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Modeling Post-Fire Mortality in Pure and Mixed Forest Stands in Portugal—A Forest Planning-Oriented Model

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Abstract: Assessing impacts of management strategies may allow designing more resistant forests to wildfires. Planning-oriented models to predict the effect of stand structure and forest composition on mortality for supporting fire-smart management decisions, and allowing its inclusion in forest management optimization systems were developed. Post-fire mortality was modeled as a function of measurable forest inventory data and projections over time in 165 pure and 76 mixed forest stands in Portugal, collected by the 5th National Forest Inventory plots (NFI) plus other sample plots from ForFireS project, intercepted within 2006–2008 wildfire perimeters' data. Presence and tree survival were obtained by examining 2450 trees from 16 species one year after the wildfire occurrence. A set of logistic regression models were developed under a three-stage modeling system: firstly multiple fixed-effects at stand-level that comprises a sub-model to predict mortality from wildfire; and another for the proportion of dead trees on stands killed by fire. At tree-level due to the nested structure of the data analyzed (trees within stands), a mixed-effect model was developed to estimate mortality among trees in a fire event. The results imply that the variation of tree mortality decreases when tree diameter at breast height increases. Moreover, the relative mortality increases with stand density, higher altitude and steeper slopes. In the same conditions, conifers are more prone to die than eucalyptus and broadleaves. Pure stands of broadleaves exhibit noticeably higher fire resistance than mixed stands of broadleaves and others species composition.

Keywords: pre and post-fire management decision-making; post-fire mortality; stand structure; forest heterogeneity; fire-adapted silviculture

1. Introduction

Forests cover more than one third of Portugal (3.2 million of hectares), ranking eighth in Europe as highest country with forestlands, where the forest sector represents 3% of gross domestic product (GDP) and 12% of exports, and they are a key element in the Portuguese landscape pattern [1]. Nonetheless, Portugal has the highest incidence of wildfire events in the Mediterranean basin [2].

Fire hazard and spread depend on both the canopy fuels and the understory fuel structure (e.g., [3,4]). In terms of the most affected areas nationwide, statistics (1996–2012) indicate that eucalyptus (*Eucalyptus globulus* Labill) and maritime pine (*Pinus pinaster* Ait) stands are flammable forest cover types that dominate northern and central Portugal, accounting 35.9% and 41.3% of forest burned, respectively. In fact, industrial plantations are highly combustible when compared to evergreen oak woodland called “montados” (i.e., 5.2% cork oak—*Quercus suber* L., and 2.9% holm oak (*Quercus rotundifolia* L.) that predominate in the south-west and southeast of Portugal, respectively) [5]. Pine forest cover results in high fire severity, whereas the mixed forest corresponds to more desirable pre-fire stand conditions [6]. In Portuguese mainland, with the monospecific plantations being problematic in terms of risk of fires and pathogenic problems, the introduction of species diversity may be important for the forest sustainability [7–9]. In enhancing the heterogeneity of forest, burn severity may be substantially reduced [10]. However, mixed forests in Portugal are a small part of the forest area (5.13×10^3 ha, 16% of the total forest area). In fact, limited effort has been devoted to promote mixed-species stands in Portugal as compared with the effort devoted to quantifying productivity on single-species stands [11]. This information could be an important tool for forest managers’ options.

Understanding and predicting forest growth and yield requires information on the drivers of tree mortality. Catastrophic disturbances have been estimated either by using fire behavior simulators (e.g., [12,13]) or by using fire-severity descriptors that are based on measurements of tree tissue damage, which use two main categories of observable indicators to assess tree mortality: crown and bole injury (e.g., [14–16]). However, the above approaches require data (e.g., tree tissue damage, fire intensity or specific meteorological conditions at the time of the fire event) that seldom are available for forest managers beforehand, and thus restrict its applicability for predicting the long-term consequences of forest management alternatives [17,18]. In the other hand, many studies demonstrate that variables “controllable” by the manager (e.g., mean diameter and stand density) are related with fire damage (e.g., [19–21]). Stand structure is related to fire intensity [22], fire severity [23] and with damage/mortality [18,24–26]. Furthermore, stand-level prescriptions provide the biological framework for managing the stands in conditions of lower fire hazard [24,27–29].

Most of the post-fire mortality models developed in Portugal have addressed fire-effects on pure stands of maritime pine (e.g., [30–32]) and cork oak [33]. Information on mortality prediction in uneven-aged stands is comparatively scarce. However, individual tree mortality has been predicted both from fire injury indicators and tree characteristics [34,35]. A set of post-fire mortality models within a forest planning context has been presented by [18,26] in pure eucalyptus and maritime pine stands, respectively, as a function of variables that may be “controlled” by forest managers, and none of these apply to mixed-forests. Nevertheless, the introduction of ecosystems with mixed-species stands might contribute to important goals of sustainable forest management, such as higher biological diversity, more resistance and resilience to disturbances, and restoration of Portuguese forests [7,36]. Promoting mixed forest has also been identified as an adaptation strategy in forest management to cope with climate change [37]. Therefore, understanding the way trees respond to fire is crucial for understanding forest dynamics in Mediterranean ecosystems [38].

In this research, a three-stage modeling technique was used to predict mortality in pure and mixed forest structure in Portugal. The inclusion of these steps will provide adequate predictions to properly examine mortality among plots, quantify and distribute among trees [39]. Specifically, a set of stand and tree models were developed: (1) to predict whether mortality occurs in a specific stand if a wildfire takes place; (2) to quantify the proportion of dead trees in stands where mortality occurs; and (3) to estimate the probability of a tree to die if fire occurs. One hypothesis is that stand mortality is affected by stand structure and stand composition, as well as by site conditions. Considering the tree mortality rate, our hypothesis is that it is affected by the effects of species, individual size and competition factors. For this purpose, the modeling was restricted to include only explanatory variables that are directly available or easily measurable by practical inventories (i.e., representing forest structure and topographic characteristics) and easily projected over the planning horizon. This enables some control

in mortality. Indirect data that may be related to fire behavior (e.g., slope) were also included in the analysis. In addition, we evaluated which stand composition (pure or heterogeneous) has lower mortality, especially when taking into account the risk of wildfires.

These models are planning-oriented by nature as they enable the manager to quantify effects of different management options on the expected wildfire damage. In addition, such models bears relevant management implications with the identification of forest cover types that are more fire damage-prone as they provide a critical insight into wildfire risk assessment, and also may help reverse the current mixed-forest trends in Portugal. Finally, these models are instrumental to address risk and uncertainty in an adaptive framework and may be applied in forest management optimization systems [40,41].

2. Materials and Methods

2.1. Data Collection

2.1.1. Wildfire Perimeters and Inventory Plots Status

Three major forest species cover Portugal forestlands: eucalyptus, cork oak, maritime pine, encompassing 25.8% (8.12×10^3 ha), 23.7% (7.37×10^3 ha) and 23.4% (7.14×10^3 ha), respectively. The remaining area is occupied by holm oak (10.5%), stone pine (*Pinus pinea*, 6%) and other broad-leaved tree species and conifer species (17%) [1]. These forests encompass a wide variety of ecosystems ranging from intensive silviculture plantations for wood production to plantations for coastal dune protection and agroforestry systems.

Portugal is the European country most affected by wildfire with a mean annual fire incidence of 3% of its forest and wildland surface area in the 2000–2011 period, corresponding to an annual average of 1.4×10^5 ha [42]. Therefore, the development of preventive forest management including fire hazard reduction strategies should be of primary importance.

This study used data of 3436 fire events (about 125,000 hectares burned) in several sites that burned in the three fire seasons from 2006 to 2008 in Portugal, comprising “official” Portuguese wildfire polygons larger than 5 ha (Figure 1a), and the available forest inventory stand data. Burned area mapping in this period was obtained by automated classification of medium-resolution remote sensing data (i.e., Landsat Multi-Spectral Scanner (MSS), Landsat Thematic Mapper (TM) and Landsat Enhanced TM+).

First, GIS tools (ArcGIS® 9.3 software, Esri, Redlands, CA, USA) were used to identify the plots from the 5th National Forest Inventory (NFI, carried out in 2005–2006 period) where a wildfire occurred between 2006 and 2008. The wildfire perimeters and the 12,258 plots of the NFI (with 5267 plots of forest stands) were overlaid for that purpose (Figure 1b). In total, 38 NFI plots with 795 trees had been measured prior to wildfire occurrence (pre-fire inventory). In the same period, 203 additional burned plots distributed all over the country from the framework of ForFireS Project [43], and encompassing 1725 trees were further measured (post-fire inventory in 2007 and 2008) (Figure 1d). All these plots were sampled in areas where the fire perimeter was known and trees had not been harvested.

In total 241 plots (165 pure and 76 mixed forest stands) representing 2520 individuals containing tree-level data for 16 species (2 oaks, 8 other broadleaves, 1 eucalyptus, and 5 conifers) from a network of plots distributed across the country with different site conditions and stand characteristics, representing the environmental variation of the forest type, were considered for the study (Figure 2). Both the individual tree evaluation in the plots and mortality due to fire (i.e., classification of whether a tree died or not), was checked only once (roughly 1 year after the wildfire occurrence). Trees were considered dead when no green foliage was present regardless of its location on the tree [43,44]. Status (Survival “S” or dead “D”) was recorded for each tree sampled (Table 1).

The pre-fire inventories encompassed evaluating and collecting all the information available in the corresponding NFI database. The post-fire inventories encompassed the measurement of biometric variables (e.g., tree height (h), m; and diameter at the breast height 1.30 m (dbh), cm) for trees larger

than 7.5 cm (5 cm in the case of eucalyptus trees), along with topographic characteristics of the plot (elevation, aspect, slope). Site slopes ranged from 12 to 32 degrees, and Southwest and Northwest orientations were prevalent in the study plots. Since the objective of the model was to predict post-fire mortality over long horizons within a planning-oriented framework, biometric variables tested for the model were restricted to easily measurable tree (Table 1) and stand characteristics (Table 2, pure stands; and Table 3, mixed stands) without considering cambium injury variables. The former variables allow the forest manager to predict the effect of changes in stand structure and species compositions on the expected mortality.

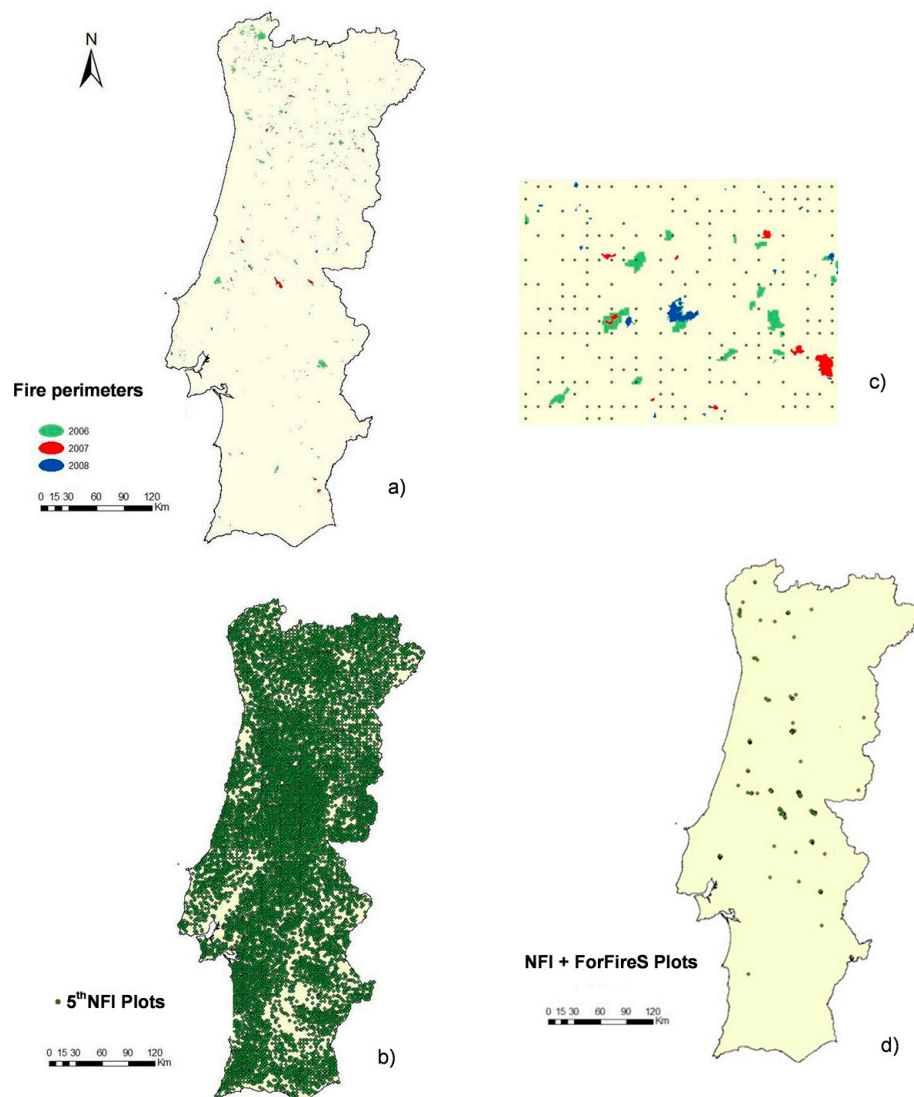


Figure 1. Inventory plots location for data acquisition: (a) the map displays the distribution of fire perimeters occurred in Portugal between 2006–2008 larger than 5 ha; (b) the 5th National Forest Inventory (NFI) plots covering the forest area of Portugal in a systematic 2×2 km grid (12,258 plots); (c) the overlaid from fire perimeters and plots of the 5th NFI; and (d) the sample plot 38 NFI (795 trees) from the post-fire inventory of plots in 2007 and 2008 and additional 203 plots from ForFireS Project (1725 trees).

Table 1. Descriptive statistics for tree level data and individual tree mortality by species (Tree status: D, dead; S, Survival,) tested as model predictors in the range of study ($n = 2520$, 16 species), concerning the period of analyses (2006–2008).

Tree Species	Tree Status	n	dbh (cm)		h (m)		g (m ²)	
			Mean	Range	Mean	Range	Mean	Range
Ec	S	177	15.24	5.20–59.30	15.13	5.40–30.40	0.022	0.002–0.276
	D	762	10.06	5.00–46.30	12.24	1.40–28.20	0.008	0.002–0.168
OB	S	37	10.88	7.00–21.00	6.92	4.90–11.60	0.010	0.004–0.035
	D	43	10.19	7.00–23.00	5.97	3.12–9.90	0.009	0.004–0.042
OC	S	11	25.09	7.00–59.00	15.09	7.98–26.90	0.073	0.004–0.273
	D	5	13.40	9.00–21.00	9.79	8.22–11.44	0.015	0.006–0.035
Pp	S	263	19.17	6.00–51.00	13.89	5.50–28.50	0.035	0.003–0.204
	D	981	14.63	7.00–51.00	11.09	3.80–28.50	0.021	0.004–0.149
Ppi	S	7	31.23	18.00–43.00	17.45	7.35–24.40	0.086	0.025–0.145
	D	4	13.70	8.50–22.60	7.22	3.97–8.90	0.017	0.006–0.040
Qr	S	20	16.82	8.00–39.00	5.09	3.83–7.60	0.028	0.005–0.119
	D	10	19.08	7.00–64.00	4.99	3.40–7.50	0.051	0.004–0.321
Qs	S	58	20.01	4.30–62.00	6.72	2.70–13.90	0.044	0.001–0.302
	D	48	17.53	4.50–59.80	6.34	2.95–10.70	0.042	0.002–0.281
Qsp	S	42	12.21	7.00–24.00	8.61	5.00–13.80	0.013	0.004–0.045
	D	52	10.09	7.00–21.30	7.25	4.20–12.50	0.009	0.004–0.035

where dbh is the tree diameter at breast height (cm); h is the total tree height (m); g is basal area of the tree (m²). Ec: *Eucalyptus globulus*; OB: Others Broadleaves; OC: Others conifers; Pp: *Pinus pinaster*; Ppi: *Pinus pinea*; Qr: *Quercus rotundifolia*; Qs: *Quercus suber*; Qsp: Other oak trees. Range: minimum–maximum.

2.1.2. Reverse Engineering to Rebuild the Tree Characteristics

In the case of the 203 additional plots that had not been measured before wildfire (post-fire inventory), to take advantage of available inventory data, reverse engineering was used to re-build the forest before the fire [44,45]. This was especially needed to estimate tree height before wildfire, as fire often destroys part of the crown thus complicating height measurements. In the case of plots with standing burned trees, pre-fire diameter was assumed to be unaffected by fire. Pre-fire height was estimated using equations developed by Tomé, M. et al. [46] for maritime pine, [47] for eucalyptus, and [46] for the rest of species i.e., cork oak, holm oak and stone pine.

2.2. Post-Fire Model Description

The three-stage modeling system developed in this study comprises three models: the first two at stand level and the remaining one at tree level. For the two former cases, the information required for model development considers one observation per plot, and it is reasonable to assume that they are independent between each other, as the plots are located without following any specific pattern. Under this assumption, the multiple fixed-effects logistic regression seems an adequate fitting procedure. However, the data used for the development of the latter model (at tree level) presents a hierarchical structure, i.e., several trees were measured in each sample plot. This means that a within-plot correlation (between trees of the same plot) in the response variable is expected. Accordingly, we have considered multiple mixed-effects logistic regression to develop this model, as this technique allows the inclusion of random effects in some (or all) parameters to account for the expected correlation between trees of the same plot. Finally, we did not quantify the probability of a stand being impacted by fire (fire occurrence), we only assessed what happens when a stand is impacted by fire (i.e., if mortality would occur, what would be the mortality and which trees would die).

Table 2. Descriptive statistics for variables tested as model predictors at stand level for pure stands.

Variable (Code)	Stands with Dead Trees (<i>n</i> = 96)						Stands without Dead Trees (<i>n</i> = 68)					
	Eucalyptus		Conifers		Other Broadleaves		Eucalyptus		Conifers		Other Broadleaves	
	Range	Mean (S.d.)	Range	Mean (S.d.)	Range	Mean (S.d.)	Range	Mean (S.d.)	Range	Mean (S.d.)	Range	Mean (S.d.)
Avgdbh	2.92–14.50	9.03 (3)	7–26.25	13.75 (5.81)	7.5–38.03	18.85 (9.05)	7–27.45	11.49 (3.63)	13–32.8	20.18 (6.76)	8–73.36	30.11 (17)
Avgh	3.49–15.24	10.18 (3.35)	3.8–19.37	9.78 (4.08)	3.93–9.4	6.45 (1.53)	6.5–21.9	13.84 (3.68)	3.47–19.73	12.01 (4.42)	4.7–18.23	8.12 (4.23)
dg	5.59–26.03	8.98 (4.17)	5.14–45.09	18.64 (11.9)	13.6–45.09	28.77 (10.14)	6.03–45.09	13.54 (8.13)	10.08–45.09	27.16 (15.78)	17.04–45.09	34.14 (9.96)
G	0.31–11.04	4.91 (2.57)	0.077–38.16	7.15 (9.46)	0.08–26.51	3.9 (6.54)	0.08–29.73	7.62 (7.2)	0.27–33.13	8.2 (11.01)	0.1–13.81	4.09 (3.75)
G/dg	0.012–1.80	0.66 (0.42)	0.0017–3.78	0.78 (1.1)	0.002–1.95	0.23 (0.48)	0.002–3.4	0.8 (0.84)	0.006–3.2	0.71 (1.1)	0.002–0.81	0.15 (0.19)
N	60–1299	691.48 (347.55)	20–1539	318.7 (353.86)	20–220	72 (57.09)	20–1811	617.4 (429.62)	20–623	181.62 (213.82)	20–140	46.96 (33.91)
Sd	0.78–5.37	3.28 (1.3)	0–12.41	3.63 (3.13)	0–26.02	7.31 (8.67)	0–7.91	2.88 (1.89)	0–11.72	4.3 (4.27)	0–19.8	4.58 (6.01)
Sh	0.4–6.96	3.43 (1.98)	0–5.46	1.57 (1.38)	0–3.81	0.96 (1.08)	0–5.07	2.2 (1.23)	0–4.09	1.34 (1.46)	0–5.91	0.75 (1.28)
Sd/dg	0.03–0.88	0.45 (0.25)	0–1.34	0.33 (0.35)	0–1.26	0.34 (0.43)	0–1.07	0.27 (0.21)	0–1.13	0.33 (0.37)	0–0.93	0.18 (0.25)
Altitude	0–272	179 (81)	0–893	330.42 (171.77)	76–800	296.55 (152.55)	0–491	192 (150.53)	106–931	441 (331.3)	0–861	313.39 (224.44)
Slope	0–26.6	10.27 (6.2)	0–29	13.3 (7.92)	0–22.8	8.27 (6.53)	0.6–32	13.09 (8.68)	1.8–27	11.48 (6.8)	0–25.2	9.38 (6.27)

Where Altitude is measured in meters (m), Avgdbh, mean tree diameter at breast height of the stand; Avgh, the average tree height; dg, the quadratic mean diameter (cm); G, stand basal area (m²/ha); G/dg, non-linearly a density measure related to the number of trees per hectare, N, tree density number of trees per ha; G, stand basal area (m²/ha); sd, standard deviation of tree diameters; sh, standard deviation of tree heights of the trees in the stand. The predictor Sd/dg expresses the relative variability of tree diameters. The variable is close to “1” in rather uneven stands and approaches “0” in homogeneous stands (0 < Sd/dg < 1); Slope, in degrees (°), Range: minimum–maximum. (S.d.): Standard deviation.

Table 3. Descriptive statistics for variables tested as model predictors at stand level for mixed stands.

Stands with Dead Trees			Stands without Dead Trees	
(n = 56)			(n = 20)	
Variable (Code)	Range	Mean (S.d.)	Range	Mean (S.d.)
Altitude	0–940	337.78 (232.79)	0–919	268.15 (285.51)
Avgdbh	7.64–25.67	15.41 (4.84)	7.99–26.88	14.7 (5.54)
Avgh	3.72–22.7	10.99 (4.19)	4.92–17.06	11.15 (3.48)
dg	5.64–31.88	13.04 (5.31)	10.08–26.03	13.66 (4.93)
G	0.55–30.52	9.29 (7.89)	0.93–33.18	8.81 (8.76)
G/dg	0.02–3.33	0.95 (0.94)	0.051–3.29	0.79 (0.88)
N	40–1279	398.02 (297.73)	60–1769	486.3 (433.8)
PBr	0–0.98	0.27 (0.33)	0–0.82	0.25 (0.29)
PCon	0–0.99	0.56 (0.35)	0–0.95	0.4 (0.29)
PEc	0–0.97	0.16 (0.3)	0–0.95	0.35 (0.41)
Sd	0.7–15.4	6.57 (3.31)	1.42–16.96	6.54 (4.53)
Sh	0.55–6.49	3.13 (1.58)	0.69–6.53	3.37 (1.82)
Sd/dg	0.06–1.54	0.58 (0.37)	0.09–1.02	0.49 (0.3)
Altitude	0–940	337.78 (232.79)	0–919	268.15 (285.51)
Slope	0–32	13.53 (7.77)	0.6–22.6	13.7 (6.06)

PBr is the proportion of other broadleaved trees in the stand (“1” indicating that stand is purely occupied by broadleaves), *PCon* is the proportion of conifers and *PEc* is the proportion of eucalyptus in the stand. For the other parameter definitions, see Table 2. Range: minimum–maximum; (S.d.): Standard deviation.

2.2.1. Statistical Approach

Fixed-Effects Logistic Regression

Although most cumulative distribution functions would work in modeling mortality, the most used is the logistic (e.g., [48,49]) because it is mathematically flexible and has a meaningful

interpretation [50]. The logistic function predicts a probability of an occurrence ranging continuously between 0 and 1. The dependent variable is dichotomous (e.g., death and survival as event/non-event, respectively). A cut-off point may be defined in order to assign “1” to the death event and a “0” to the non-death event [48].

$$Y = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_p x_p)}} \quad (1)$$

where Y is the dependent variable, representing a measure of total contributions of all the independent variables used in the model, x_1 to x_p are independent variables, β_0 is the intercept, and β_1 to β_p are parameters to be estimated or regression coefficients.

The logistic function was used to model stand-level mortality due to wildfires. The *glm* function of the R statistical software [51] that estimates the parameters of the logistic equation through maximum likelihood was used in the first two stages of the proposed approach to develop the post-fire stand mortality models.

Different combinations of biometric variables from groups pertaining to tree size as an indicator of tree vigor (e.g., tree diameter at breast height (*dbh*)), competition expressed by a variety of stand density measures (e.g., basal area (*G*)) and easy-to-calculate competition indices (e.g., basal area of the trees larger than the given tree, *BAL*), and average variables (quadratic mean diameter (*dg*)) were tested to express the mortality rate [48,52,53]. However, indirect measurements that may be related to fire behavior (e.g., slope) were included in the analysis.

Mixed-Effects Logistic Regression

Mixed-effects modeling is based on the fact that some (or all) parameters are formed by a fixed part, common to the whole population, and a random effect, specific for each subject (in this case, each plot). For the special case of logistic regression, the model becomes a generalized linear mixed-effects model with a logit link function. The expression is equivalent to the Equation (1), except that in this case the vector of parameters β (β_0 , and β_1 to β_p) is now expanded with a vector of random effects u : not all the parameters need to include a random effect but at least one of them should include a fixed and a random part to be considered a mixed-effects model. The vector u is assumed to follow a multivariate normal distribution with mean zero and a variance-covariance matrix to be estimated in the fitting procedure, in addition to the fixed-effects parameters and the error variance. The fitting procedure is based on a log-likelihood maximization and was performed with the *glmer* function of the *lme4* package [54] of the R statistical software [51]. Within the mixed-effects modeling context, we have evaluated the predictions made only with fixed-effects parameters, i.e., the mean prediction. Therefore, note that mixed-effects modeling was only considered in the fitting procedure in order to account for the existing hierarchical data structure rather than for estimating random effects whose aim would be the improvement in the model prediction. Due to the nested structure of the data (trees inside plots), parameters associated with plot variables (e.g., slope, *G*, and *N*) are considered only fixed parameters because these variables are already accounting for the variability between plots. However, the parameters associated to tree-level variables (e.g., group of species, *BAL*, *dbh* or *h*) might have a random effect that accounts for the variability between plots.

2.2.2. Stand-Level Modeling

To predict mortality in a stand after a wildfire, a plot-level binary variable indicating whether mortality did occur in the inventoried stands was created. As suggested by [55], this variable takes the value “1” if some mortality occurred within the stand, i.e., at least one tree bigger than a certain *dbh* died (5 cm for eucalyptus or 7.5 cm for the remaining species), and the value “0” if no death occurred in the stand. This modeling approach thus provides information to differentiate the stands where some mortality occurs from the other stands. Thus, the data used to develop this sub-model included all sample plots (e.g., plots with and without occurrence of mortality). A number of stand-level features

defining site conditions, composition and biometric variables as described in Tables 2 and 3 were used for estimating the mortality of wildfire ($PsDead$).

For modeling purposes and because there are tree species that tend to share similar traits, a preliminary analysis was performed to decide how to group the species present in the inventory. The stands were classified according to the proportion ($0 \leq P_{covertype} \leq 1$) of each cover type in the stand, i.e., the proportion of “eucalyptus” in the stand (PEc), proportion of “conifers” (PC) (including *Pinus pinaster*, *Pinus pinea* and short-needled conifers such as *Pinus sylvestris*, *Pseudotsuga menziesii* and other conifers) and the proportion of “other broadleaves” including Mediterranean evergreen broadleaves such as cork and holm trees (PBr). Oak stands (including *Quercus suber* and *Quercus rotundifolia*) and deciduous and evergreen species (including *Acacia* spp., *Alnus glutinosa*, *Betula* spp., *Castanea sativa*, *Fraxinus* spp., *Quercus pyrenaica*, *Quercus robur*) were grouped within the “other broadleaves” cover type. This was done for two main reasons: (i) statistical analysis showed that oak mortality did not differ from broadleaved stands; and (ii) the relatively small number of oak stands (cork and holm) observations detected in the dataset to be included in an “oak” cover type composition. Eucalyptus stands were left out of the “other broadleaves” group because of its specific stand characteristics and the relevance as an economic resource that supports a large and significant pulp and paper industry, one of the key businesses in Portugal (Figure 2).

As a direct follow-up, to quantify post-fire mortality in 153 stands where mortality did occur one plot-level variable was created, such as: proportion of events—the number of trees that died as a consequence of a wildfire within a stand (which is calculated from the number of dead trees and the total number of trees in the plot). The *glm* function of R used this information to apply the logistic regression. Therefore, this sub-model ($PdMort$) described fire damage as the proportion of trees that died in the stand per hectare as a consequence of a wildfire, i.e., number of dead trees divided by total trees in the stand ($trees \cdot ha^{-1}$). In our analysis, the mortality of the Mediterranean evergreen broadleaves (cork and holm) stands did not differ from other broadleaved stands. Thus, as in the previous sub-model $PsDead$, for modeling purposes the stands were classified according to the proportions ($0 \leq P_{covertype} \leq 1$) of three cover types (“eucalyptus”, “conifers” and “other broadleaves”). A number of stand-level variables related to topography (slope, altitude, aspect), biometric variables (e.g., mean tree diameter at breast height of the stand, $Avgdbh$) and structure (e.g., standard deviation of tree heights, sh) were tested.

2.2.3. Tree-Level Modeling

In this third stage, the predicted variable was the probability of tree death in the event of fire. Thus, only trees present in stands where mortality was predicted with the stand-level model $PdMort$ were used to fit the tree mortality model. For modeling purposes, a tree-level binary categorical variable was created. This variable takes the value “1” if the tree dies, and “0” if the tree survives. The model was parameterized for 16 of the most Portuguese common species, using 2520 individual tree record in total inventoried in burned plots, of which 1905 were present in stands where mortality was predicted as a consequence of fire. For modeling purposes, to take advantage of available inventory data of trees per each species and individual tree characteristics, single trees were reclassified in four classes of cover types: i.e., “eucalyptus” ($n_{Ec} = 939$), “other broadleaves” ($n_{Broad} = 174$), “conifers” ($n_{Con} = 1271$) and “oak trees” ($n_{Oak} = 136$). In this model we distinguish the oak trees (cork and holm oak) from the other broadleaves. This was done because previous studies focusing on the factors influencing post-fire tree survival and regeneration capacity showed that fire injury and individual tree characteristics are the main factors [21,56], which depends on fire-resistance or avoidance mechanisms, and in flammability of species [22]. The model $PdTree$ includes dummy variables for the different cover types. In the case the tree is from one of the cover types the value of the dummy variable is “1”. Here a logistic regression mixed-effects model that assigns a probability of mortality to an individual tree given its size (e.g., stand height (h), basal area of the tree (g), and quadratic mean diameter of trees (dg)) (Table 1), species identity (represented by classes of cover types), competitive environment

(distance-independent competition index that incorporates tree size such as BAL , dbh/dg , dbh^2/dg^2 , and ht_i/ht) and physical environment which are biologically related to the mortality process were used (Summary statistics of the data sets used are presented in Tables 1–3). The explanatory variables were selected by testing whether they improved the model.

The data linkages used to develop post-fire stand and tree mortality oriented models as a tool to support fire-smart management of any forest stand structure in Portugal is illustrated in Figure 2.

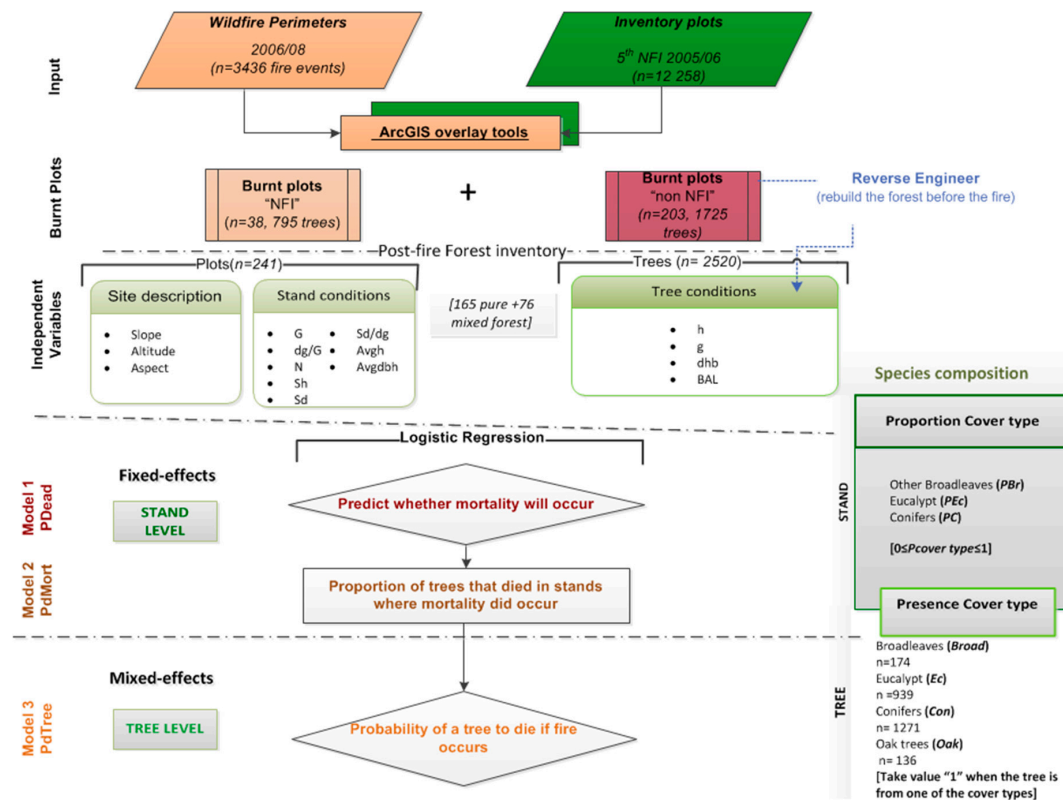


Figure 2. Methodology applied to modeling post-fire for a wide range of stand structure and forest composition in Portugal within a forest planning context. See Tables 2 and 3 for variable descriptions.

2.2.4. Assessment of Model Selection

The final multivariate model was obtained by testing all possible combinations of independent variables using all possible logistic models [57], combined with an understanding of the process of post-fire mortality. It is important to always keep in mind the difference between obtaining a model to fit and having the theoretically correct model [50]. Thus, model building considered the ecological consistency of predictors (i.e., signs of coefficients that are biologically reasonable), the importance of the variable in terms of forest inventory and management, as well as its simplicity and statistical performance. Statistical performance assessment was based on the $p < 0.05$ significance level, as judged by the z value statistic, the Akaike Information Criterion (AIC) parameter improvement, the Receiver Operating Curve (ROC) and the index of concordance and correct classification rate (CCR) [48]. The presence of collinearity was assessed by adding new variables in the model and observing the effect to the slope coefficients and estimated standard errors [50].

The ROC curve plots the probability of detecting true signal (sensitivity) and false signal (specificity) over all possible threshold values for the cut-off points. To evaluate the discriminatory ability of a cut-off point, it is common to summarize the information of the ROC curve into a single global value or index (e.g., area under the ROC curve). Models with a ROC value equal to 0.7, 0.8 and

0.9 provide acceptable, excellent and outstanding discrimination, respectively, between “mortality” and “survival” [50]. The concordance analysis procedure was further used to help interpret results [50,58].

An intuitively appealing way to summarize the results of a fitted logistic regression model is the use of a classification table. In this study, a fixed cut-off (c) or threshold between “0” and “1” was specified. If the estimated survival probability was less than c , the outcome value was “dead” otherwise it was “survival”. Three different approaches using the selected mortality equation ($PsDead$) were compared to define the cut-off point: (1) the value that maximizes the CCR (e.g., [59]); (2) the value where the sensitivity curve and the specificity curve cross [50]; and (3) the average observed percentage of event occurrence in the original data [48]. In order to assess the performance of each method and select the best cut-off point value, tables with the correct classification error rates (CCR) were constructed.

Due to the limited amount of mortality data (number of plots), no specific dataset was set aside for model fitting and validation purposes. The emphasis of this research was in obtaining the best possible parameter estimates. The authors are aware of the advantages and disadvantages of splitting the data set for model validation purposes (well discussed for instance in [60]). Thus, evaluation of the fixed-effects logistic models was based on the development of ROC curves and of classification tables of correct/incorrect responses for prediction of survival/dead trees for the fitting dataset.

Regarding the mixed-effects logistic model different variables to explain probability of post-fire tree mortality have been considered, and for the best set of variables different combinations of parameters tested to be expanded with random effects. The best mixed-effects model was selected on the basis of the Akaike’s information criterion (AIC).

3. Results

3.1. General Response Patterns

The average proportion of dead trees in stands where mortality occurred as a consequence of wildfires was 75.60% (i.e., 1905 dead trees out of 2520) (Table 1). The data collected regarding the number of survival trees are in line with the percentage of forest area burned per species between 2000 and 2011 [5] (i.e., 29% *Pinus pinaster*, 43% *Eucalyptus*, 8% *Quercus suber*, 2% *Quercus rotundifolia*—Table 1). Species showed very different baseline mortality rates (Table 1), and as a consequence plot-level mortality is highly sensitive to species composition. Only 22.10% of the pine trees survived fire while 45% of the broadleaved trees and 57% of the oak trees (cork and holm oak) were alive (Table 1). The dataset showed that mortality had occurred in 63.48% of burned stands (153 out of 241 stands), and a preliminary data analysis revealed that tree density and age structure diversity were higher in stands where mortality did occur (Table 2—pure stands, and Table 3—mixed stands). All trees died in 74 plots (Table 4). The data used for model development included sample plots where the proportions of dead trees were relatively large.

Table 4. Proportion of dead trees over number of sample plots.

Proportion of Dead Trees (%)	0	1–20	21–40	41–60	61–80	81–99	100
No. of plots	88	19	16	18	11	15	74

3.2. Stand-Level Mortality

3.2.1. Predicting Whether Stand Level Mortality Will Occur

The first logistic model $PsDead$ predicts the probability of stand-level mortality (Table 5), discriminating the stands where all trees survive from the stands where at least one tree dies included as predictive variables the G , G/dg , Sd/dg related with stand structure, where G is the stand basal area (m^2/ha), and dg is the quadratic mean diameter of trees (cm). The predictor G/dg is a density

measure non-linearly related to the number of trees per hectare. Sd is the standard deviation of trees' diameters at breast height (cm). The predictor Sd/dg expresses the relative variability of tree diameters. The variable is close to "1" in rather uneven stands and approaches "0" in homogeneous stands ($0 < Sd/dg < 1$). PBr is the proportion of other broadleaved trees in the stand ($0 \leq P_{covertime} \leq 1$) where "0" indicates no presence and "1" indicates the stand is purely occupied by broadleaves; PEc is the proportion of pine trees in the stand. The sum of PC , PEc and PBr gives "1". The variable PC is the specie composition omitted for inclusion in the model.

Table 5. Estimated parameters, standard errors (SE), z values statistics and p-values for the model $PsDead$ predicting whether mortality will occur in a stand.

Effect	Variables	Estimate	SE	Z Value	p-Value
β_0	Intercept	1.3816	0.3380	4.0876	<0.0001
β_1	PEc	−2.1698	0.4192	−5.1757	<0.0001
β_2	PBr	−1.0619	0.4438	−2.3929	0.0167
β_3	G	−0.5553	0.1264	−4.3934	<0.0001
β_4	G/dg	4.3280	1.1765	3.6790	0.0002
β_5	Sd/dg	3.2549	0.8187	3.9760	<0.0001

The model indicates that higher variability in tree diameter (Sd/dg) and high stand density (G/dg) increase the likelihood of tree death in the stand (Table 5). On the contrary, in stands with the same density but higher basal area (i.e., higher tree diameters) the probability of mortality to occur is lower. The probability of death to occur is smaller in eucalyptus even-aged stands and higher in conifer stands when compared to the broadleaves (Figure 3). The values were calculated according to the model $PsDead$ for a stand with $7.55 \text{ m}^2/\text{ha}$ of Basal area (G) and 1.22 of stand density (G/dg). The model was successful in predicting whether mortality occurred after wildfire in 82% of the stands (i.e., percentage of concordant pairs). The area under the ROC curve (0.821) indicated excellent discrimination [50].

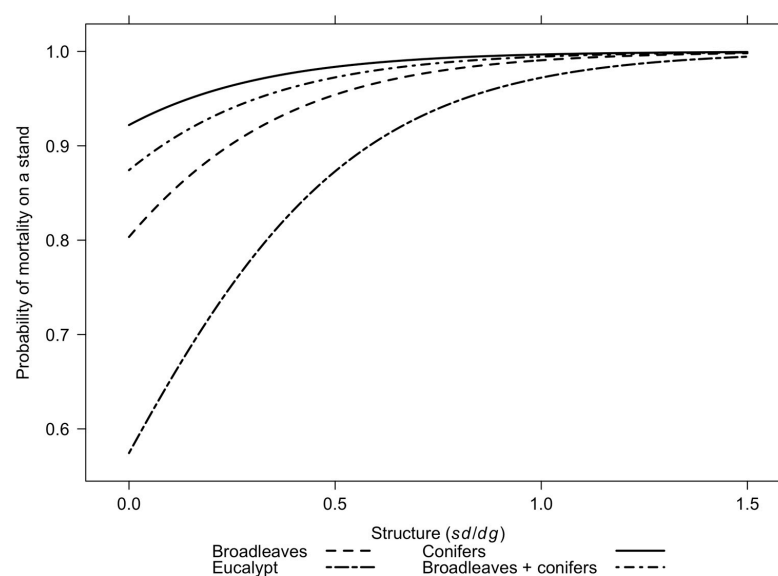


Figure 3. Effect of the relative variability of tree diameters (predictor Sd/dg) on the probability of mortality on a stand considering pure stands of eucalyptus ($PEc = 1$, $PBr = 0$), conifers ($PEc = 0$, $PBr = 0$), other broadleaves ($PBr = 1$, $PEc = 0$) and mixed stands of other broadleaves and Conifers ($PBr = 0.5 + PEc = 0$). The values were calculated according model $PsDead$ for a stand with $7.55 \text{ m}^2/\text{ha}$ Basal area (G) and 1.22 stand density (G/dg).

3.2.2. Estimating Stand-Level Post-Fire Mortality

The stand-level model *PdMort* quantifies the degree of post-fire mortality (proportion of dead trees) in stands where mortality did occur (Table 6). It is affected by stand biometric variables measured in the field (*Avgdbh* is the mean tree diameter at breast height of the stand, cm) as well as by topography (Slope—measured in degrees, and altitude—measured in meters) with high accuracy as predictors. *PEc* and *PBr* are the proportion of eucalyptus and other broadleaved trees in the stand, respectively. Again, the *PC* variable is the type of specie composition omitted for inclusion in the model.

Table 6. Estimated parameters, standard errors (SE), z values statistics and p-values statistics and p-values for the model *PdMort* predicting degree of mortality caused by a wildfire.

Effect	Variables	Estimate	SE	Z Value	p-Value
β_0	Intercept	0.3573	0.0392	9.118	<0.0001
β_1	<i>PEc</i>	−0.1364	0.0258	−5.293	<0.0001
β_2	<i>PBr</i>	−1.3878	0.0361	−38.495	<0.0001
β_3	Slope	0.0525	0.0013	39.118	<0.0001
β_4	Altitude	0.0017	0.0001	28.711	<0.0001
β_5	<i>Avgdbh</i>	−0.0393	0.0018	−20.832	<0.0001

The percentage of mortality in a stand due to fire decreases as tree size increases. Steeper slopes and higher altitude contribute to increase mortality. Stands with more broadleaves, followed by eucalyptus stands, suffer less mortality than stands with higher proportion of conifers (Table 6, Figure 4). For example, mixed stands with a mean diameter at breast height of the stand (*Avgdbh*) of 30 cm present higher mortality (i.e., higher proportion of dead trees) than pure stands of broadleaves. On the other hand, stands dominated by eucalyptus and conifers have a higher proportion of dead trees (Figure 4a). The composition of other broadleaves and eucalyptus are the most resistant group of mixed forest (Figure 4b). Conifer stands with higher presence of other broadleaves and/or eucalyptus suffer less damage than pure pine stands.

The model shows a concordance of 67.8% and the area under the ROC curve is 0.69. No collinearity among variables included in the model was observed.

3.3. Estimating Post-Fire Tree Mortality

Two biologically realistic models were built to predict the probability of tree mortality in Portuguese forests. The final mixed-effect model fitted *PdTree1* includes three parameters: group of cover type, a variable of density (stand basal area (*G*)) and a measurement of tree dimension and productivity (diameter at breast height (*dbh*)) and random effects both in the Intercept and the parameter associated with *dbh* (Table 7). *PdTree1* accounts for the specific behavior of only three species groups in respect to fire, where “Con”, “Ec” and “Broad” are dummy variables indicating whether the tree is a conifer, a eucalypt or other broadleaves—in this case including the oak trees (e.g., if the tree is *Q. suber*, Broad equals “1” and “0” otherwise);

PdTree2 (Supplementary Table S1) is the only fitted model where a distance-independent competitive effect is included through the predictor *dbh/dg*.

The model *PdTree1* indicates that trees in stands with higher *G* are less prone to die if a wildfire occurs, and trees with high *dbh* have also lower mortality probability, i.e., the mortality decreased as *G* and the corresponding *dbh* increased (Table 7). The highest coefficient corresponds to conifers, followed by eucalyptus and other broadleaves. This is the order for the less resistant (conifer) to the most resistant (Figure 5, Table 7).

The *PdTree1* model had the highest fitting capacity (i.e., model efficiency with higher value of concordance—0.76) and performed significantly better than *PdTree2*, according to both the Akaike’s information criterion (AIC, 1353.3), with an area under the ROC curve (0.733) which indicated acceptable discrimination [50].

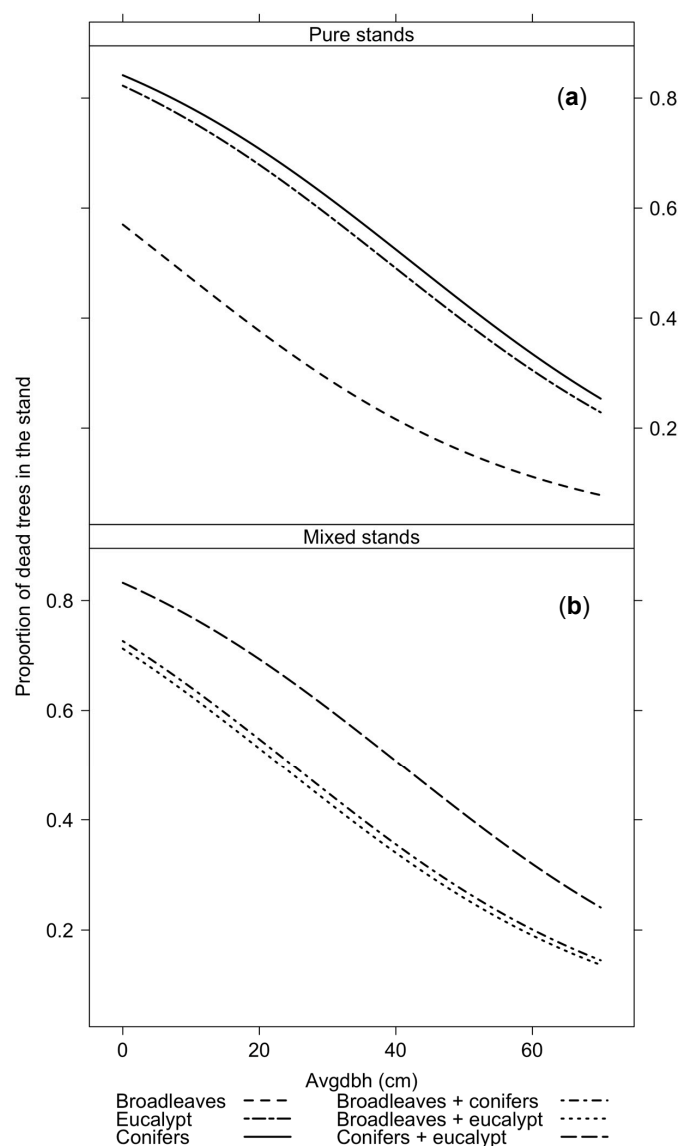


Figure 4. Effect of stand average diameter at breast height (Avgdbh in cm) on the proportion of dead trees in the stand for different cover types considering: (a) pure stands of Eucalyptus ($PEc = 1$, $PBr = 0$), conifers ($PEc = 0$, $PBr = 0$) and other broadleaves ($PBr = 1$, $PEc = 0$); and (b) mixed stands of other Broadleaves and Conifers ($PBr = 0.5 + PEc = 0$), other broadleaves and Eucalyptus ($PBr = 0.5 + PEc = 0.5$), and Conifers and Eucalyptus ($PEc = 0.5 + PBr = 0$). The values were calculated according to model *PdMort* for a stand located at 300 m above sea level with a slope of 15° .

Table 7. Estimates of mixed-effects parameter, random effects variances (σ_i^2) and covariances ($\sigma_{i,j}$) for the model *PdTree 1* predicting the probability of an individual tree die due a forest fire ($n = 2520$).

Effect	Variables	Estimate	SE	Z Value	p Value
β_0	Intercept	4.493	0.9044	4.968	<0.0001
β_1	<i>Ec</i>	2.296	0.6599	3.480	<0.0001
β_2	<i>Con</i>	3.143	0.4721	6.657	<0.0001
β_3	<i>G</i>	−0.1778	0.04572	−3.890	<0.0001
β_4	<i>dbh</i>	−0.1299	0.04559	−2.849	0.00438
$\sigma_{\beta_0}^2$	-	12.54	-	-	-
$\sigma_{\beta_4}^2$	-	0.06780	-	-	-
$\sigma_{\beta_0, \beta_4}$	-	−0.3681	-	-	-

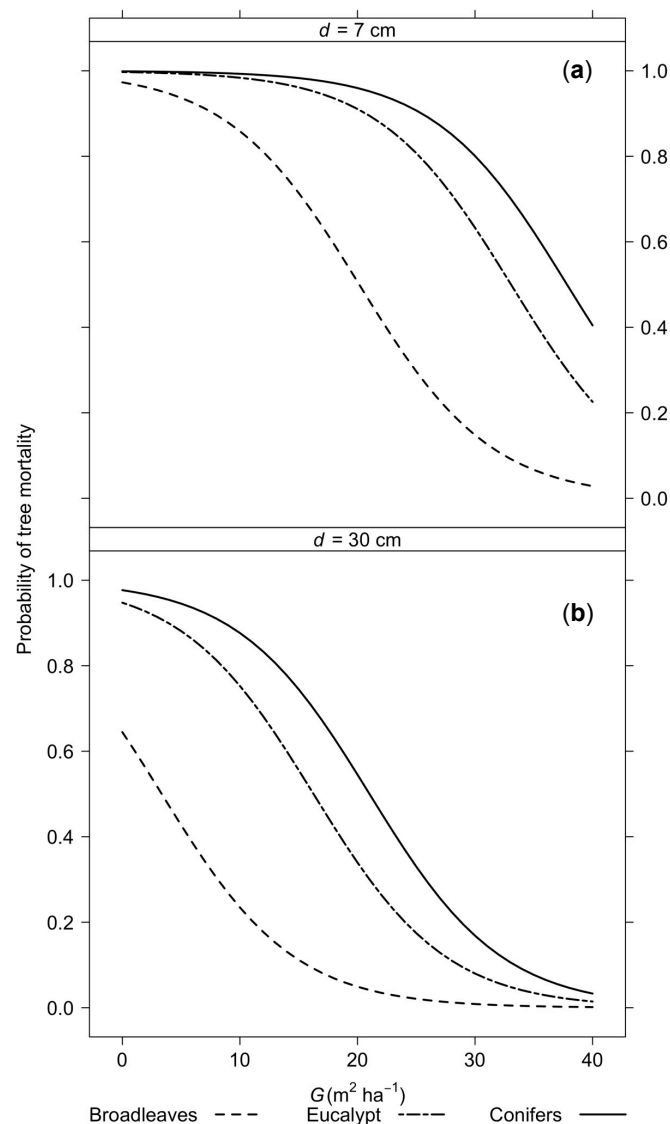


Figure 5. Effect of basal area (G , m^2/ha) and two extreme values of dbh : (a) 7 cm; and (b) 30 cm on the probability of each tree species mortality. The values were calculated according to *PdTree1* for a stand with a slope of 15° .

3.4. Cut-Off Point Value Selection

The most appropriate cut-off points were calculated for the model *PsDead* predicting whether mortality will occur in a stand (Table S2). If the value that maximizes the correct classification rate (CCR = 76.8%) was used as criteria to choose the cut-off point, its value would be 0.47. According to this value, mortality would occur in 73% of the plots while mortality did actually occur only in 63.48%.

Around 22.6% of the predictions were false positives (i.e., stands that did not have any dead trees but were classified as if mortality had occurred) and 25% were false negatives (i.e., stands that had dead trees but were classified as if mortality had not occurred). Having in mind that a compromise has to be found between classification of dead trees and good prediction of mortality and survival rates, a cut-off point value of 0.47 is recommended as we get a better match between the stands where mortality is predicted and the stands where mortality indeed did occur.

The tree-level mortality model (*PdTree*) are used after knowing the number of dead trees in the stand (*PdMort*), thus no cutting-value is needed to check which trees die. In this case, probably given the trees with higher mortality values are selected until reaching the number of trees predicted to die.

4. Discussion

The results suggest that the set of models are logical, and may provide reasonable estimates of post-fire mortality over long-term planning horizons. The logistic modeling approach used in this study has been used earlier for predicting tree-mortality as a consequence of regular mortality (mortality due to competition between trees) and irregular mortality, i.e., mortality due to wind damage [61,62], prescribed fire [63,64] and wildfire [17,18,21,64,65]. In addition, the modeling approach using different steps has been used to model natural tree mortality [55,66,67]. Here we use the Portuguese Forest Inventory and Project ForFireS dataset to parameterize, for a total of 16 common Portuguese tree species, a logistic regression model that assigns post-fire mortality.

The advantage of the three-stage modeling technique used compared to other approaches is the possibility of detecting stands where no mortality occurs. Otherwise, traditional models always generate some mortality for all plots [55].

Post-fire mortality has been studied using a variety of direct and indirect methods (e.g., [12,68]). In the literature we can find two main types of models, the ones based on variables reflecting fire injury indicators and those based on biometric information. Here, while the proposed approach employs some concepts that featured in earlier work (e.g., [17,18]) on the whole, the selected post-fire mortality models tend to differ significantly from other well-known classic approaches for fire-induced mortality (e.g., [34,35,69]). However, the use of the latter methods in long-term forest management planning is constrained by the difficulty to predict accurately the fire injury/severity variables they use (e.g., crown-kill, bole-kill or fire intensity are information rarely available to forest beforehand).

In fire-prone ecosystems, active fuel management may be used to preserve forest stands from fire damage [17,23,27]. Indeed, damage and survival depended on tree and stand characteristics that may be changed through forest management enabling some control on fire mortality. This is the first attempt to develop post-fire mortality models for any stand structure and species composition in Portugal as a function of explanatory variables that are directly available or measurable/predicted by practical inventories and easily projected over the planning horizon. The role fire meteorology was not included in the model mainly because the weather before and/or during a specific fire event is very difficult to generate reliable meteorological data over long periods to be used in a long-term forest management planning context (e.g., 60 years planning horizons). Nevertheless, indirect variables that may be related to fire behavior such as the slope and the vertical structure of the stands were included in the modeling analysis.

As stressed above, the set of three models does not use fire-related variables, but information on species composition and forest structure. In this sense, the models provide: (i) a quantitative framework to address long-term planning periods; (ii) insight into different behavior or post-fire mortality between pure and mixed stands, helping to understand the performance of any forest structure; and (iii) information for making pre-fire management decisions over a wide range of tree sizes and species and in a variety of stand conditions in Portugal, which has been lacking in previous discussions.

4.1. Forest Composition, Heterogeneity and Structure

The models show that forest cover composition has an impact on the proportion of dead trees after a wildfire. The post-fire mortality models developed indicate that the conifers are the most prone to suffer mortality after wildfire, whereas the broadleaves are more resistant to fire (Figure 5). This confirms the generally low fire susceptibility observed in most broadleaved trees compared with other forest types, probably explained by differences in fuel load composition, moisture content, flammability, and broadleaves resprouting ability (e.g., [3,34,35,70,71]). Previous studies argued that the conifers have higher flammability because their contents in resins and oils [32,70]. Other authors attribute the difference between broadleaves and conifers to the fact that the forest management regimens applied to both of the forest tree types is different, being broadleaves more resistant to the fire occurrence (e.g., [36]). For instance, in Portugal, eucalyptus and maritime pine stands are usually

industrial plantations with high stand densities, and highly prone to fire [22,72]. In fact, commercial eucalypt plantations are very flammable due to the nature and accumulation of their litter and bark fuels with high levels of biomass, and thus prone to intense wildfires [20]. In the case of mixed eucalyptus and pine stands, fire hazard may be even higher, when compared with pure stands of eucalyptus or pines [72]. On the other hand, many of the oak stands (i.e., *Q. Suber* and *Q. rotundifolia*) are classified as “montado”, which is an agroforestry management regime, with low tree stocking, which reduces considerably the fire occurrence and propagation [4] (proportion of dead trees, Table 7). One explanation may be the high resprouting capability of some Mediterranean *Quercus* species such as *Q. rotundifolia*, *Q. suber* and *Q. coccifera* [73,74], which can lead to *Quercus* dominated forest in places with high fire recurrence. Thus, understanding the relationships between composition of the forest cover and burn severity is important for developing management guidelines leading to fire-resilient forests.

Forest heterogeneity (mixed stands) was shown to be associated with low proportion of dead trees in the stand (Figure 4). This is in accordance with results from [10] who explored the relationship between forest heterogeneity and burn severity at the stand-level concluding that pure conifer stands present more severe fires than mixed stands. Thus, forest managers may consider enhancing the heterogeneity of forests when implementing fuel treatment schemes giving more importance to mixed stands. In fact, higher mortality is expected in coniferous stands rather than in broadleaved species, because most species from the former group are not able to resprout when the entire canopy is burned [34].

In general, biometric variables that impacted post-fire mortality included tree diameter (*dbh* of the tree, average *dbh* of the stand and variability of tree diameters *Sd/dg*), and indicators of density such as basal area (*G*) and competition index (*dbh/dg*). The coefficients of biometric variables regarding stand structure are in concordance with findings from international studies (e.g., [17,75]) and studies focused on Portuguese conditions [18,26,34]. The stand-level model indicates that even-aged stands with higher tree diameters have lower probabilities of mortality after a fire than irregular stands with smaller-sized trees (model *PsDead*). These small and dominated trees will be more exposed to a given intensity fire than larger trees, especially for low to moderate severity fires [21].

Further, eucalyptus stands with a reduced variability of tree diameters (*Sd/dg*) results in lower probability of mortality than conifers stands (Figure 2). Mortality in stands with higher densities is expected to be higher (*PdMort*). These results agree with findings of [22,76] who stated that the level of injury and mortality for a given species is a combined outcome of fire behavior, tree size and stand structure. Extensive model testing led to the rejection of other biometric variables as predictors of stand-level damage after a wildfire.

Regarding the individual tree mortality *PdTree* the coefficients of biometric variables also confirmed the findings of previous studies. For tree-level mortality prediction of forest species in Portugal, best-fitting model *PdTree1* indicates that stand basal area (*G*) and *dbh* traits affected the mortality rate (basal area (*G*) was negatively related with tree mortality). This is in concordance with other studies [17,18,20,33]. In addition, size (*dbh*) has a greatest effect on mortality rate at the level of the individual tree, with larger trees size exhibiting mortality rates much lower than smaller trees, consistent with a decrease in mortality reported by several studies [18,26,71]. These two variables are related, so for a fixed value of basal area (*G*) if the stand density increases, it means that average tree diameters are smaller. This means that fire would more likely be more intense and more trees are likely to die. Indeed, fire intensity varies and this could result in different probability curves depending on species and intensity [70].

The results suggest that both slope and stand location (i.e., altitude) also impact mortality. In the stand-level model (*PdMort*), steeper slopes increase the probability of death to occur in a stand and also the expected damage (Figure 3). This is in concordance with other studies developed in Portugal [2,5,20]. This effect may be explained as slope increases fire spread rate and consequently increases fire intensity [77]. Additionally, altitude has a significant impact on fire behavior possibly

due difference in fuel moisture present in a given stand, and weather conditions, in particular, with temperature and precipitation and the compounding effects of fuels [78]. In our case, altitude correlates positively with the degree of mortality in burned areas. Thus, forest managers may want to consider avoiding severe topographic conditions (e.g., steeper slopes when planning new plantations), in order to increase resilience to fire and management of wildfire damage.

Validation of the models was done through studies of the performance of the functions. No specific validation datasets were set-aside and later used for that purpose. Two main reasons justify this decision. Firstly, the relatively small number of observations in the stand dataset used. Secondly, we were more interested in obtaining the best possible parameter estimates. There are advantages and disadvantages of splitting the dataset for model validation purposes as discussed by [60]. However, they concluded that cross validation by data splitting and double cross validation may provide little, if any, additional information in the process of evaluating regression models.

4.2. Pre and Post-Fire Smart Management: Applicability

This research estimated a set of three models to predict mortality that present a real step forward for managing mixed stands under fire risk conditions, and identifying management options that reduce the expected losses due to fire. This may be critical to design prescriptions that may reduce ecological and economic wildfire damage through adequate planning, as a management objective in numerical planning calculations or easy integration of post-fire mortality in forest simulators and optimization systems, particularly in ecosystems where wildfires are a recurrent disturbance. It is useful to interpret the current study in the broader context of fuel management, whereas stand management strategies are widely accepted as effective means to establish less flammable and more resilient forests and landscapes in recently burned area.

In the framework of forest management planning, the stand-level models *PsDead* and *PdMort* are useful for planning when the growth and yield model used does not provide the dimensions of each of the trees. First, model *PsDead* may be used to predict whether mortality may occur in a stand after a wildfire (i.e., there is at least one dead tree in the stand). If the stand presents mortality, model *PdMort* gives the proportion of dead trees in the stand (i.e., the total number of trees that will die is provided). For this reason no threshold value is needed to convert the estimated probability into a dichotomous variable (e.g., death or survival). Because *PdMort* cannot be used for a specific tree, the model *PdTree* to predict the probability of a tree to die should be applied. Thus, the selected model at tree-level *PdTree* may be used to predict the probability of mortality of each tree in the stand and to build a list of all trees in the stand ordered according to this probability (which means that the trees should simply be sorted from higher to smaller mortality probability, trees with higher probability are ranked first in the list). The management planning model may then select the trees that will be assumed to die for planning purposes by going down the list and stopping when the number of trees that are estimated to die by model *PdMort* is reached.

Another way to use these set of models in forest management scheduling and scenarios analyses is in the framework of a full risk profile, especially when first generate fire occurrence with an earlier model for pure and mixed forest stands [44,79,80], after which the degree of damage can be predicted with the second model *PdMort*. Thus, the quality of the models is dependent on the quality of the equations used for that purpose. In a management planning context, the *PdTree* post-fire mortality model is very important when the growth and yield simulation uses an individual tree model (which means that every tree may have different characteristics).

5. Conclusions

This research encompassed the development of post-fire stand and tree mortality management-oriented models for improved pure and mixed forest planning in Portugal. Given the general uncertainty related to large-scale forestry scenario analyses, and the uncertainty related to mortality as a phenomenon, the selected mortality models were considered to have an appropriate

level of reliability. Indeed, the set of models perform similarly to other planning-oriented models developed for pure stands in Portugal. The predicted proportion of dead trees in pure maritime pine stands using the stand-level mortality model *PdMort* presents a very similar response pattern than the model developed by Garcia-Gonzalo et al. [18]. If model *PdMort* is used for pure eucalyptus stands, it also gives similar results as the model developed by Marques et al. [26].

The advantage of the current post-fire models system is that they are suitable over a wide range of tree sizes and species (i.e., forest with mixed and pure species composition) and in a variety of stand conditions (i.e., even-aged and uneven-aged forests) in Portugal. Considering all the species in the same model and recognizing the important differences among forest cover types is instrumental to incorporate fire-smart management considerations into forest planning. In addition, these models can easily be implemented in decision support systems that may allow the manager to minimize the expected losses due to wildfires when developing management plans either at stand-level [17,28,29,40,81,82] or at landscape-level [27,83]. Moreover, they help to reduce the uncertainty by predicting the outcomes of different management alternatives [84]. Thus, this set of models confirmed the potential of the proposed approach, and can be valuable to integrate effectively long-term fire-effects into any forest management planning. Future research efforts on this topic would benefit from the existence of information from permanent plots, measured over time, and where detailed data on the understory (evolution of fuel load) and overstory composition and structure are collected.

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