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Assessing the Risk of Losing Forest Ecosystem Services Due to Wildfires

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Abstract

Disturbances such as wildfires are an integral part of forest ecosystems, but climate change is increasing their extent, frequency, intensity and severity, compromising forest ecosystem services (ES) that are fundamental to human well-being. Thus, evaluating the risk of losing ecosystem services due to wildfires is essential for anticipating and adapting to future conditions. Here, we analyze the spatial patterns of the risk of losing key forest ES and biodiversity (that is, carbon sink, bird richness, hydrological control and erosion control) due to wildfires in Catalonia (NE Spain), taking into account exposed values, hazard magnitude, susceptibility and lack of adaptive capacity. We also determine the effect of climate and different forest functional types on the risk of losing ES under average and extreme hazard conditions (defined as median and 90th percentile values of the Fire Weather Index, respectively), as well as on the increase in risk. Our results show that hazard magnitude is the most important component defining risk under average conditions. Under extreme conditions, exposed values (carbon sink capacity and erosion control) emerged as the most important components of risk. Climate was the main driver of ES at risk under average conditions, but the high vulnerability of non-Mediterranean conifer forests with a low adaptive capacity gained importance under extreme conditions. The increase in risk between average and extreme conditions was driven by precipitation, as the highest increases in risk were found in relatively wet forests with low average risk at present. These results have direct implications on the future risk of losing ES to wildfires in Mediterranean forests but also in other regions, and they could contribute to future policies by anticipating conditions associated with particularly high risk that can be used to guide efficient forest management.

Key words: Adaptive capacity; Bird richness; Carbon sink; Climate; Disturbances; Erosion control; Forest functional type; Hydrological control; Susceptibility; Vulnerability.

Highlights

- We analyze the risk of losing forest ecosystem services due to wildfires.
- Non-Mediterranean conifers show the highest risk under extreme hazard conditions.
- Wet forests with low risk at present will have the highest risk in the future.

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Introduction

Forests provide multiple functions and ecosystem services (ES) fundamental to society, such as mitigating greenhouse gas emissions, regulating water flow (Canadell and Raupach 2008; Miura and others 2015), and supporting plant and animal habitats that hold terrestrial biodiversity (Pan and others 2013). Disturbances are an integral part of forest ecosystem dynamics (Turner 2010; Ding and others 2012), but climate change is altering the extent, frequency and intensity of these disturbances (Seidl and others 2017; Abatzoglou and others 2018), resulting in changes in the ES provided by forests (Thom and Seidl 2016; Leverkus and others 2018). Identifying where and to what extent different forest types and ES will be at risk from these disturbances is still a challenge, but it could be critical for guiding effective management and policy interventions.

Wildfires are one of the most common disturbances affecting forests around the world (Van Lierop and others 2015; Bowman and others 2017; Abatzoglou and others 2018). Nevertheless, more extreme fire weather has been leading to unprecedented fire events around the world such as the 2019–2020 Australian bushfires or the 2017 Portuguese fires (Bowman and others 2020, 2017). A huge impact on ES could therefore be expected (Moritz and others 2014), but the effects of such events vary according to the environmental context and the ES in question. Previous studies have reported negative effects of wildfires on ES. Decreases in infiltration and increases in runoff have been reported (Vukomanovic and Steelman 2019), particularly in water-limited environments (Vieira and others 2016), as well as changes in the quality of water for human consumption (Vukomanovic and Steelman 2019). Erosion control – understood as the capacity of vegetation to control soil erosion due to water – diminished after wildfires, especially during the first post-fire rainstorms (Shakesby 2011). Previous studies have shown a reduction in the carbon sink capacity of forests after wildfires (Seidl and others 2014). In contrast, fires can also be beneficial for ES since they can generate open habitats that offer a variety of services for humans (for example, food and pollination) (Pausas and Keeley 2019). Given these conflicting results, the identification of both the forest types that can either lose or gain ES due to wildfires and the main causes of these changes constitutes a research priority.

The risk of losing ES is not easily quantifiable. Here, we follow the IPCC to define the components of risk, which is thus defined as ''the potential for consequences where something of value is at stake and where the outcome is uncertain'' (IPCC 2018). Risk results from the interaction between exposure, the climate-related hazard and vulnerability, with the latter understood as ''the propensity or predisposition to be adversely affected by the disturbance (for example, wildfires), including sensitivity or susceptibility to harm and lack of capacity to cope and adapt'' (IPCC 2018). Most of the previous studies assessing forest vulnerability and risk of wildfires have not been based on all the IPCC components, or they have used only specific indicators or variables (Duguy and others 2012; Román and others 2013; Oliveira and others 2018; Buotte and others 2019; Ghorbanzadeh and others 2019; Fremout and others 2020). Previous research indicates that forests subject to a high hazard magnitude (that is, high danger of wildfire or high Fire Weather Index) usually show major impacts on forest ES such as carbon storage, biodiversity, water quality and soil erosion (Shakesby 2011; Thom and Seidl 2016; Harper and others 2018).

More recently, a general framework that includes all the IPCC components and is readily applicable to the main climate-change-related hazards to forests has been proposed (Lecina-Diaz and others 2020). This framework includes the main components of forest vulnerability and risk: exposed values, hazard magnitude, susceptibility and lack of adaptive capacity. Exposed values refer to the ecosystem services that could be affected by the hazard (or disturbance), whereas hazard magnitude quantifies the likelihood of the fire-related hazard. Susceptibility is the predisposition to be affected by the fire hazard, which is defined by forest characteristics that modulate the immediate effects of the hazard. Finally, lack of adaptive capacity refers to the ability of forests to respond to fire hazards within a predefined timeframe (that is, lack of resilience) (Lecina-Diaz and others 2020). These components are defined by intrinsic and extrinsic factors, as well as by explicit indicators that depend on the hazard considered. Although a methodology combining the indicators and components of risk has been also proposed by Lecina-Diaz and others (2020), it has not yet been applied.

The current climate has a large influence on wildfires, especially in extreme conditions (Crockett and Westerling 2018; Holden and others 2018). Nevertheless, the impact of wildfires also depends on forest type and specific functional traits, as plant species have evolved different strategies to trigger, resist and recover from fires. For instance, some species accumulate seed banks that germinate by fire, whereas for other species seed germination is induced by the opening of serotinous fruits or cones (Keeley and Fotheringham 2000). These strategies can influence adaptive capacity (for example, the recovery rate), as some forest functional types have traits that make them able to survive or reestablish after fire (for example, seeding or resprouting capacity), whereas others have limited post-fire regeneration capacity (for example, non-Mediterranean conifers, including several *Pinus* species) (Rodrigo and others 2004). Moreover, forest types could differ in fire-prone areas such as the Mediterranean Basin as regards the amount of ES exposed, and also the danger of fire (for example, Mediterranean-conifers such as *Pinus halepensis* have greater wildfire danger) (Mitsopoulos and Dimitrakopoulos 2007). Thus, the individual components that determine risk due to wildfires is influenced by current climatic conditions and forest functional type, but the repercussions of these factors on the ES at risk are not completely understood. Furthermore, climate change is increasing the frequency of extreme climate events (Seidl and others 2017). As regards wildfires, future increases in extreme climate events are expected to increase the probability of ignition, fire size, and severity and the length of the fire season (Flannigan and others 2005; Lozano and others 2016; Parks and others 2016; Ruffault and others 2018). Climate change projections in the Mediterranean Basin suggest increases of more than 50% in days resulting in extreme wildfire events, owing to increasing temperatures and decreasing humidity, especially during the summer season (Bowman and others 2017). The shift to a situation in which current extremes will become the new normal will certainly bring consequences for forest ES. Increases in the geographic extent, duration, intensity and severity of wildfires may change the distribution of the forest ES at risk, and so ''new'' high risk areas may emerge (Alvarez and others 2012). In fact, previous studies suggest that wildfires could increasingly affect northern latitudes and higher elevations in mountain ranges in the Mediterranean (Vilà-Cabrera and others 2012; Duguy and others 2013), as well as in other areas of the world (Keyser and others 2020). As these areas have not burned historically, the increasing frequency of fires due to climate change will compromise their adaptive capacity (for example, replacement of forest by shrubs) and the provision of key ES (Young and others 2019; Keyser and others 2020).

The general objective of this study is to assess the spatial patterns and drivers of the risk of losing ES due to wildfires, focusing on a region (Catalonia, NE Spain) in the temperate-Mediterranean ecotone that is diverse in terms of both climate and forest type. We take advantage of a general framework recently defined by Lecina-Diaz and others (2020), and we have developed it still further and applied it to the specific case of wildfires. Specifically, we address three questions: (1) which component (exposed values, hazard magnitude, susceptibility, lack of adaptive capacity) is the risk of losing ES most sensitive to?; (2) is the risk of losing forest ES due to wildfires under average and extreme hazard conditions (that is, median and 90th percentile values of the Fire Weather Index, respectively) primarily determined by climate or by forest functional type?; and (3) which climatic factors and forest functional types are associated with higher increases in risk between average and extreme conditions? Given that fire danger is one of the most relevant factors in burned areas (Palheiro and others 2006; Amatulli and others 2013; Pérez-Sánchez and others 2017), and that regeneration strategies have proved critical for forest reestablishment after fire (Keeley and Fotheringham 2000; Rodrigo and others 2004), we hypothesize that hazard magnitude has the greatest influence on ES at risk, followed by lack of adaptive capacity (hypothesis 1). We also hypothesize that the increases in risk between average and extreme conditions are largely driven by climate, but as wildfires are increasingly affecting areas that are not frequently burned by large wildfires (Young and others 2019; Keyser and others 2020), we expect the greatest increases in risk to be found in the most humid forests, which are dominated by species with lower post-fire adaptive capacity (hypothesis 2).

Material and Methods

Study Area

The study area is Catalonia (NE Spain), a region of 32,000 km^2 located between 40°50′ and 42°90′ latitude North and 0°20′ and 3°32′ longitude East. It has a heterogeneous geomorphology and high climatic diversity, encompassing mountainous areas such as the Pyrenees (up to 3,143 m.a.s.l), inland plains and coastal zones along the Mediterranean Sea. The climate is Mediterranean, with mean annual temperature ranging from 1 to 17.1 °C and mean annual precipitation ranging from 350 to 1,460 mm (Ninyerola and others 2000). The region's northern areas are the most humid and the coldest (that is, mean annual precipitation = 1300 mm; mean annual temperature = 5 °C), whereas its southern areas are the hottest and driest (mean annual precipitation = 350 mm with mean annual temperature = 15 °C) (Ninyerola and others 2000). Around 40% of the area is covered by forests (MCSC 2005), mainly dominated by tree species from the Pinaceae and Fagaceae families (pines and oaks).

Definition of Risk and Its Components

We applied the conceptual framework defined in Lecina-Diaz and others (2020) to assess forests' risk from wildfires. This framework is based on the main concepts of vulnerability and risk defined in the latest IPCC report (IPCC 2018), modified and adapted to the case of forests. These components are structured in a timeline considering the critical processes and variables before, during and after the wildfire event. Before the wildfire occurs, all forests are exposed but they differ in their 'value', quantified here in terms of the ES that can be lost, or *Exposed Values*. However, these ES could only be lost if the wildfire occurs. Thus, in a given location the magnitude of the disturbance/hazard and its probability distribution can be quantified using integrative hazard indexes, which define the *Hazard Magnitude*. When the wildfire occurs, some characteristics of the forest modulate the immediate effects of the wildfire (for example, forest structure, bark thickness), thus affecting *Susceptibility*. Finally, after the wildfire, forests may recover using a variety of regeneration strategies, which define their A*daptive Capacity*. Hence, risk is defined as follows:

$$Risk = E \cdot HM^{S} \cdot LAC \qquad (1)$$

where E refers to Exposed values, HM is the Hazard Magnitude, S is susceptibility and LAC is lack of adaptive capacity. We define E as the presence of ES that could be adversely affected by the wildfire, in this case, carbon sink, bird richness, hydrological control and erosion control (Table 1). HM is the probability distribution of the hazard (or disturbance), in this case assessed using the Fire Weather Index (FWI) (Van Wagner 1987), modified by some additional variables (see below). S is the predisposition to be affected by a wildfire depending on characteristics that modulate the immediate effects of the hazard. Finally, LAC corresponds to the lack of capacity of a forest to recover after a wildfire in the mid-term. Note that E and HM refer to the situation before the wildfire, whereas S refers to the situation during the wildfire and LAC corresponds to the forest's condition after the wildfire. Furthermore, each component is defined by different indicators that are (1) intrinsic, referring to internal characteristics of the forest (for example, species characteristics); or (2) extrinsic, referring to external factors typically operating at broad spatial scales (for example, topography) (Lecina-Diaz and others 2020) (Figure 1 and Table A1).

Data Sources and Indicators Used

We used different data sources to define the indicators of the different components of risk, that is, exposed values, hazard magnitude, susceptibility and lack of adaptive capacity (Figure 1). Our reference scale is the forest stand (plot), based on the Third Spanish National Forest Inventory (NFI-3), which was conducted in Catalonia between 2000 and 2001 (Ministerio de Medio Ambiente 2007). This inventory consisted of a systematic sampling of permanent plots with a sampling density of one plot per km^2 of forest area, where woody species were identified and measured within variable circular size (5 m radius for trees with dbh ≥ 7.5 cm, 10 m radius for trees with dbh ≥ 12.5 cm, 15 m radius for trees with dbh ≥ 22.5 cm, and 25 m radius for trees with dbh ≥ 42.5 cm). As NFI-3 sets the reference scale for the study, all the indicators were computed at the plot scale (Figure 1 and Table A1). We used data from 7,147 to 9,732 plots, depending on the ES considered.

A complete list and additional details of the indicators (definition, scale, references, etc.) is given in Table 1. Further details of each indicator are provided in the Supplementary Material (Section 1).

- Exposed values (E). Here, we have considered carbon sink, bird richness, hydrological control and erosion control. Carbon sink is the rate of carbon uptake by forests, measured as the difference in carbon stocks (computed from the above-ground and below-ground tree biomass of living trees using species-specific allometric equations; Gracia and others 2004; Montero and others 2005; Vayreda and others 2012b) between the Second and Third National Forest Inventory (NFI), in tons/ha·year. Bird richness has been used as a proxy of biodiversity, and was assessed by using the Second Catalan Breeding Bird Atlas (Estrada and others 2004), counting the total number of species associated with forest habitats (that is, forest specialist and forest generalist species) present in 1 × 1 km pixels centered around each NFI-3 plot. Hydrological control is the capacity of forests to control flooding (that is, the amount of water that is intercepted by forest canopy or retained by soil), assessed as (1—water exported/precipitation) as predicted by the model of De Cáceres and others (2015) for each NFI-3 plot. Erosion control has been defined as the percentage of erosion avoided by the presence of forests, that is, the difference of the Revisited Universal Soil Loss Equation (RUSLE) considering soil without vegetation (that is, Fcover (in c-factor) = 0) and the actual forest cover on the plot (Supplementary material Appendix 1 Section 1.1).

- Hazard Magnitude (HM). We have used the distribution of daily Fire Weather Index (FWI) values from June–September obtained from the Joint Research Centre at a spatial resolution of 0.28 degrees (Joint Research Centre 2017). The FWI combines temperature, wind speed, relative humidity, and precipitation on a daily basis (including the cumulative effect of the weather in the previous days) to estimate the fire danger (Van Wagner 1987). We have used the Monte Carlo method to obtain repeated random samples of the distribution of daily FWI values. We have incorporated forest continuity at the landscape scale and human visitation (defined by a combination of population, distance to buildings and distance to roads) as modifiers of the hazard magnitude (Supplementary material Appendix 1 Section 1.2). We thus obtained a range of hazard magnitude values (that is, a distribution) for each plot.
- Susceptibility (S) is defined by intrinsic and extrinsic factors that modulate the immediate effects of the wildfire. Intrinsic factors include structural and functional characteristics. The structural characteristics considered are the forest's vertical and horizontal continuity and its fuel load (total shrub biomass and fine biomass from trees). As regards functional traits, we have considered bark thickness and flammability, obtained from bibliographic sources at the species level. The extrinsic factors correspond to firefighters' extinction capacity (distances to water bodies, fire stations and fire lookout towers) (Supplementary material Appendix 1 Section 1.3).
- Lack of Adaptive Capacity (LAC) is calculated as 1—adaptive capacity. Adaptive capacity is defined by intrinsic and extrinsic factors. Intrinsic factors are mainly species regeneration characteristics (that is, resprouting and seeding capacity). Extrinsic factors are the external characteristics that promote species recovery, which are defined by the site index estimated from linear models with tree basal area increment (in cm^2/year) as the response variable and radiation, aridity, stoniness and topographic index as explanatory variables (Supplementary material Appendix 1 Section 1.4).

Weighting and Aggregating the Indicators

Except for the exposed values and the FWI, the indicators listed in Figure 1 were standardized (that is, divided by their maximum value) to obtain a range from 0 to 1. The standardized indicators need to be combined, but uncertainties arise in the weighting and aggregating of individual indicators (Gan and others 2017). We applied three of the most widely used weighting methods: (i) equal weights, assigning the same weight to all indicators in a component; (ii) statistical weights, using the statistical importance of the indicators based on their variance, as explained in a Principal Component Analysis; and (iii) expert weights, corresponding to the average value of the weights assigned independently by each of the co-authors of this article (Supplementary material Appendix 1 Table A4). We conducted Pearson's correlation tests between the estimates of *HM*, *S* and *LAC* resulting from the three different weighting methods. Correlation coefficients were always higher than 0.83, showing that in our study the effect of the weighting method was relatively minor (Supplementary material Appendix 1 Tables A5-A7). Thus, we selected the statistical weights for assessing risk in all further analyses.

Aggregating the Components and Associating them with Values at Risk

We combined the components using Eq. 1. As the relationship between the hazard magnitude and immediate loss of exposed values that define susceptibility is non-linear, mediated by the exponent *S*, we used FWI data from the literature that corresponded to complete forest loss (immediate losses of values) to adjust the susceptibility coefficient, *S* (Supplementary material Appendix 1 Section 3). Following Eq. 1, we raised the distribution of hazard magnitude obtained in each plot to its susceptibility and truncated the results so that the maximum immediate loss was 1 (that is, 100% of values were lost). By multiplying the result by the lack of adaptive capacity and the exposed values we obtained one distribution of values at risk in each plot for each ecosystem service at risk. From the distribution of ES at risk, we defined two conditions: average and extreme. Average risk conditions were defined by extracting the median value of each distribution. Extreme risk conditions corresponded to the 90th percentile of each distribution.

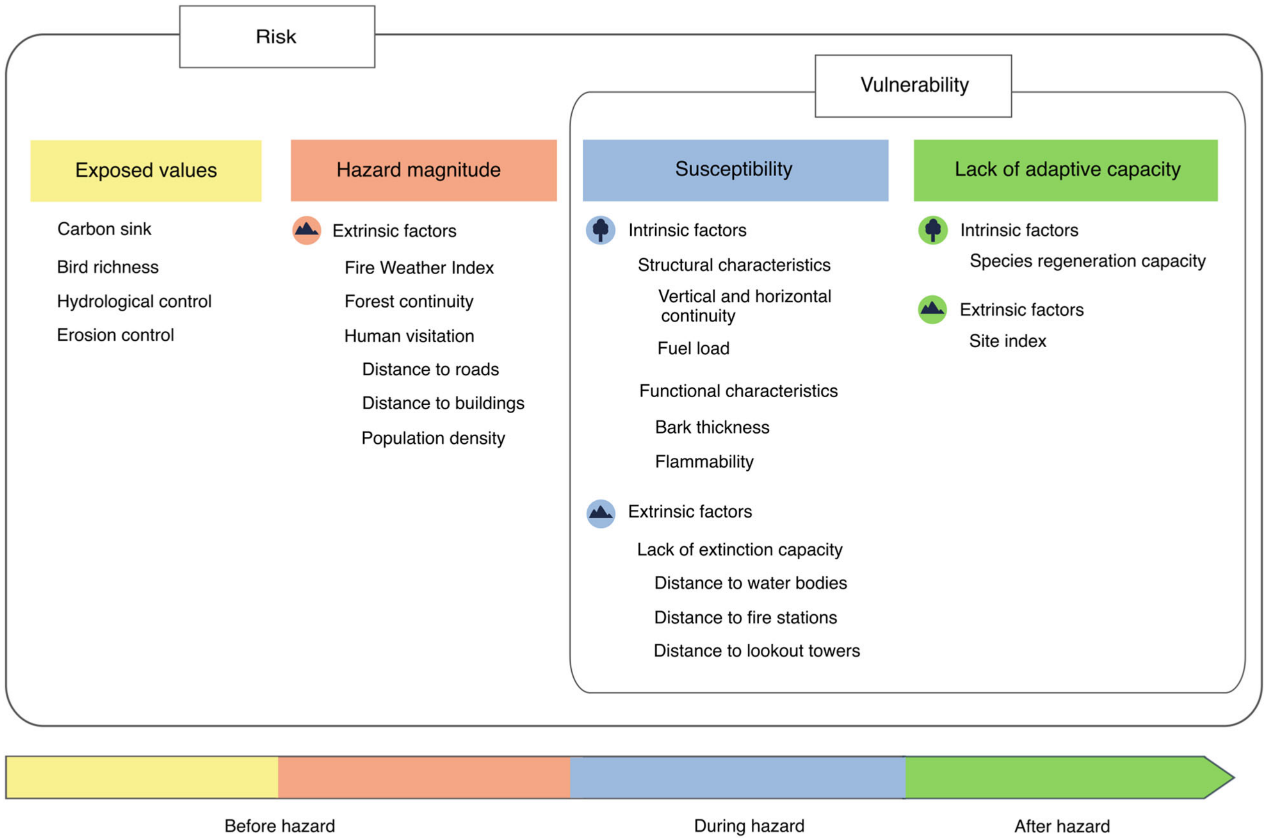

Figure 1. Components and indicators used in the general framework of forest vulnerability and risk from wildfires and their corresponding temporal dimension (before, during and after hazard).

We mapped the ES at risk under average and extreme conditions, generating one map for each ecosystem service and condition. We also mapped the relative changes in risk associated with extreme vs. average hazard conditions using the log-ratio of extreme to average conditions (that is, log((percentile 90th of the risk)/(median risk))).

Data Analysis

To analyze the influence of the components of risk (*E*, *HM*, *S* and *LAC*) on the spatial variability of the risk of losing forest ecosystems services, we conducted Pearson's correlation tests between them to assess whether the different components of risk were spatially associated with each other.

To analyze the effect of the components of risk (*E*, *HM*, *S* and *LAC*) under average and extreme risk conditions, we conducted a sensitivity analysis using the 'tgp' R package on a random sample of 500 plots. This analysis is based on a fully Bayesian Monte Carlo sensitivity analysis, drawing Random Latin hypercube samples at each Markov Chain Monte Carlo iteration to estimate the main effects and first order and total sensitivity indexes (Gramacy 2016).

To determine the effect of climate and forest functional type on the risk of losing forest ES under average and extreme hazard conditions, we conducted regression trees for the four ES at risk (that is, carbon sink, bird richness, hydrological control and erosion control) and the two situations (that is, average and extreme). The explanatory variables were forest functional type (that is, broadleaf evergreen, broadleaf deciduous, Mediterranean conifer and non-Mediterranean conifers (Table A10 and Figure A13)) and climate (Mean Annual Temperature (Temp) and Mean Annual Precipitation (Prec) from the Catalan Digital Climatic Atlas (period 1951–1999 at a resolution of approximately 180 m)) (Figure A13) (Ninyerola and others 2000). Regression trees were conducted using the 'caret' R package, based on recursive partitioning techniques that repeatedly split the predictor variables into multiple sub-spaces, so that the outcomes in each final sub-space are as homogeneous as possible (Kuhn and others 2015). To increase the robustness of the regression tree models, we used a random subset of 80% of the data to produce the model – or train it (using repeated cross-validation for control) and the other 20% of the data for testing (cross-validation).

To determine the influence of climate and forest functional type on the increase in risk associated with extreme vs. average hazard conditions, we conducted regression trees for the log-ratio of the risk under extreme and average conditions (log((percentile 90th of the risk)/(median risk))), with forest functional type and climate (Temp and Prec) as explanatory variables (Figure A13).

Results

Influence of Exposed Values, Hazard Magnitude, Susceptibility and Lack of Adaptive Capacity on the Risk of Losing Ecosystem Services

The spatial distribution of the risk components (exposed values, hazard magnitude, susceptibility and lack of adaptive capacity) showed some common patterns depending on the risk condition (that is, average or extreme) and the exposed value considered (Figure 2). Under average conditions, the highest hazard magnitude was in southern areas, corresponding with areas at the highest average risk for all ES, whereas the lowest hazard magnitude and risk were observed in northern areas (Figures 2 and 3). Under extreme conditions, the highest hazard magnitude was in central and southern areas, corresponding with the highest risk for bird richness and hydrological control (Figures 2 and 3).

The sensitivity analysis showed that under average conditions, hazard magnitude was the risk component having the greatest influence for all ES, whereas susceptibility and lack of adaptive capacity were the least influential (Table 1). Under extreme conditions, hazard magnitude remained a very influential factor but its importance was lower than under average conditions and, with respect to carbon sink and erosion control, exposed values became more important than hazard magnitude (Table 1).

Effect of Climate and Forest Functional Type on the Risk of Losing Forest Ecosystem Services

The regression trees showed that climate and forest functional types (Figure A13) were meaningful factors in defining groups of ES at risk from wildfires under average and extreme conditions. Under average conditions, annual precipitation (hereafter precipitation) was the main factor defining risk groups for all ES except for erosion control. In particular, humid forests (that is, with precipitation > 697, 733 or 768 mm/year depending on the ES, see Figure 4) had the lowest risk of losing carbon sink capacity, bird richness and hydrological control capacity in the event of a wildfire. For these three ES, high risk was also associated with warm conditions (temperature > 10 °C). Functional type was also important, with all forest types except Mediterranean conifers being at higher risk of losing carbon sink, and non-Mediterranean conifers being at higher risk of losing bird richness. As regards erosion control, high risk was determined primarily by forest type (higher for non-Mediterranean conifers) and relatively warm temperatures (> 7.8 °C, Figure 4).

Under extreme conditions, the factors defining risk groups were similar to those under average conditions in terms of importance and direction. Nevertheless, some differences were observed in the relative importance of the variables and specific thresholds (Figure 4). In general, the importance of forest type increased and, for all four ES, non-Mediterranean conifers were associated with the highest risks. Precipitation remained the main factor determining the risk of losing bird richness and hydrological control capacity, but with slightly higher thresholds than under average conditions. Warm temperatures also remained associated with high risks for carbon sink and hydrological control, albeit with slightly lower thresholds (around 9 °C). In contrast, high temperatures (> 13 °C) were associated with the lowest risk of losing erosion control capacity.

Influence of Climate and Forest Functional Type on Potential Increases in Risk

Great changes in risk (that is, high log-ratios of extreme vs average conditions) are determined by the distribution of hazard magnitudes, and hence largely by the FWI distribution at each location. The highest increases in risk were observed in forests with low average risk (that is, northern areas, Figure 5A), whereas the lowest increase in risk was observed in areas where average risk was the highest (that is, in the southern areas, Figure 5A) (Figure A14). Precipitation was the main factor determining a change in risk, with two different thresholds, depending on the group considered. The lowest increase in risk was observed in forests with less than 606 mm/year of precipitation,

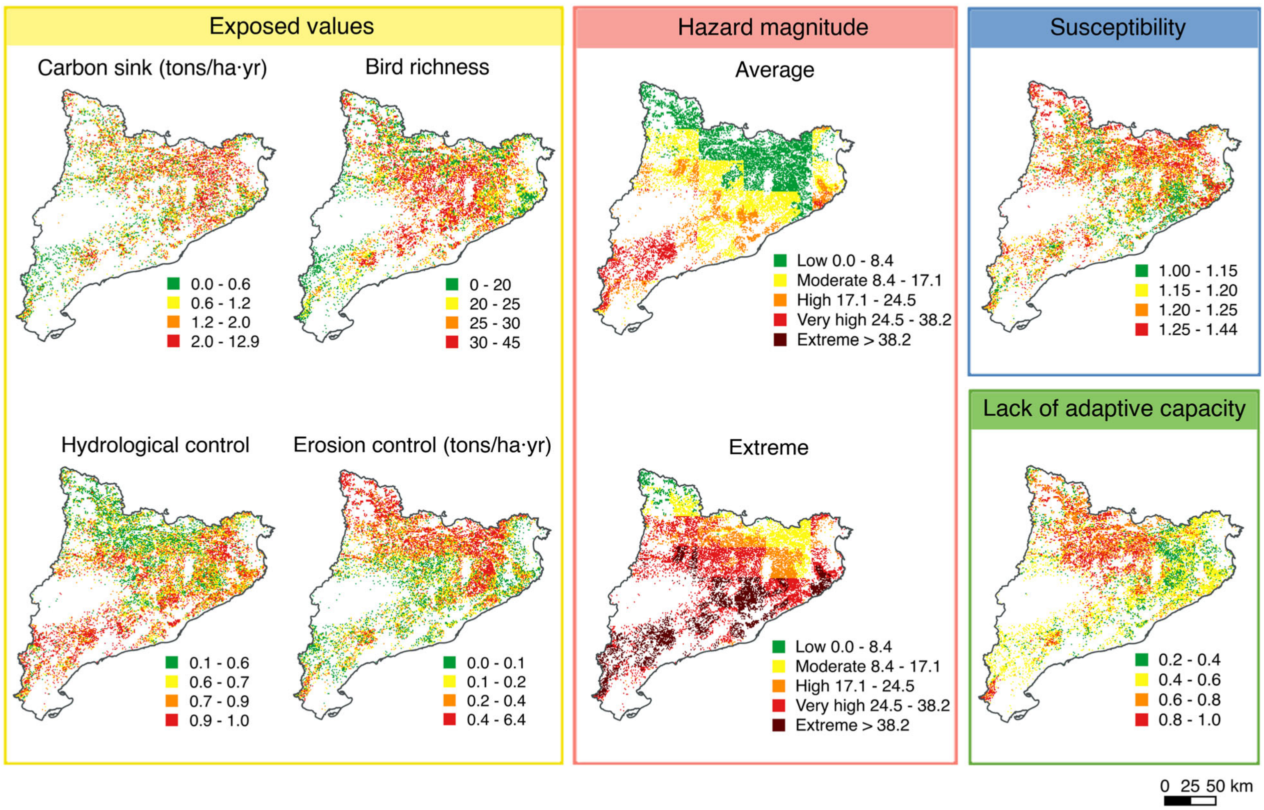

Figure 2. Spatial distribution of the exposed values (carbon sink, bird richness, hydrological control and erosion control), wildfire hazard magnitude (average and extreme), susceptibility and lack of adaptive capacity in the study area (Catalonia, NE Spain).

whereas the highest increase in risk was observed in forests with more than 815 mm/year of precipitation (Figure 5B). High increases in risk between average and extreme conditions were associated with forests with high carbon sink capacity, high erosion control and low hydrological control, whereas the correlation with bird richness was weak (correlations of 0.27, 0.46, -0.30 and 0.03, respectively – Supplementary material Appendix 1 Table A12).

Discussion

Overall, hazard magnitude was the most important component defining risk under average conditions and, interestingly, exposed values emerged as the most important component of risk when conditions were extreme. As initially hypothesized (hypothesis 2), climate was the main driving factor of ES at risk under average conditions, but forest functional type – in particular dominance by non-Mediterranean conifers – gained importance under extreme conditions. Nonetheless, the increase in risk (change from extreme to average ES at risk) was driven by precipitation, with the highest increases in risk found in relatively wet forests with low average risk.

Influence of Exposed Values, Hazard Magnitude, Susceptibility and Lack of Adaptive Capacity on the Risk of Losing Ecosystem Services

As initially hypothesized (hypothesis 1), hazard magnitude was the most important component of risk, especially under average conditions (Table 1). The FWI is the main indicator of hazard magnitude as defined here, and it is one of the most widely used indexes to predict fire danger. The FWI has been related to wildfire occurrence and burnt area in Mediterranean regions (Palheiro and others 2006; Amatulli and others 2013; Pérez-Sánchez and others 2017). Our results are consistent with previous studies which found that areas with high fire occurrence and large burnt areas suffered strong impacts on their forest ES (Thom and Seidl 2016; Harper and others 2018; Pausas and Keeley 2019). Although previous studies have shown that adaptive capacity was a relevant component of

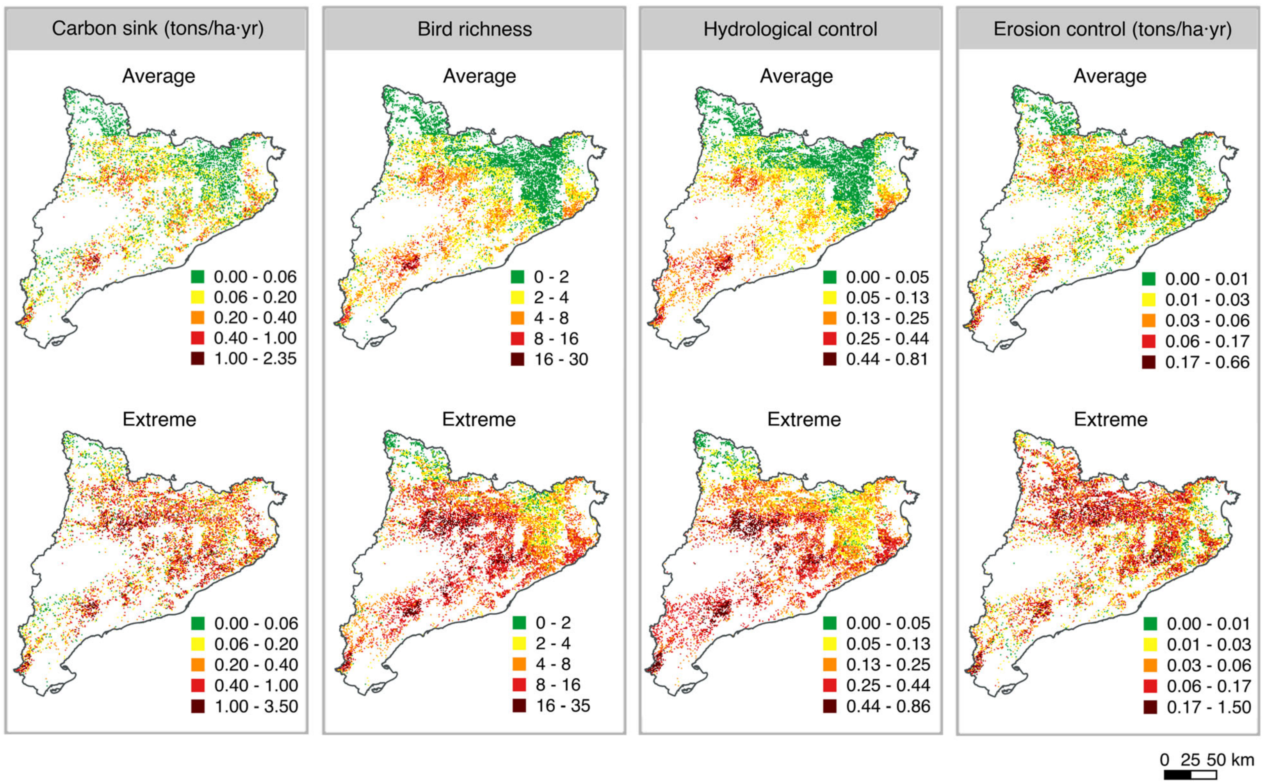

Figure 3. Spatial distribution of ecosystem services at risk (carbon sink, bird richness, hydrological control and erosion control) in the study area (Catalonia, NE Spain) under average and extreme wildfire hazard conditions.

Table 1. Mean Values of the Total Effect Sensitivity Indices Estimated from the Markov Chain Monte Carlo (MCMC) Iterations Conducted in the Sensitivity Analyses (Figures A5-A12), for Each of the Components of Risk (Exposed Values, Hazard Magnitude, Susceptibility and Lack of Adaptive Capacity) Under Average and Extreme Hazard Conditions.

	Carbon sink		Bird richness		Hydrological control		Erosion control	
	Average	Extreme	Average	Extreme	Average	Extreme	Average	Extreme
Exposed values	0.42	**0.46**	0.38	0.44	0.26	0.23	0.62	**0.73**
Hazard magnitude	**0.53**	0.43	**0.54**	**0.46**	**0.57**	**0.53**	**0.69**	0.47
Susceptibility	0.17	0.13	0.18	0.12	0.22	0.17	0.36	0.24
Lack of adaptive capacity	0.15	0.18	0.19	0.23	0.24	0.26	0.38	0.24

The highest values for each ecosystem service at risk under average and extreme conditions that are given in bold indicate the highest influence of the component to risk (or the highest sensitivity of risk to the component).

vulnerability and risk (Román and others 2013; Thorne and others 2018), we found it to be among the least influential factors of ES at risk according to the sensitivity analysis (Table 1). However, adaptive capacity is highly dependent on the forest functional characteristics (for example, Mediterranean conifers have post-fire regeneration strategies whereas non-Mediterranean conifers do not (Rodrigo and others 2004)) and it varies strongly in terms of space (see below).

When conditions were extreme, hazard magnitude lost importance and exposed values became the most important factor for carbon sink and erosion control (Table 1). Under extreme conditions, the extent of high hazard magnitude increased towards central and northern areas (Figure 2), consistent with previous studies suggesting that extreme wildfires could move towards higher latitudes and elevations in the Mediterranean (Vilà-Cabrera and others 2012; Duguy and

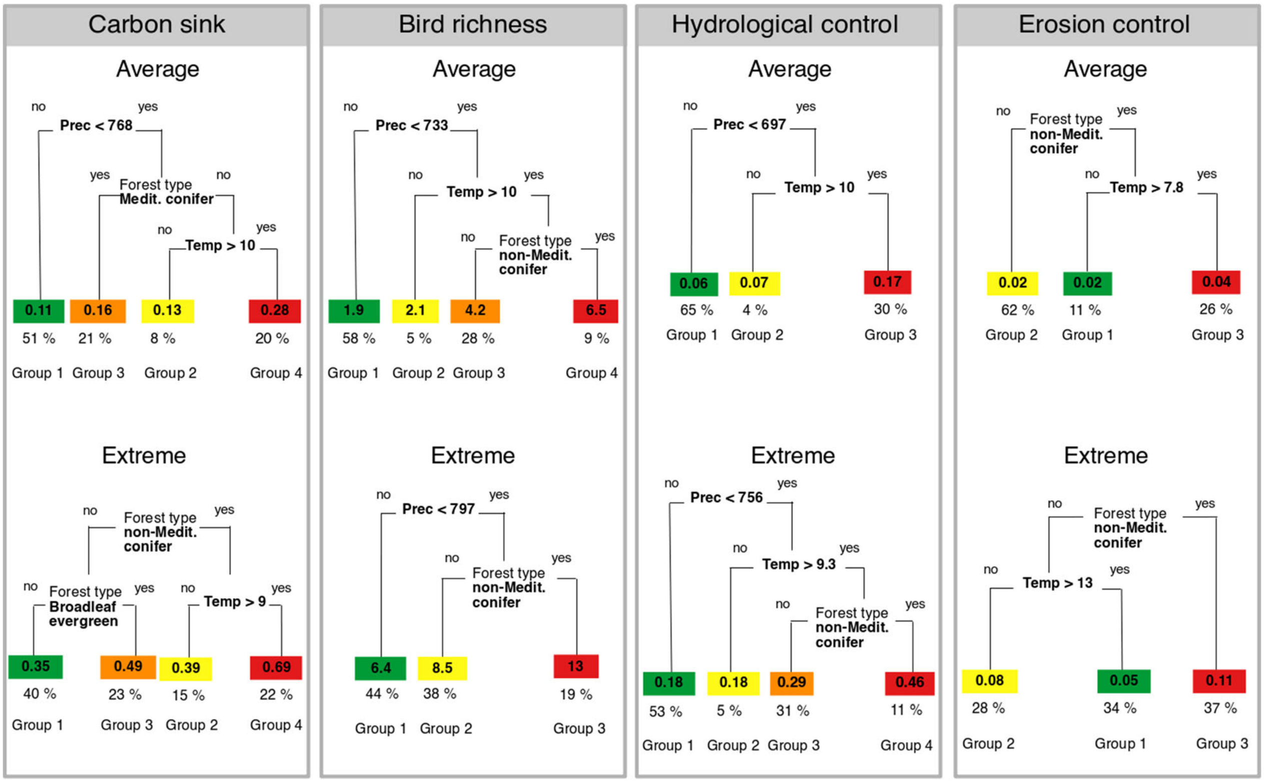

Figure 4. Regression trees of ecosystem services at risk to wildfires under average and extreme conditions, as a function of climate (Prec: mean annual precipitation, Temp: mean annual temperature) and forest functional type (broadleaf evergreen, broadleaf deciduous, Mediterranean conifer, and non-Mediterranean conifer). Values in color boxes correspond to the mean value of the ES at risk in the group, from green (lowest risk) to red (highest risk), and percentage values indicate the percentage of plots in each group.

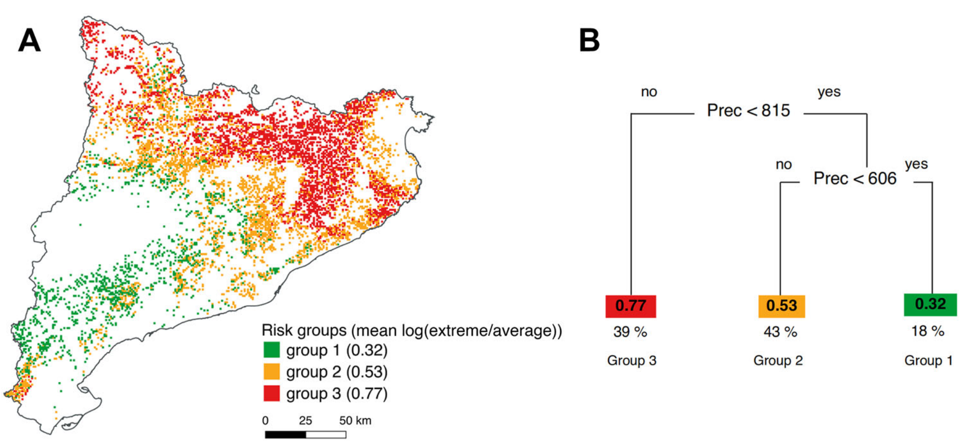

Figure 5. (**A**) Spatial distribution of the log-ratio of extreme vs. current hazard conditions; (**B**) regression tree of the log-ratio as a function of climate (Prec: mean annual precipitation, Temp: mean annual temperature) and forest functional type (broadleaf evergreen, broadleaf deciduous, Mediterranean conifer, and non-Mediterranean conifer). In the regression tree, values in color boxes correspond to the mean value of the log-ratio of the group, from green (lowest risk) to red (highest risk), and percentage values indicate the percentage of plots in each group.

others 2013). These areas are characterized by broadleaf and non-Mediterranean conifer forests that store more carbon than Mediterranean conifers located in southern areas (Table A9) (Vayreda and others 2012a). Moreover, broadleaf and non-Mediterranean forests tend to be located in areas that are humid but also steep, and thus have higher rain erodibility, vegetation cover and slope-length steepness factors, resulting in high erosion control (Table A9). Therefore, the increase in the extent of risk under extreme conditions would lead to more exposed carbon sink and erosion control being at risk and, consequently, more ES could be lost if a wildfire occurred.

Effect of Climate and Forest Functional Type on the Risk of Losing Forest Ecosystem Services

The risks to ES were primarily driven by climate. Under average conditions, humid forests had the lowest risk of losing all ES except erosion control. This is an expected result because low precipitation has a strong effect on burnt area by decreasing fuel moisture and increasing flammability (Littell and others 2009; Holden and others 2018). Less humid and warm conditions put carbon sink at the highest risk for all forest functional types except Mediterranean conifers (that is, *Pinus halepensis*, *Pinus pinea*, *Pinus pinaster*) (Figure 4). Low precipitation and warm temperatures increased hazard magnitude which, together with the high levels of carbon sink found in all forests except Mediterranean conifers (Table A9) (Vayreda and others 2012a), resulted in the highest risk of losing carbon sink. As regards bird richness, non-Mediterranean conifers (for example, *Pinus sylvestris*, *Pinus nigra*, *Pinus uncinata*, *Abies alba*) and forests growing under warm conditions were at the highest risk (Figure 4). Temperature was found to negatively affect bird richness in the study area (Lecina-Diaz and others 2018), as most of the forest birds are cold-dwelling species located at the southern limit of their distribution in Europe (Regos and others 2017). Although changes in bird communities are common shortly after fire due to changes in habitat and resource availability, bird richness returns to pre-fire levels after a few years (Saracco and others 2018; Zlonis and others 2019). However, post-fire habitat changes in non-Mediterranean conifer forests could be exacerbated by these species' lack of post-fire adaptive capacity (Table A9) (for example, replacement by other tree species, such as broadleaves (De Cáceres and others 2013)), with consequences for forest bird communities. As regards erosion control, the highest risk was observed in non-Mediterranean conifers at relatively warm temperatures (> 7.8 °C, Figure 4). Non-Mediterranean conifers' lack of post-fire adaptive capacity compared to the rest of forest functional types (Rodrigo and others 2004; Tapias and others 2004) could also result in higher erosion risk, due to growth limitations after fire (Maringer and others 2012; Reyes and others 2015), but temperature limited the risk due to hazard magnitude in these forests, at least under average hazard conditions (that is, low FWI in areas with low temperature) (Figure 4).

Under extreme conditions, climate was still a relevant factor for all ES at risk, albeit with different precipitation and temperature thresholds (Figure 4). More humid and colder areas were at higher risk than under average conditions, concurring with previous studies relating less arid climates with more biomass to extreme fire severity (Lecina-Diaz and others 2014). In contrast, the importance of forest type increased, with non-Mediterranean conifers having the highest risk to ES (Figure 4). Under these conditions, the factor that differentiates forest functional types is the highest lack of adaptive capacity presented by non-Mediterranean conifers, which resulted in this forest type being the one with the highest risk to ES. However, previous studies have shown that warming climate is furthering unfavorable post-fire growing conditions, regardless of the forest functional type (for example, lower seedling and resprouting capacity due to unsuitable climate) (Enright and others 2015; Stevens-Rumann and others 2018). Nevertheless, non-Mediterranean conifer forests in humid regions have previously been affected by extreme wildfires and shown limited regeneration compared with the other forest types (Retana and others 2002; Rodrigo and others 2004; Pausas and others 2008). This is generally consistent with previous studies that have described them as vulnerable due to their lack of regenerative capacity, which is closely linked to seed dispersal from surviving trees (Vilà-Cabrera and others 2012; Christopoulou and others 2014). Consequently, these forests often transitioned into other forest types (mainly dominated by resprouter species), or even into other types of vegetation, such as shrublands (Retana and others 2002; Pérez-Cabello and others 2010), resulting in very high impacts on their ES.

Influence of Climate and Forest Functional Type on Potential Increases in Risk

Although wildfires are an integral part of forest ecosystems, ongoing climate change is likely to exacerbate wildfire risk in many areas, making the extreme hazard conditions now being found much more common. Thus, characterizing forests based on a change from (currently) average to extreme conditions could provide new insights into ES at risk from future wildfires. As hypothesized (hypothesis 2), the highest increases in ES at risk occurred in the most humid forests in the study area, which are currently at low risk. These relatively wet forests grow without any water limitations, so they are associated with high carbon sink capacity and erosion control (Table A12). Although these forests are not frequently affected by wildfires (Díaz-Delgado and others 2004; Brotons and others 2013), previous studies have suggested an increase in wildfires in northern latitudes and higher elevations in Mediterranean regions (Duguy and others 2013). Climate change will increase the severity and intensity of drought events in the Mediterranean, resulting in increases of more than 50% in days favorable to extreme wildfire events (Vilà-Cabrera and others 2012; Bowman and others 2017). By the 2080s, future scenarios of temperature increases of 2–4 °C in southern Europe also entail reduction in precipitation of up to 30% (Vautard and others 2014), and increases in wildfire activity are expected in other regions of the world in future (Moritz and others 2012; Liu and others 2013; Coogan and others 2019). Therefore, new areas with a high to forest ES that may appear due to climate change should be considered a priority in management policies aimed at reducing susceptibility or improving adaptive capacity.

Concluding Remarks

Our research assessed the current and future risk of losing ES (carbon sink, hydrological control and erosion control) and biodiversity (bird richness) in the event of a wildfire, highlighting the large differences between forest functional types. In this respect, management approaches favoring broadleaf species over non-Mediterranean conifers can be promoted to increase adaptive capacity and consequently decrease the risk of losing ES. However, it is not clear how future climate conditions may change species distributions and fire regimes, and how these changes will affect future hazard magnitude, susceptibility and adaptive capacity, which collectively define risk. We have approximated future hazard conditions using extreme values of current hazard magnitudes, but a better understanding of the future distribution of hazard magnitude remains a key challenge. This study constitutes an important advance in the quantification of forest vulnerability and risk that could be generalized to other systems. Given the increases in the intensity of forest disturbance regimes in Europe (Seidl and others 2011), and the increasing vulnerability to fire in other regions of the world (Buotte and others 2019), our findings could contribute to future policies by anticipating conditions associated with particularly high risks that could be used to guide efficient forest management.

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DATA AVAILABLE

Data are available at: https://doi.org/10.6084/m9.figshare.13636748.v1.

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