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Original Article

The impact of climate and management on recent mortality in *Pinus pinaster* resin-tapped forests of inland Spain

Rafael Calama[1,*], César Martínez[2], Javier Gordo[2], Miren Del Río[1], María Menéndez-Miguélez[1] and Marta Pardos[1]

[1]Institute for Forest Research (ICIFOR-INIA), Spanish National Research Council (CSIC), Ctra A Coruña km 7.5., Madrid 28040, Spain
[2]Servicio Territorial de Medio Ambiente, Junta de Castilla y León, Avda, Duque de la Victoria 5, Valladolid 47001, Spain
*Corresponding author: E-mail: rcalama@inia.csic.es

Abstract

Recent forest decline and amplified mortality have been documented around the world, mainly triggered by the rising water stress associated with more frequent extreme weather events. However, other abiotic and biotic factors may predispose and contribute to these processes. Mediterranean forests are among the biomes considered highly vulnerable to drought-induced decline and mortality. *Pinus pinaster* ssp. *mesogeensis*, is a typical western Mediterranean Forest species widely distributed in Spain, where traditional management has focused on a mixed timber-resin production. In the last decades, the species has experienced a severe and generalized process of decline and mortality, especially on inland areas in the Spanish Northern Plateau. The main objectives of this study were to (1) provide an accurate assessment of *P. pinaster* mortality in resin-tapped forests within the region, (2) identify the main predisposing and inciting abiotic factors controlling the process of dieback and mortality of the species and (3) develop a model for forecasting the annual rate of mortality at landscape scale. We used operational data collected by the Forest Service during 2012–2019, including annual censuses of tree mortality carried out in lots under resin-tapping and periodical forest management inventories. Analysis using spatiotemporal generalized linear mixed models indicated widespread mortality of the species in the territory, which in some areas reached 20 per cent of the trees over an 8-year period. Tree mortality is triggered in warm and dry years and was accelerated following the extreme droughts of 2017 and 2019. High stand stocking and tree aging have been identified as predisposing factors increasing susceptibility to forest decline and mortality. In addition, stands where the species grows mixed with *Pinus pinea* are more vulnerable, pointing to a possible displacement of *P. pinaster* in the territory. The developed spatiotemporal generalized linear mixed model allows unbiased estimates of the annual rate of mortality to be calculated through the territory. The model may be used by forest managers in order to identify the most vulnerable areas where the application of adaption strategies should be prioritized, in order to preserve these forests and their associated provision of ecosystem services.

Introduction

In recent decades, processes of forest decline and dieback have been widely documented around the world (Peñuelas et al., 2001; Williams et al., 2013). These processes have led to amplified forest mortality affecting different species, regions and biomes (Allen et al., 2010; Senf et al., 2020; Hartmann et al., 2022). This generalized and abrupt increase in tree mortality is mainly attributed to the rising water stress associated with higher temperatures and more severe droughts recently observed in the context of global warming (Camarero et al., 2015; McDowell et al., 2018; Hammond et al., 2022). However, forest decline and mortality is a complex process involving different biotic and abiotic factors, which may be interrelated and act synergistically, so climate *per se* may not be explaining the whole process. According to Manion (1991), factors controlling decline and mortality have commonly been classified into three different levels. First, long-term stressors, which cause tree weakening and rising vulnerability of trees to decline, such as historic climate, site, stand conditions and past management legacies, have commonly been considered predisposing factors (Hennon et al., 2009; Neumann et al., 2017; Searle et al., 2022). Second, inciting factors, which include those short-term events resulting in severe and sudden damage, may trigger decline and mortality in previously weakened trees (Rehfeldt et al., 2009). These inciting factors commonly include weather events such as extreme droughts, heatwaves or severe frosts. Finally, biotic agents such as pests, fungi or other pathogens act as contributing stressors, accelerating the mortality of the trees (Desprez-Loustau et al., 2006).

As a consequence of the plethora of interacting factors affecting tree mortality, it is challenging to achieve a clear understanding of this process (Neumann et al., 2017.). Depending on the available data sources, various approaches for tree mortality mapping exist: from detailed dendrochronological studies based on specific tree data (Camarero et al., 2015) to remote sensing techniques that offer the possibility to analyze long-term periods across large spatial scales (Senf et al., 2020), despite their lower reliability. A common data source in mortality analyses is forest inventory data, including long-term experimental plots (e.g. Carnicer et al., 2011; de la Cruz et al., 2014), which allow a balance between reliability (data based on field measurements) and representativeness (from local to large spatial scales). Forest inventory data are usually analyzed using empirical tree mortality models,

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which have long been used in forest modeling to simulate forest dynamics (Vanclay, 1994). Although they do not focus directly on the underlying mechanisms, they provide useful correlational relationships to better understand mortality patterns (Hülsmann et al., 2017). Most of the mortality models predict mortality (at tree or stand level) from tree and stand attributes and site conditions (Weiskittel et al., 2011). Thus, they are adequate to explain a part of the observed variability in mortality, but usually also show high uncertainty (Monserud and Sterba, 1999). One important limitation is that census intervals in forest inventories tend to be greater than one year, hampering the analysis of the impact of annual weather conditions on tree mortality, which could reveal crucial information for understanding climate-driven mortality processes. Another constraint is that due to the stochastic character of mortality, tree mortality rates are difficult to estimate because sample sizes are commonly limited (Archambeau et al., 2020), which makes identifying the spatial patterns and spread processes of mortality more complicated. Therefore, data sources based on landscape scale and short periodicity are required for detailed analysis of spatio-temporal patterns of mortality (Liu et al., 2007). This kind of dataset based on field data are scarce, so most of the studies at landscape level are based on remote sensing or combined data (e.g. Bost et al., 2019).

Mediterranean forests are among the biomes considered highly vulnerable to drought-induced processes of decline and mortality (Carnicer et al., 2011; Spathelf et al., 2014). Maritime pine (*Pinus pinaster* Ait.) is a species characteristic of the Western Mediterranean forests, being the most widespread conifer in Spain and Portugal (Nunes et al., 2020). The subspecies *mesogeensis* Fieschi & Gaussen mainly occupies inland areas and the mountains surrounding the Spanish Northern and Southern plateaus. These forests have traditionally been managed for a mixed production of timber and resin, with a recent reactivation of resin tapping over the last decade following a declining period at the end of the 20th century (Soliño et al., 2018). This subspecies is highly adapted to sandy and stony soils and grows under a climate characterized by irregular rainfall concentrated in the spring and fall seasons and extreme summer drought with high temperatures. In recent decades, there have been an increasing number of studies highlighting a progressive decline of the species in Spain, recording different symptoms such as reduced growth, crown transparency and defoliation, discolouration of the foliage and premature death. This decay process was first observed mainly in forests located on the Northern Plateau of Spain (Madrigal-González and Zavala, 2014; Prieto-Recio et al., 2015; Gordo et al., 2020), but was subsequently also identified in other areas of inland Spain (Navarro-Cerrillo et al., 2018; Férriz et al., 2021; Moreno-Fernández et al., 2021; Valeriano et al., 2021).

Most of these studies agree that high stand stocking, lack of management and subsequent high competition for below-ground resources (water) are the main predisposing factors leading to increased likelihood of mortality at tree or plot level (Prieto-Recio et al., 2015). Other variables such as stand age, stand structure, species composition or soil characteristics have also been found to influence Maritime pine mortality (Bravo-Oviedo et al., 2006; Madrigal-González and Zavala, 2014; Férriz et al., 2021). Climate may play a dual role, both as an inciting and predisposing factor. Continental winter together with spring droughts and high summer temperatures may act as triggering factors, resulting in increased mortality (e.g. Prieto-Recio et al., 2015). Both Gea-Izquierdo et al. (2019) and Navarro-Cerrillo et al. (2018) observed that decay and mortality of *P. pinaster* is associated with reduced rates of growth following recurrent and frequent droughts occurring as long as 20 years prior to the death of the tree. Finally, biotic agents have been postulated as contributors to tree mortality, including *Ophiostasmales* fungi and mistletoe (Álvarez et al., 2015; Gea-Izquierdo et al., 2019), although the specific role played by these pathogens in tree mortality remains an open question. Further, it should be noted that the potential impact of resin taping on mortality has also not yet been analyzed. Moreover, the restricted spatial scale of previous studies, mainly focusing on tree or plot scale (e.g. Prieto-Recio et al., 2015; Gea-Izquierdo et al., 2019), means that it is difficult to make an accurate assessment of the real incidence of the mortality at landscape scale. Since most of the earlier studies rely on a single observation of decay-mortality recorded in the monitoring plots (but see Bravo-Oviedo et al., 2006), the temporal pattern of expansion of the mortality process cannot easily be assessed. Furthermore, due to the sampling schedule, it is not possible to identify the exact season or even year in which trees died, thus making it difficult to identify the inciting factors. Despite the existing knowledge on the potential factors controlling the decline of the species, this knowledge has not been transferred to modeling tools that allow the rate of mortality to be predicted at operational forest-management scales. The only exception is the stand-level mortality model developed by Bravo-Oviedo et al. (2006). However, this model only considers stocking and other stand-level variables as potential predictors, but does not test the effect of climate or biotic triggering covariates.

In our study, we aim to analyze the recent processes of dieback and mortality observed in *P. pinaster* resin-tapped forests on the Northern Plateau of Spain using management-oriented data collected by the regional Forest Service in tapped forests. To this end, we define three specific objectives:

- To provide an accurate assessment of *P. pinaster* mortality within the region and analyze the spatiotemporal pattern of the mortality processes.
- To identify the main predisposing and inciting abiotic factors controlling the process of dieback and mortality in these forests
- To develop a model for forecasting the rate of mortality at landscape scale, considering climate and management scenarios

Our main hypotheses are (i) decline and mortality in *P. pinaster* stands is a generalized phenomenon widely extended through the territory; (ii) stand-level conditions, especially stocking, may act as the main predisposing factors; (iii) increasing structural and specific diversity of the stands may mitigate the processes of decline; and (iv) water stress associated with rising temperatures and extreme droughts is the main factor triggering decline.

Material

Forest management and resin tapping in the study area

Until the beginning of the 21st century, the resin-tapping activity in *P. pinaster* was very limited in the province of Valladolid, with only two small lots (basic collection unit) and less than 8000 trees being tapped every year (Finat et al. 2015). Most of the areas where resin tapping had historically been conducted were naturally regenerated through regeneration fellings, while the main objective of forest management had shifted to timber production. This situation has changed again considerably since 2010, when a significant rise in resin, rosin and turpentine prices on the international market, together with high rates of unemployment

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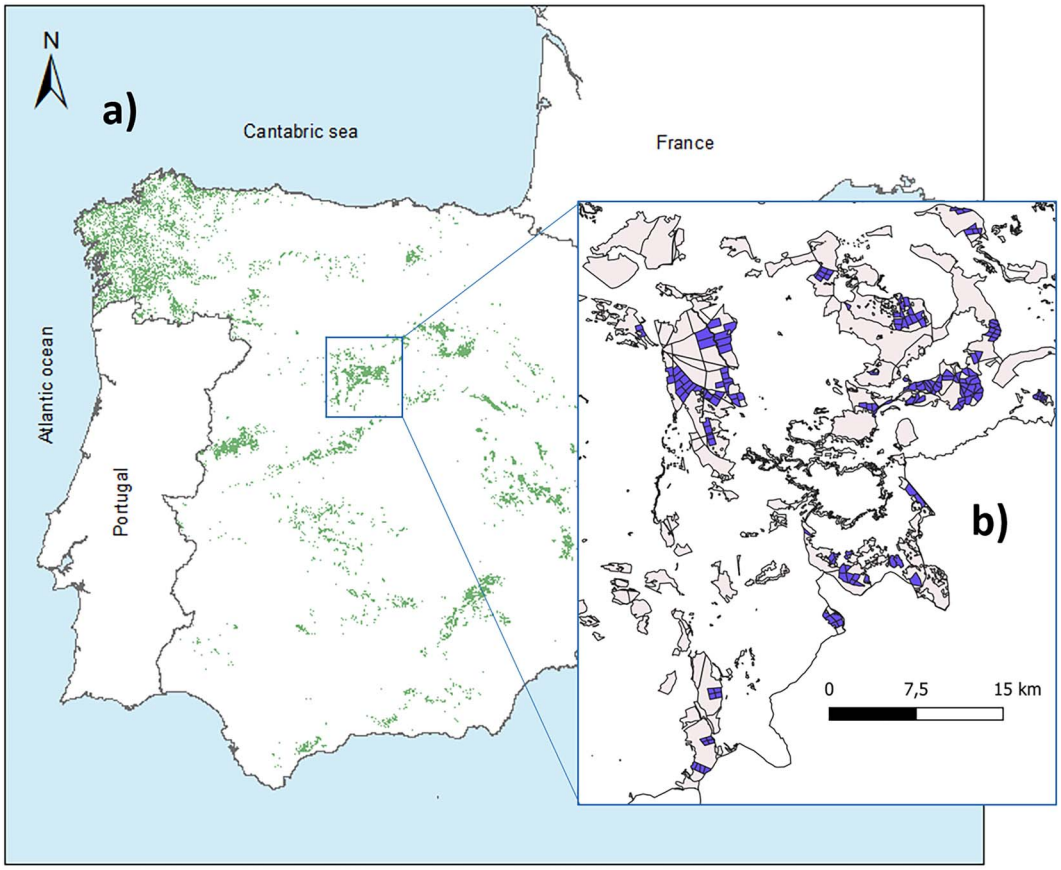


Figure 1. Study area located within the distribution area of *Pinus pinaster* in Spain (a), and lots under resin tapping (dark shaded) plotted over the area occupied by public forests in Valladolid province (b).

in inland Spain, led to the resurgence of the activity (Soliño et al., 2018; Tomé et al., 2020). Consequently, in 2012, the Forest Service publicly tendered the tapping of 26 lots, covering 1630 ha and including more than 110 000 trees. These figures continued increasing until 2016, when most of the public forested area suitable for resin tapping was profitable (Figure 1). The forests in this study are mainly even-aged, managed to promote resin production and comprise pure (57 per cent of the total studied area) or mixed (with *P. pinea*) stands. In mixed stands, *P. pinea* is exploited for cone and nut production, not being resin-tapped.

Annual monitoring of pine mortality

Since 2012, coinciding with the recent increase in the resin-tapping activity in the province of Valladolid, the regional Forest Service has carried out annual systematic monitoring of tree mortality in public forests where resin tapping is performed. This inventory is used to determine the total amount that resin workers should pay for the right to collect resin over the course of the year and to estimate the total volume of timber to be felled in salvage cuttings. In the first year in which resin tapping is commenced in a lot, the maximum number of trees to be tapped in the lot is estimated through a tree-by-tree inventory. This maximum number is determined according to the total area of the lot, size of the trees (only trees with dbh > 30 cm can be tapped), species (only *P. pinaster* can be tapped) and health of the trees. Thereafter, every year at the end of the resin period (October), forest rangers count and mark the number of dead trees, which are subtracted from the total amount of trees to be assigned and tapped in the subsequent year. In addition, during this annual inventory, new trees reaching the threshold size are incorporated into the lot. Thus, if Nr_{ij} is the number of trees tapped in the i^{th} lot during the j^{th} year, the number of trees to be tapped in the $j^{th}+1$ year is given by

$$Nr_{i(j+1)} = Nr_{ij} + I_{ij+1} - D_{ij} \quad (1)$$

where D_{ij} represents the number of dead trees counted at the end of the resin period in the i^{th} lot during the j^{th} year, and I_{ij+1} is the number of new trees to be tapped in the year $j+1$. From this, we can define the annual rate of pine mortality in tapped trees in the i^{th} lot during the j^{th} year, M_{ij}, as

$$M_{ij} = \frac{D_{ij}}{Nr_{ij}} \quad (2)$$

Our data set includes 408 observations of annual rate of pine mortality, measured in 63 different resin lots covering a timespan between 2012 and 2019. These lots cover more than 4500 ha and the study includes almost 270 000 trees.

Forest structure, composition and stocking

Stand-level attributes of the lot (forest structure, composition and stocking) were obtained from the single inventory carried out in each public forest of the province every 10 years. The circular inventory plots, with a fixed radius of 15 m, are located within a systematic sampling grid of 200 m × 200 m. Tree species and diameter at breast height (dbh) of all the trees with dbh > 7.5 cm were measured for all trees within the plot. Tree height was only

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recorded for a subsample of trees in order to determine dominant height. Stand age was computed by coring (at stump height) a dominant tree of the dominant species of the plot. From these records, we determined the following variables at plot level:

- Basal area (m^2ha^{-1}) *BA*: separately for each species and total
- Number of stems per ha *N*: separately for each species and total
- Mean squared diameter (cm) *dg*: separately for each species and total
- Age (years) *T*: separately for each species
- Dominant height (m) *HD*: separately for each species
- Site index (m) *SI*: computed separately for each species, using Calama et al. (2003) for *Pinus pinea* and Bravo-Oviedo et al. (2004) for *P. pinaster*
- Percentage of representativeness of the *P. pinaster* in the plot *%pt*
- Reineke's stand density index *SDI*: given the formulation of this metric it was only computed for the total

All the data from the inventoried plots in a given resin-tapping lot were averaged to provide a single value per lot.

To characterize the structural diversity of the lot, we calculated different indices based on mean squared diameter *dg*, given the relationship between tree size and mortality. First, we computed Gini's coefficient of inequality for the total mean squared diameter of the plots within a lot:

$$Gc_dg = \frac{\sum_{i=1}^{n} (2i - n - 1)\, dg_i}{n \sum_{i=1}^{n} dg_i} \quad (3)$$

where n represents the number of plots in the lot, dg_i is the total mean squared diameter of plot i and i is the rank (in ascending order of dg) of plot within the lot.

We also computed the Shannon index to determine the variability in total mean squared diameter *dg*, assuming 10 cm range classes.

$$Sh_dg = \sum_{j=1}^{S} p_j \log_2 (p_j) \quad (4)$$

where S represents the number of 10 cm-range *dg* classes within the lot, and p_j is the percentage of plots within the lot belonging to the j_{th} *dg* class.

Finally, we computed the coefficient of variation of the mean squared diameter between the plots of the lot, defined as the ratio between the mean value of *dg* and the standard deviation:

$$CV_{dg} = \frac{\overline{dg}}{STD(dg)} = \frac{\sum_{i=1}^{n} dg_i / n}{\sum_{i=1}^{n} \left(dg_i - \overline{dg}\right)^2 / n - 1} \quad (5)$$

Table 1 shows the mean forest attributes for the studied lots.

Climate data

In order to identify whether there is a climatic control over the observed process of dieback in *P. pinaster*, climate data, including mean and maximum monthly temperatures and monthly rainfall, were collected for the period 2011–2019. From this data, monthly water deficit, defined as the difference between monthly rainfall and monthly ETP (computed according to Thornwaite's method), was calculated. Monthly data were aggregated (rainfall and deficit) or averaged (temperatures) to define seasonal and yearly values. Given the orographic homogeneity of the territory, we used data from a single meteorological station (Valladolid Central Meteorological Station, 41°39′08.4"N 4°43′24.1"W).

Table 1. Mean value (and range) for the main dendrometric attributes of the resin-tapped lots included in the study

	Pinus pinaster	*P. pinea*	Both species
Lot area (ha)			70
			16–255
BA	10.5	3.2	13.7
	0.8–24.1	0–13.8	6.9–24.4
N	146	54	201
	10–476	0–348	80–537
dg	31.8	30.3	31.0
	17.4–41.3	11.2–50.0	15.5–41.2
T	52	55	
	23–87	17–98	
HD	14.7	12.3	
	9.3–17.3	5.9–17.1	
SI	16.5	17.6	
	13.0–21.4	12.6–20.3	
%Pt			0.760
			0.054–1
SDI			257
			128–467
GC_dg			0.105
			0.024–0.226
SH_dg			1.290
			0–2.223
CV_dg			0.200
			0.049–0.431

Methods

Exploratory analysis and spatio-temporal dependence

In a first step, a correlation analysis between the annual rate of pine mortality *M* and the potential explanatory covariates presented in the materials section was done. Given the heteroscedastic pattern of the variance of *M*, we carried out a weighted correlation analysis. Visual assessment of the spatio-temporal pattern of pine mortality was carried out using maps of temporal evolution.

Decay and dieback processes may show high spatial and temporal dependence, pointing to patterns of propagation. We checked for spatiotemporal patterns of correlation in the observed rate of mortality in lot i and year j, M_{ij}. To do this, we computed the general empirical spatiotemporal correlation at an interval of distances (i.e. spatial lag) $\mathbf{h}$ and a temporal difference $\boldsymbol{\tau}$ (Cressie and Wikle, 2011):

$$\rho_{ik} = \frac{1}{N(h)} \frac{1}{N(\tau)} \times \frac{\sum_{i,k \in N(h)} \sum_{j=2}^{T} \left(M_{i\,j} - \overline{M}_i\right) \left(M_{k\,j-\tau} - \overline{M}_k\right)}{\sqrt{\sum_{i,k \in N(h)} \sum_{j=2}^{T} \left(M_{i\,j} - \overline{M}_i\right)^2 \sum_{i,k \in N(h)} \sum_{j=2}^{T} \left(M_{k\,j-\tau} - \overline{M}_k\right)^2}} \quad (6)$$

where i, k refer to two lots, the centroids of which are separated by a distance included within the interval of distances (h). N(h) is the number of pairs of lots located within a given distance h. N(τ) is the number of pairs of temporal observations separated by the time lag τ. $\overline{M}_i$ and $\overline{M}_k$ are the averaged value of mortality

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rates M for lots i and k over the T studied years. Eq [6] represents a Pearson's correlation, thus the null hypothesis for $\rho_{ik} = 0$ can be tested by means of a Student's t test, and confidence intervals can be constructed by computing the critical values of ρ for a 95 per cent probability, even under non-normal assumptions (see e.g. Edwards et al. 2020).

From equation [6], we first obtained the spatial correlation function and the derived spatial correlogram by fixing $\tau = 0$. The existence of significant positive spatial correlation up to a given lag distance may indicate that the rate of mortality is controlled by spatial factors which have an influence at that scale. Thereafter, the temporal autocorrelation function and the temporal correlogram function among the observations for a given spatial unit are easily derived by fixing h = 0. Significant temporal autocorrelation supports the evidence for temporary dependencies, including factors such as meteorological conditions and inherent dynamic cycles of the damaging agents. However, given the shortage of the series (8 years), results from temporal autocorrelation, especially at higher lags, should be cautiously interpreted. In the end, significant positive spatiotemporal correlation for a given interval of distance ($h \neq 0$) at a temporal time lag $\tau \neq 0$ can be interpreted as a process of delayed propagation of the decay – mortality among neighboring lots, a pattern commonly observed in the initial stages of biotic-origin infections.

Modeling approach

The maximum value of the number of dead trees in a given resin lot and year (D_{ij}) is constrained by the total number of resin-tapped trees in lot i during that year j (N_{ij}). The count characteristic and upper boundary in D_{ij} suggest a model based on a binomial distribution, where the response variable is defined on an events/trials (dead trees at the end of the campaign/total number of trees to be tapped at the beginning of the campaign) characterization (Gumpertz et al., 2000; Zhu et al., 2008), and all the trees within a given lot in a given campaign have the same probability of being damaged. For a binomial distribution with N_{ij} resin-tapped trees and a probability of death during the campaign π_{ij}, the probability distribution function for D_{ij} is

$$f(y = D_{ij}) = \begin{pmatrix} N_{ij} \\ D_{ij} \end{pmatrix} \pi_{ij}^{D_{ij}} (1 - \pi_{ij})^{N_{ij} - D_{ij}} \quad (7)$$

The first (mean) and second moments (variance) of the distribution are defined as

$$E(D_{ij}) = \pi_{ij} N_{ij} \quad (8)$$

$$\text{Var}\ (D_{ij}) = \pi_{ij} (1 - \pi_{ij})\ N_{ij} \quad (9)$$

The probability of death π_{ij} is modeled using generalized linear models theory through the logit link function, thus

$$logit(\pi_{ij}) = \log\left(\frac{\pi_{ij}}{1 - \pi_{ij}}\right) = \mathbf{X}\boldsymbol{\beta}, \text{with } \hat{\pi}_{ij} = \frac{e^{X\beta}}{1 + e^{X\beta}} \quad (10)$$

where $\mathbf{X}$ is a vector of potential explanatory covariates and $\boldsymbol{\beta}$ is a vector of estimable parameters. Given the nested and crossed character of data (repeated measurements from the same lot in different years, measurements of different lots in the same year), we assumed a pattern of inherent correlation between observations coming from the same lot *i* and the same year *j*. Under this assumption, a mixed-modeling approach is needed. The general expression for a binomial mixed model is given by

$$logit(\pi_{ij}) = \log\left(\frac{\pi_{ij}}{1 - \pi_{ij}}\right) = \mathbf{X}\boldsymbol{\beta} + u_i + v_j, \text{where } \hat{\pi}_{ij} = \frac{e^{X\beta + u_i + v_j}}{1 + e^{X\beta + u_i + v_j}} \quad (11)$$

and the expected number of dead trees in lot j in year j is given by

$$\hat{D}_{ij} = \hat{\pi}_{ij}\ N_{ij} = \frac{e^{X\beta + u_i + v_j}}{1 + e^{X\beta + u_i + v_j}}\ N_{ij} \quad (12)$$

where u_i. and v_j are unobserved random effects associated with lot i and year j, so that $u_i \sim N\ [0, \sigma_u^2]$ and $v_j \sim N\ [0, \sigma_v^2]$. Since $\hat{\pi}_{ij}$ equals the ratio $\hat{\mathbf{D}}_{ij}/N_{ij}$, it is equivalent to the predicted rate of mortality $\hat{\mathbf{M}}_{ij}$

Covariate selection

Potential covariates were divided into seven different groups (1) Stocking attributes: BA, N, SDI; (2) Composition: %_pt; (3) Maturity attributes: dg, HD, age; (4) Structure: GC_dg, Sh_dg, CV_dg; (5) Site quality: SI; and (6) Climate: annual and seasonal rainfall and water deficit, maximum temperature and mean temperature. To prevent multicollinearity, we proposed a sequential model where we first checked the inclusion of a single covariate from group (1), comparing all the possible models; therefore, we maintained this covariate in the model and selected the best covariate from group (2), and so on. Order of entrance for groups 1–5 was based on the individual correlations with mortality (see *Results* section), while group 6, focusing on temporal variation, was considered apart. Comparisons were made in terms of −2 times log pseudo-likelihood statistics, as well as the level of significance for the parameters associated with the fixed effects.

Goodness-of-fit statistics

Accuracy of the fitted model was assessed by checking the following goodness-of-fit statistics: mean error (E), level of significance for E, root mean square error (RMSE), normalized root mean square error (NRMSE, defined as RMSE divided by the range of the observed values) and modeling efficiency (EF, analogous to pseudo R^2). Concordance between observed and predicted values was assessed by fitting the model $obs = \alpha + \beta.pred$and checking whether parameters α and β do not significantly differ from 0 and 1, respectively, by means of a simultaneous F-test (Mayer et al., 1994).

Goodness-of-fit statistics were presented for the conditional prediction (including the empirical best linear unbiased predictors EBLUPs for the lot and year random effects), marginal prediction (not including random effects) and population averaged prediction (marginal prediction corrected using Gaussian quadrature method, see supplementary material S1). Once the final model was fitted, we analyzed the spatial pattern of the EBLUPs for the lot random effects, in order to identify the areas of higher probability of tree mortality, and check whether a pattern of spatial correlation remained.

All the statistical analysis were carried out using SAS® Studio STAT and IML libraries.

Results

Observed mortality in *P. pinaster* (2012–2019)

During the eight years covered by the study (2012–2019), a total of 30 254 dead *P. pinaster* trees were observed, varying from 1058

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Table 2. Temporal evolution of the total area under resin tapping, number of tapped trees at the beginning of the taping season, number of dead trees counted at the end of the season, rate of mortality

Year	Area under resin tapping (ha)	Number of tapped trees	Dead trees	% mortality
2012	1630	111 585	1058	0.81
2013	2819	185 515	1640	0.65
2014	3185	206 505	1826	0.84
2015	3389	212 616	4378	1.85
2016	4119	252 908	5019	1.76
2017	4158	249 587	7105	2.68
2018	4166	247 090	3390	1.23
2019	4110	244 210	5838	2.47
Total		**268 626***	**30 254**	**11.11**

*Obtained as the sum of the number of trees to be tapped in 2019 minus the number of dead trees counted that year, plus the number of dead trees observed during the whole period. Values in bold indicate total number of trees tapped duting th eperiod, total number of dead trees, and mean rate of mortality

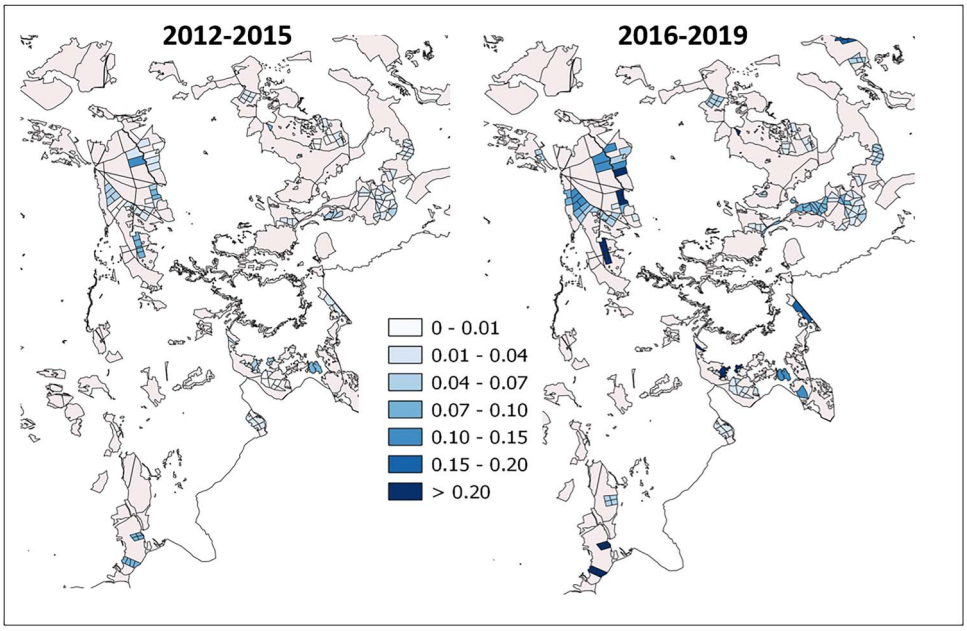


Figure 2. Observed rate of mortality at lot level. Accumulated data for 2012–2015 and 2016–2019 periods.

trees in 2012 to 7105 trees in 2017 (Table 2). The annual rate of mortality M_{ij} varied between 0.65 per cent in 2013 and 2.68 per cent in 2017, with an average value of 1.66 per cent. Moreover, the rate of mortality notably increased in the last years of the series, if compared with the first years of monitoring (Table 2, Figure 2). Assuming the total number of tapped trees in the period, given by the sum of the remnants after 2019 campaign (238 372 trees), plus the 30 254 dead trees over the whole period, we calculate an accumulated rate of mortality of 11.26 per cent. At a more local scale, Figure 2 shows the existence of lots where the rate of accumulated mortality over the eight years was above 20 per cent.

Correlation analysis

The weighted correlation analysis (Table 3) showed a positive significant correlation between the rate of mortality and the attributes related with maturity (age and mean squared diameter of both species and total) and stocking (basal area of *P. pinea* and total, and Reineke's SDI). Furthermore, the rate of mortality significantly decreased as the percentage of *P. pinaster* within the lot increased, while no significant effect of the structural diversity was detected. With respect to the climate covariates, significant positive correlations were detected between the rate of mortality and the average value of monthly mean and maximum temperatures, computed for the previous 12 months (1 October – 30 September) as well as for winter and spring seasons. Cumulative values of rainfall during the previous 12 months, as well as rainfall in the previous fall, winter and spring, were negatively correlated with mortality (thus decreased mortality). Water deficit in the previous 12 months and spring and fall seasons is negatively correlated with the rate of mortality, but note that this variable may assume positive and negative values, thus as the values for water deficit were more negative, the rate of mortality increased.

Patterns of spatio-temporal dependence

A pattern of significant positive spatial correlation for the rate of mortality was found between lots whose centroids were located up to a distance of 6000 m from one another, with a maximum of $r = 0.47$ (P-value <0.0001) for between-lot distances below 1000 m (Figure 3a). This indicated that adjacent clusters of lots tend to have similar rates of mortality in a given year and pointed to the existence of spatial factors governing the process. When testing pure temporal autocorrelation among observations from the same unit, we observed non-significant correlations ($r = -0.08$)

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Table 3. Pearson's weighted correlation coefficient r and level of significance between rate of mortality and the potential explanatory covariates

Covariate	r	P-value	Covariate	r	P-value
HD_pp	0.0374	0.5450	**Rain_12**	**−0.2461**	**<0.0001**
Age_pp	**0.1136**	**0.0653**	**Rain _fall_1**	**−0.0618**	**0.2168**
SI_pp	**−0.1248**	**0.0428**	**Rain _win**	**−0.1676**	**0.0008**
BA_pp	**0.2958**	**<0.0001**	**Rain _spr**	**−0.1406**	**0.0048**
N_pp	**0.1871**	**0.0003**	Rain _sum	−0.0741	0.1388
dg_pp	**0.1579**	**0.0057**	**Tm_12**	**0.2953**	**<0.0001**
HD_pt	0.0608	0.2428	**Tm_fall_1**	**0.1002**	**0.0448**
Age_pt	**0.1012**	**0.0516**	**Tm_win**	**0.1992**	**0.0001**
SI_pt	−0.0477	0.3601	**Tm_spr**	**0.2470**	**<0.0001**
BA_pt	0.0668	0.1995	Tm_sum	0.0368	0.4622
N_pt	**−0.1066**	**0.0401**	**Tmax_12**	**0.2883**	**<0.0001**
dg_pt	**0.1720**	**0.0009**	Tmax_fall_1	0.0285	0.5696
%_pt	**−0.2527**	**<0.0001**	**Tmax_win**	**0.2046**	**<0.0001**
BA_tot	**0.3016**	**<0.0001**	**Tmax_spr**	**0.2603**	**<0.0001**
N_tot	0.0804	0.1226	Tmax_summ	0.0525	0.2939
dg_tot	**0.1459**	**0.0049**	**Def_12**	**−0.2496**	**<0.0001**
SDI	**0.2845**	**<0.0001**	Def_fall_1	−0.0264	0.5974
GC_dg	−0.0179	0.7305	**Def_win**	**−0.1697**	**0.0006**
Sh_dg	0.0656	0.2078	**Def_spr**	**−0.1899**	**0.0001**
CV_dg	−0.0455	0.3826	Def_summ	0.0057	0.9089

Note: _pp, _pt and_tot refer to *P. pinea*, *P. pinaster*, and both species jointly; rain: accumulated rainfall, Tm: mean temperature; Tmax: mean maximum temperature; win: winter; spr: spring; sum: summer; fall_1: fall season of the previous year; _12 refer to the period between 1st October previous year – 30th September current year. Rest of symbols as defined in the text. In bold significant (*p*-value <0.10)

at a temporal lag of one year, but significant negative correlation (r = −0.47) for the observations separated by 4 years (Figure 3b). This lagged behavior may be an artifact associated with the steep increase in the mortality rate observed in the last years of the series and the short length of the series (8 years). Finally, analysis of the spatiotemporal dependence among different lots at a temporal lag of 1 year showed a general non-significant correlation at all distances (Figure 3c), indicating non-significant spread-propagation patterns.

Model for annual rate of mortality at landscape scale

The sequential procedure for constructing the model is included in Table 4. After a preliminary fit of the model a significant pattern overdispersion was detected, thus and observation-level random effect (OLRE) was included into the sequential procedure and the final fit (Harrison, 2015). The final selected model (Table 5) includes the total basal area (sum of the basal area for *P. pinaster* and *P. pinea*), mean squared diameter of *P. pinaster*, the percentage of *P. pinaster* within the lot and the average value of mean maximum temperature of the previous twelve months as covariates. The parameter estimates show that the expected rate of mortality increases in those lots with larger total basal area, larger mean squared diameter of *P. pinaster* and lower proportion of *P. pinaster* and that mortality increases in the hotter years (mean annual maximum temperature over 20°C). Covariates characterizing structural diversity or site quality were not included in the final model.

Goodness of fit statistics indicate that, with a 95 per cent confidence, we cannot reject the null hypothesis for mean error E = 0 for both the conditional (including lot and year EBLUPs) and the population-averaged responses (Table 6). Population averaged response (corrected by Gaussian quadrature) reaches a modeling efficiency EF over 0.2325 and a RMSE below 0.019. The concordance analysis based on F simultaneous test (F-conc) revealed no significant (*P*-value F > 0.01) differences between observed and predicted for the population-averaged responses. The results evidence the effectiveness of applying the adaptive Gaussian quadrature correction over marginal responses in mixed models involving non-linear functions.

Table 4. Sequential procedure for model construction

Step	Covariate	− 2log pseudo_lik	Step	Covariate	− 2log pseudo_lik
0	**Interc**	**1081.1**	**6**	Rain_12	990.72
1	**BA_tot**	**989.67**		Rain _fall_1	992.53
	BA_pp	992.64		Rain _win	991.83
	BA_pt	999.32		Rain _spr	993.98
	N_tot	1003.56		Rain _sum	992.60
	N_pp	1002.90		Tm_12	978.61
	N_pt	1005.07		Tm_fall_1	nc
	SDI	997.22		Tm_win	984.83
2	**%_pt**	**982.32**		Tm_spr	nc
3	dg_tot	985.36		Tm_sum	984.81
	dg_pt	**981.50**		**Tmax_12**	**976.45**
	age_pt	989.60		Tmax_fall_1	989.91
	HD_pt	985.47		Tmax_win	983.77
4	Shan_dg	985.12		Tmax_spr	nc
	Gini_dg	979.57		Tmax_summ	985.23
	CV_dg	981.22		Def_12	990.01
5	SI_pt	988.28		Def_fall_1	992.58
				Def_spr	993.69
				Def_summ	992.90

Note: Though in step 4 a decrease in -2log pseudolikelihood was observed after entering Gini-dg, the parameter estimate was not significant (*P*-value: 0.34). nc indicates no convergence of the model. In bold the covariate selected at each step.

Checking for residual spatial correlation

Mapping the predicted EBLUPs for the random lot effect (Figure 4) shows that once the influence of the fixed effects was discounted it is possible to identify areas with expected higher (positive values of the EBLUP) rates of mortality. These areas are mainly located

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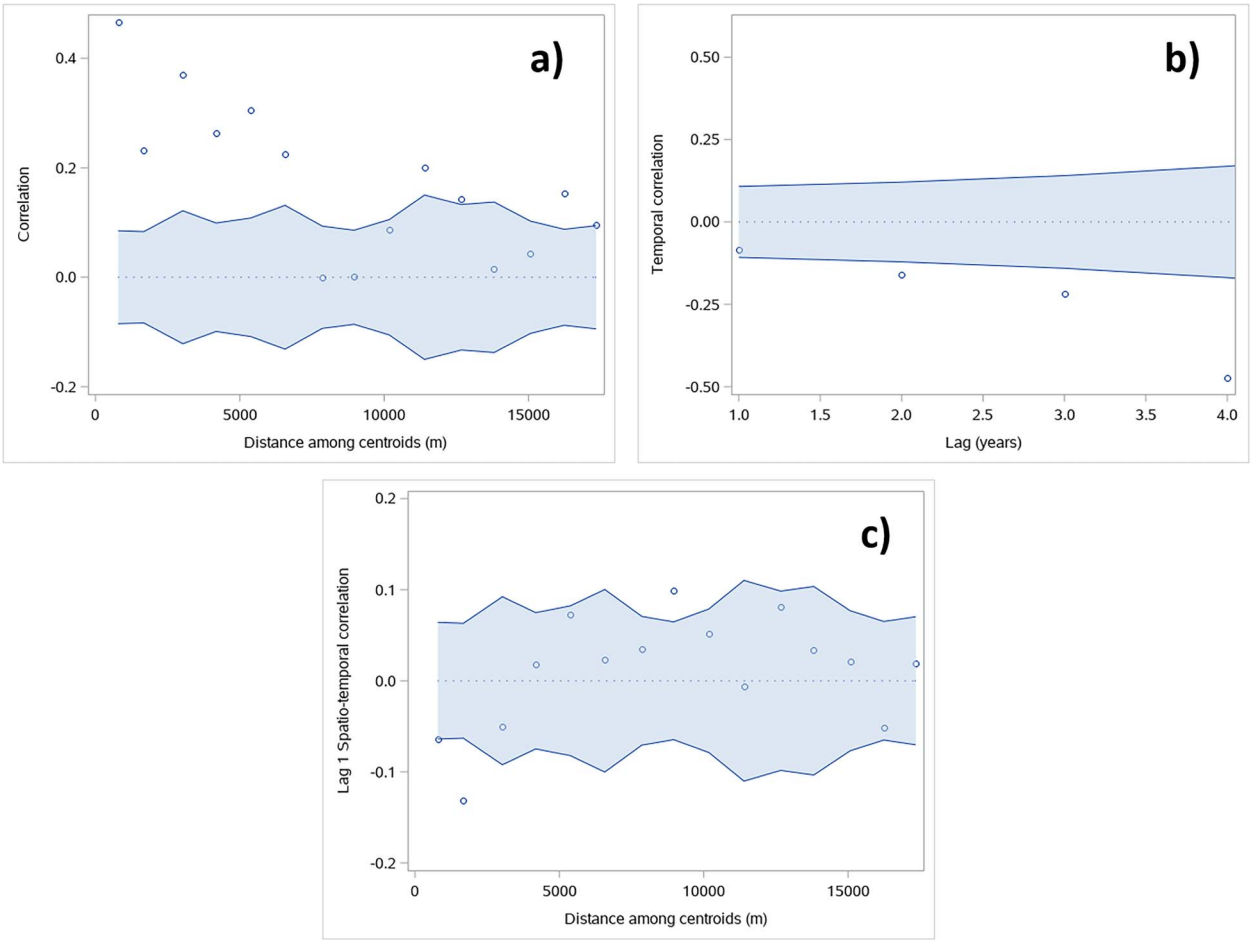


Figure 3. Patterns of spatial (a) temporal (b) and lagged 1 spatio-temporal correlation (c) observed in the studied lots. Dots indicate observed correlations ρ according to Eq. [6], and bands indicate the 95 per cent confidence interval for the null hypothesis ρ =0.

Table 5. Parameter estimates for the linear predictor (terms Xβ in Eqs. [11] and [12]) and variance components of the selected model

		Estimate	Std_error	t – statistic	P-value
Fixed effects	Intercept	−16.1992	2.4108	−6.72	0.0005
	BA_tot	0.0699	0.0269	2.60	0.0097
	dg_pt	0.0388	0.0204	1.90	0.0581
	%_pt	−1.4957	0.4807	−3.11	0.0020
	Tmax_12	0.5392	0.1197	4.50	<0.0001
Variance components	Year	0.0475	0.0348		
	Lot	0.6421	0.1419		
	Observation	0.4711	0.0439		

in the western part of the territory. An analysis of the spatial correlation among the expected EBLUPs for the lot effect (Figure 5) shows that most of the initial spatial correlation in Figure 3a has been captured by the fixed effects of the model, with a significant spatial correlation remaining up to distances of 1500 m.

Discussion

The recently observed phenomena of drought-related forest decline and dieback can be assessed and analyzed using various methodological approaches and spatio-temporal scales (Moreno-Fernández et al., 2021). In the present study, we analyze and model the process of dieback and mortality in *P. pinaster* in inland Spain using operational data collected by the forest service, which is suitable for the purpose of forest disease detection although it originally was not collected for this purpose. When compared with other methods, such as dendrochronological analysis (Gazol et al., 2020), monitoring of permanent plots (Carnicer et al., 2011), remote sensing (Neigh et al. 2014) or citizenship science (Crow et al., 2020), our approach presents certain advantages. First, our method covers a wide, continuous area and is based on a direct counting of dead trees, thus both quantification and spatial assessment of the problem can be carried out with low levels of uncertainty. Second, it is based on annual monitoring, thus allowing temporal (weather) factors triggering the process in a given year to be identified. Third, monitoring is carried out every year by professional workers in

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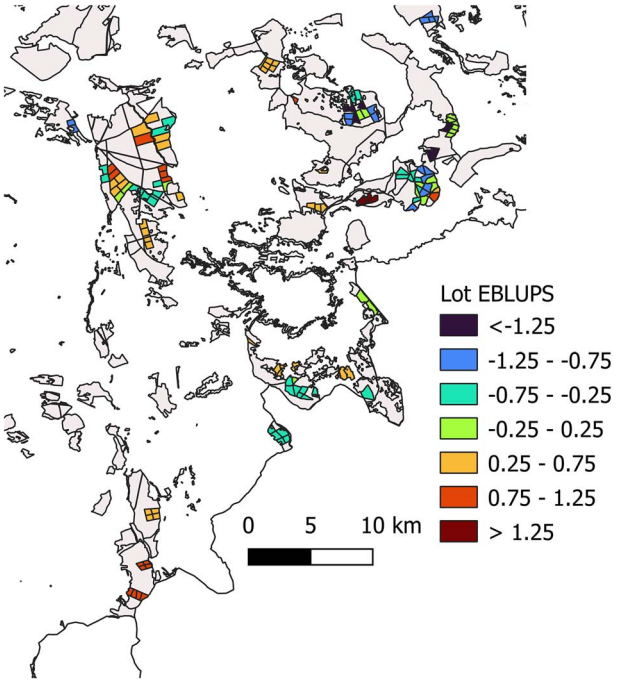


Figure 4. Map for the predicted values of the EBLUPs for the random lot effect. Positive values indicate rates of mortality larger than the expected value given by the fixed effects model.

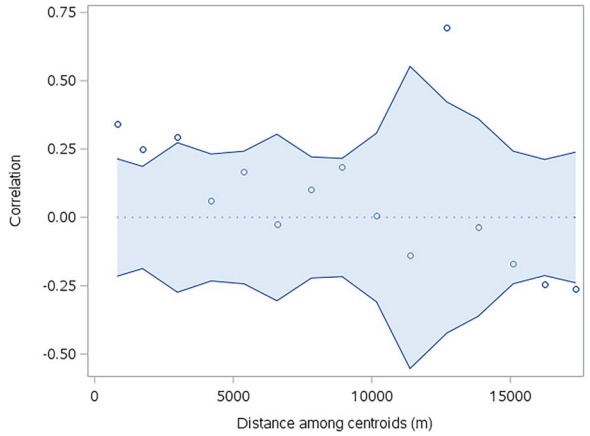


Figure 5. Patterns of spatial correlation for the EBLUPs of the lot random effect. Dots indicate correlation ρ according to Eq. [6], and bands indicate the 95 per cent confidence interval for the null hypothesis $\rho = 0$.

accordance with a homogenous protocol, thus observational biases are avoided. Taking these advantages into consideration, the evaluation and potential of forest operation data use in research work is a practice that should generally be encouraged.

However, our approach also has some disadvantages. On the one hand, the analyzed lots only include areas where resin tapping is actively taking place, i.e. managed stands with trees in intermediate age classes (50–100 years old). This means that stands where higher mortality might be expected (young pole-stage, extra-mature or unmanaged stands) are not included in the sample. Thus, the real impact of the decline and mortality processes could be even higher. On the other hand, only resin-tapped trees (larger than 30 cm) were monitored, so within the studied stands mortality rates could also be greater than estimated. As our experimental design has obvious limitations with

Table 6. Goodness of fit statistics for the selected model

	Conditional	Marginal	Population averaged
E	0.00034	0.00582	−0.00169
P-value	0.5994	<.0001	0.0847
RMSE	0.0125	0.0198	0.0188
EF	0.6603	0.1497	0.2325
NRMSE (%)	9.34	14.79	14.05
F_conc	16.2682	13.6360	4.2412
P-value F	<0.0001	<0.0001	0.0151

regard to the effect of resin tapping, future studies should focus on monitoring resin vs non-resin forests.

Our approach has allowed us to make an accurate assessment of the incidence of *P. pinaster* mortality in the Northern Plateau and to analyze the spatio-temporal trends of the process. We have detected the existence of a recent, generalized and expanding phenomenon of dieback and tree mortality in *P. pinaster* forests throughout the study area. This finding agrees with those of previous studies undertaken in the same area (Gordo et al., 2020; Prieto-Recio et al., 2015), but also with studies carried out in other areas of Spain (Genova et al. 2014; Gea-Izquierdo et al., 2019; Navarro-Cerrillo et al., 2018), including tapped and non-tapped stands. However, as far as we know, this is the first time that a quantitative estimate of the real incidence of the process at regional scale has been provided.

Predisposing and inciting factors controlling *P. pinaster* mortality

The exploratory correlation analysis and the modeling approach showed that in our study area the rate of mortality in a given lot is largely and positively correlated with traits defining stand stocking (such as basal area or Reineke's stand density index) and, to a lesser extent, with those defining stand maturity (age, mean squared diameter and dominant height). There is widespread consensus that high stand density and therefore competition for resources is one the main predisposing factors for tree decline and mortality (Dietze and Moorcroft, 2011). The effect of stand density has previously been highlighted not only in *P. pinaster* forests (Bravo-Oviedo et al., 2006; Madrigal-González and Zavala, 2014; Moreno-Fernández et al., 2021) but also in other Mediterranean forests (Camarero et al., 2011; Sánchez-Salguero et al., 2012) or temperate forests (Condés and del Río, 2015; Etzold et al., 2019). In addition, competition in dense stands may increase the susceptibility of trees to long-term water stress (Dietze and Moorcroft, 2011; Gea-Izquierdo et al., 2014) and therefore to forest decline and mortality.

The effect of size age on tree vulnerability, however, is less clear, with contradictory findings for different species (Dietze and Moorcroft, 2011). Mortality models often reveal a U-shaped pattern of mortality probability with increasing tree size (Monserud and Sterba, 1999), indicating greater mortality rates in younger and older stages. Our results reflect the right branch of this U-shaped pattern (increasing mortality with larger tree diameters), although the left (decreasing) branch cannot be captured as young stands were not included in the sampling. Results of previous studies on *P. pinaster* have identified lower vulnerability in larger trees (Prieto-Recio et al., 2015; Férriz et al., 2021) or no effect of age on tree vulnerability (Gea-Izquierdo et al. 2019). However, in a study conducted in the same region as our study (Valladolid

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province), Vergarechea et al. (2021) identified lower resistance and greater sensitivity to drought in older and larger trees due to higher hydraulic constraints observed in larger trees (Cavender-Bares and Bazzaz, 2000). These heterogeneous results may indicate a synergic effect between age and other predisposing factors, such as stand density or soil type (Vieira et al., 2009).

Our results also indicate that *P. pinaster* mortality is attenuated in pure stands compared with *P. pinaster P. pinea* mixed stands. Thus, pure *P. pinaster* stands are healthier than mixed stands. This result also agrees with the findings of previous studies indicating that *P. pinea* is better adapted than *P. pinaster* in the territory, displaying greater capacity to compete for belowground resources (Prieto-Recio et al., 2015; Vergarechea et al., 2021). This leads to a clear displacement of *P. pinaster* in those areas where both species grow in mixtures and is likely to result in the transformation of these areas into pure *P. pinea* stands in the long term (Gordo et al., 2020; Férriz et al., 2021). Our understanding of the effects of mixing two or more species on mortality is still limited, but the few studies focusing on this issue suggest that negative effects (at least for some of the species that make up the stand) are frequent (Condés and del Río, 2015; Zhao et al., 2006; Searle et al., 2022). In contrast, we have found no significant effect of the structural heterogeneity on the rate of mortality.

While stand stocking, maturity or composition can be considered predisposing factors, certain climatic events, such as extreme or recurrent droughts and heatwaves, commonly act as inciting factors for the widespread phenomena of forest decline and mortality observed in recent decades (Peñuelas et al., 2001; Allen et al., 2010). We identified strong seasonal dependence between mortality and drought temperature, with warmer and drier winter and spring conditions resulting in higher rates of mortality, as also reported by Navarro-Cerrillo et al. (2018). *P. pinaster* is considered a drought-avoiding species, which may cope with a single intense drought event, but not with recurrent droughts (Madrigal–González and Zavala, 2014). Current episodes of mortality may be linked not only with the impact of a single drought year, but with previous droughts inciting a medium-term tree-growth decline trend, resulting in leaf reduction, low C uptake, general weakening and an alteration in host–pathogen relationships (Gea-Izquierdo et al., 2019; Férriz et al., 2021). Extreme climate events may then act as both predisposing and inciting factors of mortality in the species (Prieto-Recio et al., 2015). Our data evidence a significant increment in the observed rate of mortality during the extremely dry years of 2015 and 2017, but also reveal that these effects persisted during the subsequent years.

Spatio-temporal model of *P. pinaster* mortality

The identification of predisposing and inciting factors formed the basis for constructing our spatio-temporal model to forecast the rate of mortality for a given lot in a given year. According to the model, the rate of mortality in *P. pinaster* is expected to increase in denser, older (i.e. larger mean size) and mixed lots, especially in the hottest years. Our model permits unbiased estimates of the annual rate of mortality to be obtained, with modeling efficiency over 24 per cent, providing the first landscape scale model for predicting mortality of the species.

When analyzing the spatial pattern over the raw data (Figure 3a), we detected a positive spatial correlation up to distances of 6 km, indicating that lots located up to this distance apart tend to show similar levels of annual mortality. This distance is similar to the extension of a forest management group (commonly 5000–10 000 hectares), which comprises adjacent forests sharing the same management plan. However, when other spatially correlated management-related traits are taken into account in the model (basal area, mean squared diameter or the percentage of *P. pinaster* in the mixture), spatial correlation is only significant for distances below 1.5 km. This indicates the existence of a non-controlled spatial attribute affecting mortality which acts at these smaller scales. This finer-scale variability may be linked to soil characteristics (Prieto-Recio et al., 2015; Navarro-Cerrillo et al., 2018) or even water-table depth. Gómez-Sanz and García-Viñas (2011) identified a significant relationship between soil characteristics (water holding capacity, pH and cation exchange capacity) and probability of mortality. Mantas et al. (2022), using remote sensing, not only identified the existence of a spatial pattern of clustering in declining *P. pinaster* trees at similar spatial scales but also detected hotspot areas for tree mortality. In this regard, Figure 5 evidences that, once the effect of the covariates entering the model is discounted, hotspots of higher mortality are observed in the western part of the region, mainly dominated by soils with a higher sand content and lower water holding capacity.

The analysis of the temporal and the spatio-temporal patterns of mortality (Figure 3b,c) show that there is no significant relationship between 1-year lagged observations, either for the same or for adjacent location. This result may indicate that each year mortality is triggered by independent events, not showing a pattern of contagion or spread over time. This may support the hypothesis that the main causality is that of abiotic stressors (climate events) rather than biotic ones (Prieto-Recio et al., 2015; Férriz et al., 2021).

Conclusions

The present study evidences the high vulnerability of *P. pinaster* forests to predisposing and inciting abiotic stressors. Our proposed approach permits a quantitative assessment at a wider spatial scale of the real incidence of the decline and dieback in the species, which in some areas has reached 20 per cent of the trees over an 8-year period, which is well above what can be considered baseline mortality. If these rates of mortality continue over time, as might be expected under the severe, drier and warmer climate scenarios forecasted for the territory, there is a severe risk that forests currently dominated by *P. pinaster* will suffer transformation into mixed *P. pinaster-P. pinea* forests in the short to medium term (Gea-Izquierdo et al., 2019; Gordo et al., 2020). The greater competitive capacity and resistance to drought of *P. pinea*, and the observed failure of *P. pinaster* natural regeneration in the region (Vergarechea et al., 2019) support this hypothesis.

Given the recent resurgence of commercial interest in resin tapping (Soliño et al., 2018) at national and international level, this forecasted reduction in the area occupied by the species in the territory may result in severe economic losses. In order to preserve these forests and their associated provision of ecosystem services, forest managers need to develop new adaption strategies to cope with expected scenarios. Our study provides some indications for such strategies, which should focus on applying intensive thinnings, not extending rotation lengths and promoting the conservation of pure stands of *P. pinaster* by controlling the emergence of *P. pinea* in the understory. Moreover, our modeling approach allows us to identify the most favorable areas for the species, where the aforementioned practices should be prioritized. In contrast, forest management in areas which are identified as being less favorable for the species should focus on ensuring the substitution of the species by the better adapted *P. pinea*.

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This study shows the potentiality of using data from forest management inventories and harvesting statistics to analyze and model the spatial and temporal spread of forest decline and dieback. This approach permits a continuous and homogenous inventory across a large region. However, there are certain limitations with this approach. First, only resin-tapped areas where *P. pinaster* is the dominant species and where there is a sufficient number of trees to make resin tapping a profitable activity are included in the survey. A second important constraint is that other contributing biotic factors (mistletoe or pathogenic fungi) have not been considered in the analysis. Finally, as only dead trees are considered in the monitoring, the method is not suitable for early warning detection of the processes of decay. Future research should focus on improving the monitoring system to embrace these issues.

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Authors' contributions

Rafael Calama (conceptualization, formal analysis, funding acquisition, methodology, writing – original draft), César Martinez (data curation, methodology, validation, writing – review and editing), Javier Gordo (data curation, methodology, supervision, writing – review and editing), Miren Del Rio (conceptualization, methodology, Writing – review and editing), María Menéndez-Miguélez (formal analysis, methodology, software, writing – review and editing), Marta Pardos (conceptualization, formal analysis, funding acquisition, project administration, writing – review and editing).

Conflict of interest statement

None declared.

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Supplementary data

Supplementary data are available at *Forestry* online.

Data availability

The data underlying this article were provided by Servicio Territorial de Medio Ambiente de Valladolid, Junta Castilla y León, by permission. Data will be shared on reasonable request to the corresponding author with permission of Junta de Castilla y León.

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