface texture metrics were computed from the digital elevation model derived from AS-TER (Advanced Spaceborne Thermal Emissions Radiometer), resampled to a 30-m resolution through bilinear interpolation in ArcGIS 10 (ESRI 2011). We calculated slope angle and, within a 5-cell window, the following metrics: vector ruggedness measure (VRM), terrain ruggedness index (TRI), elevation-relief ratio or dissection (DISS), surface relief ratio (SRR), surface area ratio (SAR), and topographic position index (TPI). Three temperature and moisture DEM-derived metrics were also computed: compound topographic index (CTI), heat load index (HLI), and topographic solar-radiation aspect index (TRASP). Surface metrics were obtained through geomorphometry and gradient metrics (Evans 2011), DEM Surface Tools (Jenness

2013), and land facet corridor tools (Jenness and others 2013) toolboxes for ArcGIS 10. Mean surface metrics values were calculated for each fire with the ArcGIS Zonal Statistics tool.

Fire Suppression-Related Metrics

Assessment of structures density and dispersion used high-resolution (20 m) core land-cover data of built-up areas from the GMES fast track service on land monitoring (Sánchez and Kahabka 2008). Each pixel represents the soil sealing percentage, the degree to which soil surface is covered by impervious surfaces such as buildings. Because the various structures are undifferentiated, we separated built-up areas from the remaining elements (mainly roads) to calculate building density (Hdisp). We used the road network from Open-StreetMap project (available at http://download.geofabrik.de/; accessed in August, 2013) to calculate a buffer from the road axis, considering the maximum road width. This buffer was used as a (binary) mask to remove road data from the original raster. Mean values were determined for the area of each fire, as well as the total area (and percentage) of sealed soil. Additionally, to characterize developed areas within burned patches, we computed several shape metrics with the Shape Metrics toolbox (Angel and others 2010) for ArcGIS 10, firstly for the whole area and secondly after urban area extraction. We calculated the differences between the values obtained, and normalized to the 0–1 scale. Girth (dGirth), Depth (dDepth), and Perimeter (dPer) were the shape metrics selected for further analysis, since the remaining metrics were less sensitive to small changes in area after urban extraction. OpenStreetMap roads were also used to calculate within-fire road density (RDens).

Analyses

The median, range, and interquartile range were computed as summary statistics for fire size and its putative drivers (climate–weather, fuel, topography, fire suppression-related metrics). Large-fire area distribution was summarized per land-cover class.

The analysis of fire-size variation excluded burn patches resulting from merged fires; fires for which weather data from a nearby representative location were missing; and fires for which pyrodiversity metrics could not be calculated, that is, those with null overlay with previous fires. We assessed the global relative importance of each explanatory variable to fire size with boosted regression trees (BRT), using the *dismo* package (Hijmans and others 2015) in R 3.2.0 (R Core Team 2015). BRT modeling is a nonparametric machine-learning method that combines the advantages of decision trees and boosting, handling nonlinearity, complex interactions between variables and any data distribution, and resulting in the best possible fit to data (Elith and others 2008). We applied the function *gbm.step* to the entire dataset to find the optimal number of trees with a step approach, that is, increasing the number of trees step-by-step and studying the holdout deviance drop. The relative importance of each variable is returned after a final BRT model is fitted with the optimal number of trees. As input parameters, we used the Gaussian distribution; a tree complexity of 5; a 0.01 learning rate, that is, the weight applied to individual trees; 50 initial trees; 0.5 as bagging fraction; tenfold cross-validation; and a tolerance value of 10^{-7}. As the BRT methodology is not deterministic, some fluctuations are expected in each run of *gbm.step*, thus we performed 100 runs and present the averaged results and standard deviations. Importance values of the variables were expressed as percentages (summing 100%) and their individual effects were assessed with partial dependence functions. BRT model evaluation was based on the deviance explained and Pearson's correlation between fitted and withheld (the bagging fraction) data. We inspected interactions between explanatory variables in one of the runs with the function *gbm.interactions* and identified the most relevant using interaction size.

Prior to the BRT analysis, putative drivers of large-fire size were examined to exclude highly correlated variables (> 0.7, Tabachnick and Fidell 2001) from further analysis. Redundant pyrodiversity metrics and those implicitly scaled with fire extent (Wu 2004) were also dismissed. We restricted forest composition variables to those expected a priori to increase (conifers, eucalypts) or decrease (deciduous) fire size. Table S1 in Supplementary Material Online lists the complete set of weather and climate, fuel composition and connectivity, pyrodiversity, topography, and suppression-related metrics, and identifies the initial candidates for inclusion in the BRT model. Model building was sequential (Elith and others 2008). An initial model was fitted, the least important variable was eliminated, and the process was repeated until the importance value of all retained variables was greater than 0.5%.

A second BRT analysis examined whether the relative importance of each variable changed across

fire size. We used a resampling moving window of 50 fires after ranking all fires by increasing size, similarly to Liu and others (2013) and Fang and others (2015). Function *gbm.fixed* was ran 20 times for each of the resulting 560 sampling intervals, fitting the average number of trees obtained in the whole dataset analysis to the corresponding explanatory variables and maintaining the input parameters. To distinguish the relative importance of each variable type we pooled the results into climate–weather, fuel (composition and connectivity plus pyrodiversity), topography, and fire suppression. We plotted the relative importance of each category vs. the mean fire size of each window and, to better visualize trends across the continuous spatial scale of fire size, fitted smooth curves to the plot with function *loess.smooth* from package *stats*.

RESULTS

Large fires burned 1.402 million ha in Portugal during 1998–2008, totaling 2206 mapped patches. Our sample comprised 27.6% of the number of burnt patches (*n* = 609) and 33.1% of their area (Figure 1). The remaining observations did not meet the criteria for analysis, for example, the four largest patches (43,283–66,071 ha) resulted from merged fires. Inspection of Figure 1 indicates the sample is representative across the country geography. The lower end of the fire size distribution concentrated most of the observations, and whereas fires smaller than 500 ha comprised 65% of the sample, only 10% of the fires grew beyond 1000 ha. Shrubland–grassland typically composed more of the burned area than forest (Table 1). Overall, shrubland–grassland accounted for 55% of the burned area, and cultivated land was a residual component (Table 2). Large fires essentially affected nondeciduous forest types, composed of pines (mostly *Pinus pinaster*), eucalypts (*Eucalyptus globulus*), and evergreen oaks (mainly *Quercus suber*) (Table 2); these three species dominate the Portuguese forest. Very High (25 < FWI < 39) and Extreme (FWI > 38) fire danger days accounted for 86.7% of the fires and 93.6% of the area burned, although variation in fire weather conditions spanned two orders of magnitude (Table 1). Likewise, metrics of land cover and fuel connectivity, pyrodiversity, topography, and fire suppression-related variables were generally highly variable (Table 1). Equivalent statistics for the variables not retained for analysis are presented as Supplementary Online Material.

Drivers of Fire Size

The fire-size BRT models included 12 variables (Figure 2), accounting for effects of climate–weather (CIR, BUI, ISI, Rain_Jan–Jun), fuel composition and connectivity (shrubland–grassland cover, Cov_Shrub–Grass; eMSfor; eMSshr), pyrodiversity (edge density, ED; area-weighted mean patch fractal dimension, AWMPFD), topography (DISS), and fire suppression-related metrics (Hdisp, RDens). Variation in forest type composition did not affect fire size. On average, BRT models explained $69.9 \pm 4.5\%$ of fire-size deviance, with Pearson's correlation of 0.857 ± 0.026. Six of the 12 variables accounted for 90.8% of the explained variability, with the relative importance of fuel (fuel composition and connectivity plus pyrodiversity) and climate–weather variables summing, respectively, 81.8% and 14.5%. Bottom-up drivers absorbed 85.5% of the explained fire-size variability. Nonlinear effects and response thresholds are patent in the partial dependence plots (Figure S1).

ED was the single most important driver of fire size variability ($28.9 \pm 1.0\%$), followed by eMSfor
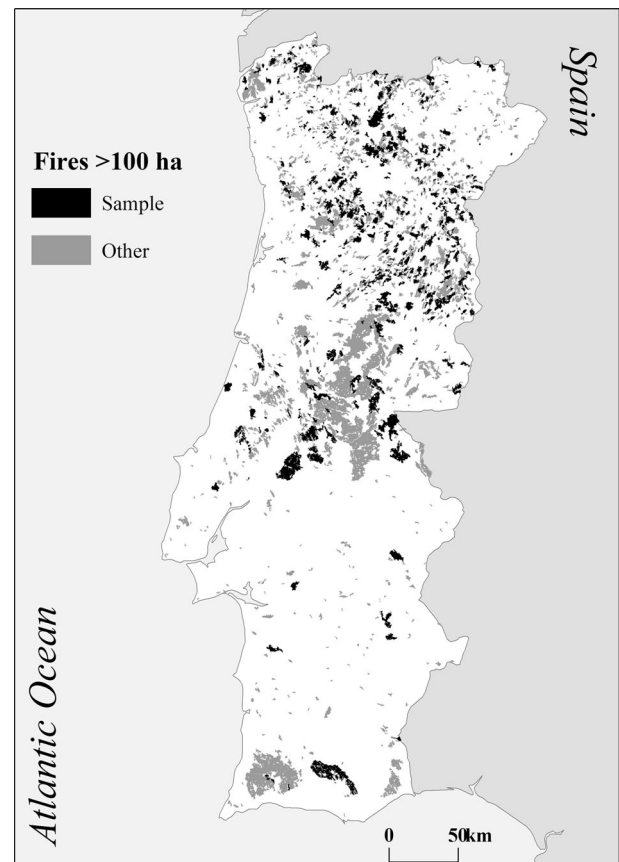

Figure 1. Burned patches larger than 100 ha in Portugal, 1998–2008, with the study sample depicted in *black*.

Table 1. Descriptive Statistics for Fire Size, Fire-Size Drivers in the BRT Models, and Additional Key Variables

Variable	Median	Range	Interquartile range
Fire size (ha)	329.0	100.1–23,219.2	183.7–759.5
Climate and weather			
Fire circularity (CIR)	0.65	0.28–0.90	0.58–0.72
Initial spread index (ISI)	10	2–52	8–14
Buildup index (BUI)	167	40–508	132–221
Fire weather index (FWI)	39	10–109	30–46
Winter–spring rain (Rain_Jan–Jun, mm)	412	39–2283	299–654
Fuel composition and connectivity			
Forest cover (%)	22.5	0–98.8	9.2–45.1
Deciduous forest cover (%)	0.0	0–65.8	0–2.0
Shrubland–grassland cover (Cov_Shrub–Grass, %)	72.1	0.2–100	47.0–85.5
Forest effective mesh size (eMSfor, ha)	2.7	0–6,232	0.4–28.3
Shrubland effective mesh size (eMSshrub, ha)	140.3	0.0–10,905	41.9–304.3
Agriculture effective mesh size (eMSagr, ha)	0.1	0.0–75.8	0.0–0.5
Pyrodiversity			
Edge density (ED, m ha^{-1})	96.1	0.03–326.92	66.85–130.86
Area-weighted mean patch fractal dimension (AWMPFD)	1.32	1.22–1.40	1.30–1.33
Topography			
Elevation (m)	588	38–1455	384–791
Slope (%)	9.3	1.3–27.0	6.5–12.4
Elevation-relief ratio (DISS)	0.52	0.40–0.61	0.50–0.53
Fire suppression-related metrics			
Building density (Hdisp, ha ha^{-1})	0.002	0–0.226	0–0.009
Road density (RDens, km km^{-2})	0.47	0–6.25	0.09–1.65

Table 2. Large Fire Area Distribution by Land-Cover Class

Land-cover class	%
Forest	38.3
Conifers	35.6
Eucalypt	17.3
Conifers–eucalypt	5.7
Conifers–broadleaves	11.0
Eucalypt–broadleaves	1.8
Deciduous oaks	5.9
Evergreen oaks	16.7
Other broadleaves	3.6
Mixed broadleaves	2.4
Shrubland and grassland	54.5
Agriculture	7.2

Forest type percentages refer to total forest cover and sum 100%.

Figure 2. Relative importance proportion of the independent variables for BRT fire-size modeling (mean ± standard deviation of 100 runs), calculated by the contribution to overall deviance reduction. Partial dependence plots showing the effect of each variable are given as Figure S1. *Bar patterns* denote distinct fire-size control categories, from *top* to *bottom*, respectively, climate–weather, fuel composition and connectivity, pyrodiversity, topography, and fire suppression-related variables. Variable abbreviations are explained in Table 1.

(21.1 ± 1.3%), eMSshr % (16.6 ± 0.5%), and AWMPFD (11.9 ± 0.7%). Fire size increased with lower ED and with higher eMSfor, eMSshr, and AWMPFD (Figure S1). Fire–weather codes averaged over the fire duration explained fire-size variation better than their maximums and were included in the mode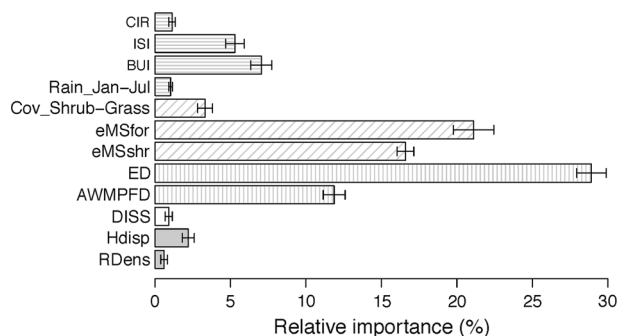l. Larger fires were associated with more extreme fire weather, with a balanced contribution between atmospheric conditions (ISI, 5.3 ± 0.6%) and drought (BUI, 7.0 ± 0.7%). Individual importance of the remaining variables

was 1–3% only, with discernible effects on fire size limited to parts of their observed distributions: higher shrubland–grassland cover slightly decreased fire size; higher CIR and Hdisp exerted increasing effects; and higher Rain_Jan–Jun, DISS, and RDens decreased fire size.

The main modeled interactions were between the six variables more influent in the BRT model (Figure 3), of which the highest was the ED–AWMPFD interaction (Table S2). While fire size was substantially increased by the concurrence of low ED and high AWMPFD, it was constrained
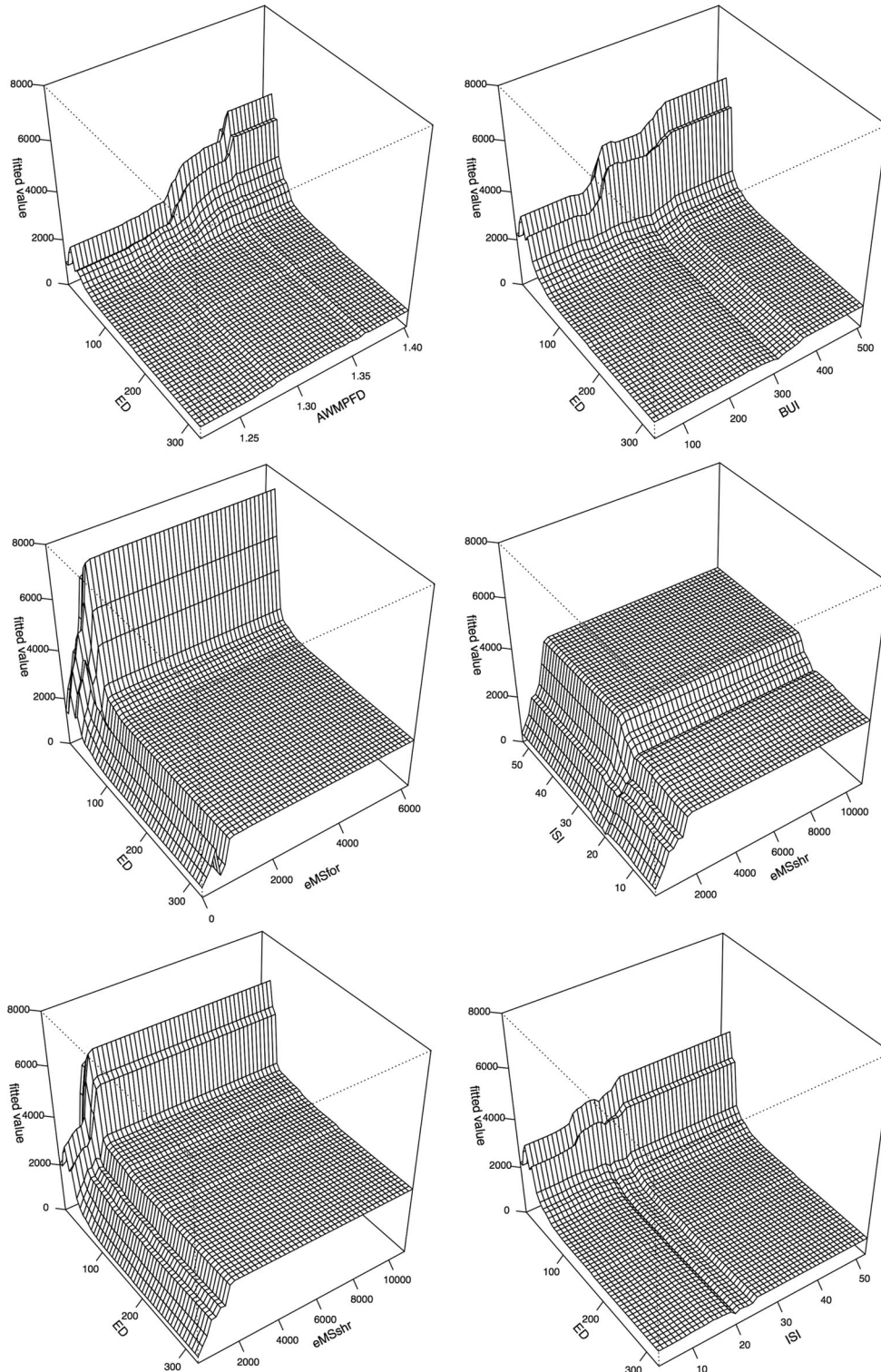

Figure 3. Three-dimensional partial dependence plots for the strongest pairwise interactions in the BRT fire-size model. Table S2 displays the size of interactions.

under the combination of high ED and high AWMPFD. Similarly, high ED constrained fire growth when either BUI or ISI were high. Large increments in fire size were predicted when low ED coincided with high fuel connectivity. Finally, the combination of high eMSshr and high ISI produced slightly larger fires.

Variation in the Influence of Fire-Size Drivers Across the Fire Size Range

Variation in the influences of categories of fire-size controls was modest across the fire size range (Figure 4). Hence, the scale of the fire had a weak effect on the relative contribution of each group of drivers, with one relevant exception. Fuel and climate–weather exerted comparable influences ($\approx 40\%$) up to 500 ha but then diverged progressively in their relative importance. Fuel became increasingly prevalent, culminating at around 60%, whereas climate–weather decreased up to a minimum of $\approx 15\%$. The relative roles of topography and suppression variables were comparably stable, respectively, at ≈ 10 and 10–20%, the latter decreasing marginally with fire size.

DISCUSSION

Variables Influencing Fire Size

Top-Down Influences

Most large fires occurred on very high or extreme fire danger days, when increasingly strong wind and low fuel moisture content combined with high, if not total, fuel consumption. This is consistent with fire weather as the switching factor from small to large fires (San-Miguel-Ayanz and others 2013). Fire size essentially responded to fire weather at ISI above 10 and BUI above 200, consistent with observed fire behavior (Palheiro and others 2006), but plateaued at ISI equal to 25 and BUI equal to 350 presumably due to the scarcity of higher values (Figure S1). Fire-spread rate increases linearly with wind speed and decreases exponentially with fine dead fuel moisture content in a variety of fuel types, for example, shrubland (Anderson and others 2015). As the consumption of Mediterranean fuels is near-total at moderate BUI (Fernandes and Loureiro 2013), the steep fire-size response at BUI above 300 may signal drought-induced break down of topographic and mesic vegetation obstacles to fire spread (Gill and Allan 2008; Slocum and others 2010).

Higher winter–spring rainfall decreased fire size marginally, presumably through longer persistence into summer of high live fuel moisture content (Dennison and others 2008) and moisture holding in favorable topographic positions (Holden and Jolly 2011).

Extremely elongated (noncircular) fires tended to be larger, reflecting stronger winds and also wind–topography interactions, whereby alignment between wind direction and physiography orientation increases fire extent (Barros and others 2012; Mansuy and others 2014). Changes in wind direction affect fire shape, hence limiting the worth of CIR as a proxy for local wind and possibly contributing to the modest role of CIR in the BRT.

Bottom-Up Influences

The dominant vegetation types (shrubland, pine, and sclerophyllous broadleaved forests) in Portugal are prone to fast-spreading, high-intensity fire, potentially more variable within than between forest types (Fernandes 2009). Differences in fire selectivity among flammable vegetation types in Portugal become increasingly negligible when fire weather supports large fire development (Barros and Pereira 2014). This explains why fire size was irresponsive to land-cover composition. Still, fire size decreased marginally when Cov_Shrub–Grass exceeded 70% (Table S1), probably because fire suppression is more challenged in forest owing to distinct fuel profiles (Finney and others 2009).

The decisive contribution of fuel connectivity metrics to fire size is unsurprising, as large fires spreading among multiple vegetation patches should respond to variation in fuel connectivity (Liu and Wimberly 2015). Fire size and burned area increase with higher connectivity of fuel patches in other mediterranean environments (Boer and others 2009; Lloret and others 2002; Loepfe and others 2010). In SE France, distinction in fire size under similar fuel composition stems from differences in fuel connectivity (Curt and others 2013).

The relevance of pyrodiversity in the BRT model through ED and AWMPFD expresses the effect of fire recurrence on fuel structure at patch level and on fuel heterogeneity at landscape level (Collins and others 2009; Parks and others 2015). ED is calculated as the sum of the boundaries of all fire-recurrence patches in relation to the total area of the fire, and its increase implies smaller or more irregularly shaped patches (Hargis and others 1998; Faivre and others 2011). Fire size decreased with higher ED, which was associated with more frequent fire, hence potentially lower fuel load, and with smaller, more complex in shape, and more diverse and even patches (Table 3). Fine-grain fuel
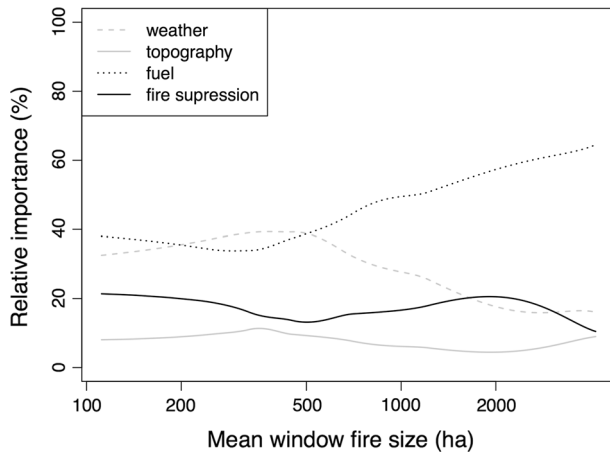
Figure 4. Smoothed variation in the relative importance of grouped fire-size controls along the fire size gradient resulting from the BRT moving window analysis. Weather = CIR + ISI + BUI + R_Jan–Jun;   fuel = Cov_Shrub–Grass + eMSfor + eMSshr + ED + AWMPFD; topography = DISS; fire suppression = RDens + Hdisp.

mosaics have been related with smaller fires or lower burn likelihood, both empirically (Minnich and Chou 1997; Vega-García and Chuvieco 2006) and in simulation experiments (Duncan and Schmalzer 2004; Ryu and others 2007). These patterns reduce fire-spread rates within slower-burning patches but also outside, due to increased chances of heading-fire split and lateral fire movement (Finney 2001). This is also in line with the finding that increasingly large fires in Portugal select increasingly old fuels (Fernandes and others 2012). AWMPFD, in comparison with ED, was less correlated with other metrics of fire-recurrence diversity and heterogeneity (Table 3) and its contribution to larger fires reflects the prevalence of irregularly shaped large patches that enhance fire growth (Ryu and others 2007).

Fire size in this study decreased with more complex and dissected terrain, which modifies wind patterns and restricts wind-driven fire runs (Holden and others 2009), and forms natural breaks associated to physical obstacles or high fuel moisture (Guyette and others 2002; Holden and Jolly 2011). Still, the direct contribution of topography to fire size was very small, which may be an outcome of high fire intensity (Moritz 1997) and drought-related low fuel moisture across the landscape (Bradstock and others 2009). Similarly, variables presumed influent on fire suppression played a limited role on fire size variability. The slight increase in fire extent due to higher Hdisp is a likely consequence of diverting fire-fighting resources to protect people and assets and neglecting perimeter control (Gill and Allan 2008). Conversely, roads allow access and often anchor suppression efforts, hence the fire-size lessening effect of higher RDens.

The BRT model explained 70% of fire-size variability, notwithstanding the absence of independent variables directly related with the processes involved in fire containment. A large fire ceases spreading, either naturally or as a result of suppression efforts, because boundary conditions (weather, fuels, topography) change. Further understanding of fire-size controls can be gained by addressing such changes from the inside to the outside of fire perimeters, as in Viedma and others (2009).

Relative Influence of Weather and Fuel Across the Fire Size Range

Fire-size thresholds corresponding to shifts in dominance from the fuel to the weather categories of fire-size controls were not found in this study, in contrast with previous work in boreal (Liu and others 2013; Fang and others 2015), mediterranean (Moritz 1997), and sub-tropical (Slocum and others 2010) ecosystems. Large fires developing under favorable weather and involving multiple vegetation patches respond to landscape heterogeneity

Table 3. Spearman's Correlation (ρ) of ED and AWMPFD with Other Pyrodiversity Metrics Not Considered for the BRT Analysis

Variable	ED	AWMPFD
Mean fire recurrence (MFR)	0.698	0.088
Patch density (PD)	0.924	0.243
Median patch size (MedPS)	−0.401	−0.095
Largest patch index (LPI)	−0.697	−0.192
Area-weighted mean shape index (AWMSI)	−0.316	0.633
Landscape shape index (LSI)	0.452	0.569
Patch richness density (PRD)	0.727	0.095
Shannon's diversity index (SHDI)	0.744	0.217
Shannon's evenness index (SHEI)	0.628	0.125

and fuel connectivity (McKenzie and others 2011; Parks and others 2012; Liu and Wimberly 2015). Hence, lack of identification of a fire size corresponding to a bottom-up to top-down transition may be inherent to the study context. Fuel fragmentation due to variation in land use and landform may be operating regionally as a top-down control that masks or inhibits the contribution of fire weather to fire spread (Mansuy and others 2014), which would also explain the decreasing influence of fire weather on fires larger than 500 ha. Additionally, the paucity of extremely large fires constrained the identification of a fire–weather threshold, as the largest 50 fires spanned two orders of magnitude.

Bottom-Up versus Top-Down Drivers of Fire Size: Relevance, Interaction Between Variables, and Management Implications

Variation in climate–weather is a relatively minor determinant of fire size in Portugal, as shown by both the overall and the moving windows BRT analyses. Instead, bottom-up variables governed fire size variation, amounting to an influence of 85%. Because most fires coincided with very high or extreme fire danger days, favorable weather conditions are certainly needed for large-fire development, consistent with fire weather as the switching factor from small to large fires in southern Europe (San-Miguel-Ayanz and others 2013; Loepfe and others 2014). As in other threshold-type fire relationships (Schoenberg and others 2003; Slocum and others 2010), our findings indicate that once the required fire weather level is reached its further increase is a poor predictor of fire size. Similarly, Liu and Wimberly (2015) reported that the likelihood of fires at least 405 ha in the western US was weather-driven but bottom-up factors determined fire size.

Interactions among fuel variables and between fuel variables and fire weather resulted in synergies leading to substantial increases in fire size, as in Fernandes and others (2012) and Koutsias and others (Koutsias and others 2012). Unequivocal separation of top-down and bottom-up influences on spatial fire patterns is only partially achievable, due to interplay between variables (Peters and others 2004; Parisien and others 2010, 2011; Parks and others 2012). High pyrodiversity restricted fire growth regardless of weather conditions, but it is inherently difficult to equate fire-recurrence metrics to specific fire-size drivers. Pyrodiversity is a proxy for fuel accumulation patterns but it reflects all the factors directly or indirectly involved in fire-

spread cessation and edge formation, namely topography (Viedma and others 2009; Lee and others 2014) and linear features such as roads and fuel breaks (Price and Bradstock 2010). Fire recurrence also depends on ignition rates and is higher where rangelands are managed by traditional burning (Fernandes and others 2012). Hence, pyrodiversity metrics in the BRT models did integrate bottom-up controls of variable nature.

The general extrapolation of this study's findings to Mediterranean Europe is plausible, particularly where climate is humid to sub-humid, but some deviation in the relative influences of environmental and anthropogenic factors is expectable because of differences in land use, landform, and fire suppression. Current fire management policies in Portugal and in the Mediterranean seek to reduce the socioeconomic and environmental disturbance associated to burned area and especially to large-fire area. Our results support diminishing fuel connectivity as an effective approach to decrease fire growth on the landscape. Fuel isolation through fuel-break networks is the primary fuel management strategy in southern Europe but its return for effort is low (Oliveira and others 2016). Changes in land use that could further fragment forests and shrublands by reversing agricultural abandonment are not foreseen by global change scenarios (Verburg and others 2010). Area-wide fuel reduction thus appears as the preferred option to restrain fire size, namely through prescribed burning complemented by managed unplanned fires (Fernandes and others 2013).

CONCLUSIONS

Favorable weather conditions and dry fuels predispose to large-fire development. However, fires escaping initial control under extreme fire weather do not become inevitably (very) large, as their expansion is contingent on landscape features. In this study, the climate–weather top-down control accounted for just 15% of the explained deviance in fire size, whereas bottom-up variables absorbed the remainder of the explained variability. The moving windows analysis disclosed a more relevant influence of climate–weather but, and despite limitations in the representation of fire weather, our main conclusion holds: bottom-up influences are the major determinants of large-fire size in Portugal and, by inference, in the western Mediterranean Basin.

The overwhelming contribution of landscape-level fuel connectivity and pyrodiversity to fire size

was manifest, with a particularly interesting increase of the influence of fuel on fires exceeding 500 ha. Interaction between explanatory variables indicated that high pyrodiversity constrains fire size under extreme fire weather. Hence, results are supportive of self-regulation of fire spread across the entire fire weather range. Pyrodiversity integrates topographic and anthropogenic effects and as such it does not express a ''pure'' fuel influence. The relevant point, especially in face of climate change, is that how large a fire becomes is mostly a function of bottom-up factors that land-use planning and management can partially address.

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