

Nationwide climate-sensitive models for stand dynamics and forest scenario simulation

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ABSTRACT

Projecting forest dynamics as a function of alternative management strategies and climatic conditions is key to develop sound forest policy and management planning. In Spain there is a need for a full set of climate-sensitive individual-tree growth and yield models suitable for country-level simulations. In this paper we present environmentally driven models for forest stand dynamics based on distance-independent individual-tree growth and yield. The data for model calibration are based on the second, third and fourth surveys of the Spanish National Forest Inventory, including 50,359 plots and 838,620 trees, representing a broad gradient in forest types and environmental conditions. The results develop a total of 182 models for diameter increment, height increment, total height, survival and ingrowth for 27 species and species groups. The models are integrated into a full forest projection system to perform simulations of forest dynamics and resulting changes in the provision of ecosystem services, including the effects of climate, and forest management. Its potential is illustrated through an array of simulations of forest dynamics in the region of Catalonia under alternative climatic and management scenarios. The resulting models and projections provide a solid basis for the simulation of national or regional climate-sensitive forest scenarios, with the possibility of being applied to other regions, and may be used for future management and planning efforts.

1. Introduction

Forest planners and managers are expected to make decisions complying with an increasingly diverse array of objectives, while considering uncertainties related to health and condition, biotic (insects and pathogens) and abiotic (wildfire, storms, avalanches, landslides, etc.) risks, both under current and projected climate (Yousefpour and Hanewinkel 2016). To address this complexity, they need quantitative tools that use the current state of forests as a starting point and project mid- and long-term consequences of alternative management strategies while including multiple sources of uncertainty.

Growth and yield models have a long history of development and can be broadly divided into statistical and process-based, although hybrid approaches also exist (Weiskittel et al. 2011). Process-based models emulate physiological and biophysical processes and are better suited to understand the behaviour of forest systems. However, statistical models are easier to develop, apply at larger scales, and are often preferred

when computational power is limited or the ability to unbiasedly predict forest development and yield over time is deemed important (Trasobares et al. 2016). Among statistical approaches, tree-level models consider individual trees as the basic unit for simulating growth, mortality and ingrowth processes (Wykoff 1990; Monserud and Sterba 1996; Trasobares et al. 2004b, a; Adame et al. 2008), which enables a more detailed and flexible description of stand structure, composition, and simulation of alternative management treatments than stand-level models (Weiskittel et al. 2011, Trasobares et al. 2016). Tree-level models can be further divided into distance-dependent (which require explicit tree spatial coordinates) and distance-independent (which operate assuming an average spatial pattern of individuals). Distance-independent models have similar predictive performance and are less computationally demanding than distance-dependent ones (Wimberly and Bare 1996). Therefore, they have often been the preferred choice to develop inventory-based forest projections systems (Monserud and Sterba 1996; Hynynen et al. 2002; Dixon 2013).

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Thanks to the systematic sampling design of national forest inventories, forest projection systems built from permanent plot data have a great potential for simulating forest development as a function of management and environmental factors at large scales. Several countries have already developed inventory-based forest projection systems that facilitate the assessment and projection of wood resources, and allowable cut levels and other ecosystem services, by combining inventory surveys with simulated projections (Monserud and Sterba 1996; Hynynen et al. 2002; Dixon 2013; Barreiro and Tomé, 2017), Stadelmann et al. 2019). In Spain, several growth and yield models exist to simulate forest dynamics, often focused on single species stand level simulations; however, suitable tools for multi-species country-level simulations are still lacking (Condés et al. 2017). Developing a forest projection simulation system for Spain would certainly be a great step forward, as it would allow: (a) evaluating the effect of alternative forest policies at several territorial levels; (b) estimating the effect of particular management decisions on the sustainable availability of forest biomass, the carbon source/sink role of forests and on a range of other forest ecosystem services (e.g. water provision, biodiversity conservation); and (c) continuously updating forest inventory estimates before new surveys are available.

During the last decade, developments in stand-level and tree-level statistical models have often focused on the explicit inclusion of climatic explanatory variables (temperature, precipitation, drought indices, etc.) because sensitivity to climate is important to evaluate climate change effects (Laubhann et al. 2009; González-García et al. 2015; Trasobares et al. 2016; Zeng et al. 2017; Rohner et al. 2018; Zell 2018), or alternative modelling approaches (Crokston et al. 2010). However, temporal replicates of national forest inventories are often limited to two or three surveys and, hence, climatic effects are mainly calibrated from observed spatial climatic variation, which leads to the challenge of disentangling climatic influences from other environmental factors affecting spatial variation of forest dynamics (Gómez-Aparicio et al. 2011; Rohner et al. 2018).

Here, we present the calibration and evaluation of a set of tree-level distance-independent growth models for stand dynamics: diameter and height increment, static height, tree mortality and ingrowth, for 27 tree species and species groups. The models developed are climate- and management-sensitive, and the available data in Spain represent a broad gradient in forest, management and environmental conditions. Ingrowth is modelled either including or not the spatial contagion from nearby forest plots. The aim of the model is to include the temporal variation of forest standing biomass over a given period and under alternative climate and management scenarios. Finally, the models are structured in a forest projection system, where management scenarios can be defined using a demand-based approach.

2. Material and methods

2.1. Data sources

The data was based on the permanent plots of the Spanish National Forest Inventory (NFI) corresponding to the second (yrs. 1986–1996), third (yrs. 1997–2007) and fourth (started in 2008) editions (see Villalencusa and Díaz 1998; Villanueva 2004). Plots of the Spanish NFI are located at the nodes of a 1-km square grid and consist of four concentric circular subplots of 5, 10, 15 and 25 m radius, where diameters and heights of trees of 7.5–12.5, 12.5–22.5, 22.5–42.5 and > 42.5 cm of diameter at breast height (dbh), respectively, are measured and recorded. For each of the two periods (NFI2–NFI3) and (NFI3–NFI4) we selected permanent forest plots with at least 10% of forest cover and presence of trees with dbh over 7.5 cm in the final survey, and with geographic coordinates determined at < 100-m precision. These criteria resulted in 50,359 and 21,987 plots selected for the NFI2–NFI3 and NFI3–NFI4 periods, respectively, entailing a total of 838,620 and 514,460 tree measurements, for the same periods respectively. The

lower number of plots for the second period is explained by the fact that the NFI4 is not finished for all the Spanish provinces (Fig. 1).

2.2. Species selection and explanatory variables

Growth and yield models were developed for a set of 27 individual species and species groups: the tree species most abundant in the Spanish territory (e.g., *Pinus sylvestris*, *Pinus halepensis* or *Quercus ilex*) or in particular regions (e.g., *Pinus canariensis* in the Canary Islands) were considered as 11 separate target entities, whereas less frequent species were grouped into 16 species groups, according to taxonomic and functional criteria (see Appendix A).

Concerning the explanatory variables (see Appendix B), we included variables related to tree-size, forest structure, competition and growth as well as environmental predictors to assess the overall growth conditions. For the tree-related forest descriptors, we used several scalar transformations (square, squared root, natural logarithm, inverse) of the initial tree diameter (d ; cm) and height (h ; m) as explanatory variables. To describe competition, stand basal area (G ; $\text{m}^2\cdot\text{ha}^{-1}$) and stand density (N ; $\text{ind}\cdot\text{ha}^{-1}$) were used to represent symmetric competition for resources, whereas basal area of larger trees (BAL ; $\text{m}^2\cdot\text{ha}^{-1}$) was used as an indication of asymmetric competition. The standard deviation of the plot diameter distribution ($SD(d)$; cm) was used as an indicator of the forest structure. Past growth was used as an indicator of tree vigour in survival models. The cumulative basal area of the extracted trees of larger size (BAL_{exi} ; $\text{m}^2\cdot\text{ha}^{-1}$) was assumed to represent the release of competition derived from silvicultural actions during the evaluated period. The stand variables were either used directly or after scalar transformations. Explicit *competition-tree size* (e.g. $BAL/\ln(dbh + 1)$ in Eq. (1)) or *past growth-tree size* (see Eq. (3)) interaction factors were used as well for improved biological consistency and accuracy.

For the environmental explanatory variables, we considered both static and dynamic predictors. The static predictors included: (a) elevation, slope, aspect, (b) soil water holding capacity (SWHC; mm) and (c) potential radiation (Rad; $\text{MJ}\cdot\text{m}^{-2}$). The dynamic environmental explanatory variables were calculated for the two periods available and included: (a) temperature (T ; $^{\circ}\text{C}$) and precipitation (P ; $\text{mm}\cdot\text{yr}^{-1}$), (b) potential evapotranspiration (PET; $\text{mm}\cdot\text{yr}^{-1}$) and (c) moisture index (PPET).

The static environmental variables were based on topographic variables, obtained from a digital elevation model at 100 m resolution from the Spanish *Instituto Geológico Nacional*, on soil data (texture, organic matter and bulk density) corresponding to plot coordinates obtained from the SoilGrids global database at 250 m resolution (Hengl et al. 2017), and the soil depth estimates (up to 2 m) were obtained from Shangguan et al. (2017). We used Saxton pedotransfer equations (Saxton and Rawls 2006) to estimate the water retention curve and the SWHC was calculated as the difference in soil water volume between field capacity (~ 33 kPa) and permanent wilting point (~ 1500 kPa), taking into account the soil volume occupied by rocks, estimated from plot surface percent rock values available from the NFI3. Finally, the average daily potential radiation accounting for topographic (slope and aspect) effects was first calculated at the daily scale for each forest plot and the 1981–2015 period (chosen to encompass the three inventory surveys) using the R package ‘*meteoland*’ (De Cáceres et al. 2018), averaged to the monthly scale and finally averaged across the whole 35-yr period.

The dynamic environmental variables were based on monthly temperature and precipitation data at 0.1° (~ 10 km) resolution for the Iberian Peninsula and corresponding to the 1981–2015 period obtained from Herrera et al. (2016). The temperature values were corrected by elevation difference between the target plot and the corresponding grid cell (with a lapse rate of -0.6°C for every 100 m). The mean annual precipitation and mean annual temperature were calculated for the NFI2–3 and NFI3–4 periods (Rohner et al. 2016), using the sampling years of each plot to define them. In the case of the Canary Islands, climatic monthly averages were taken from the WorldClim2 database

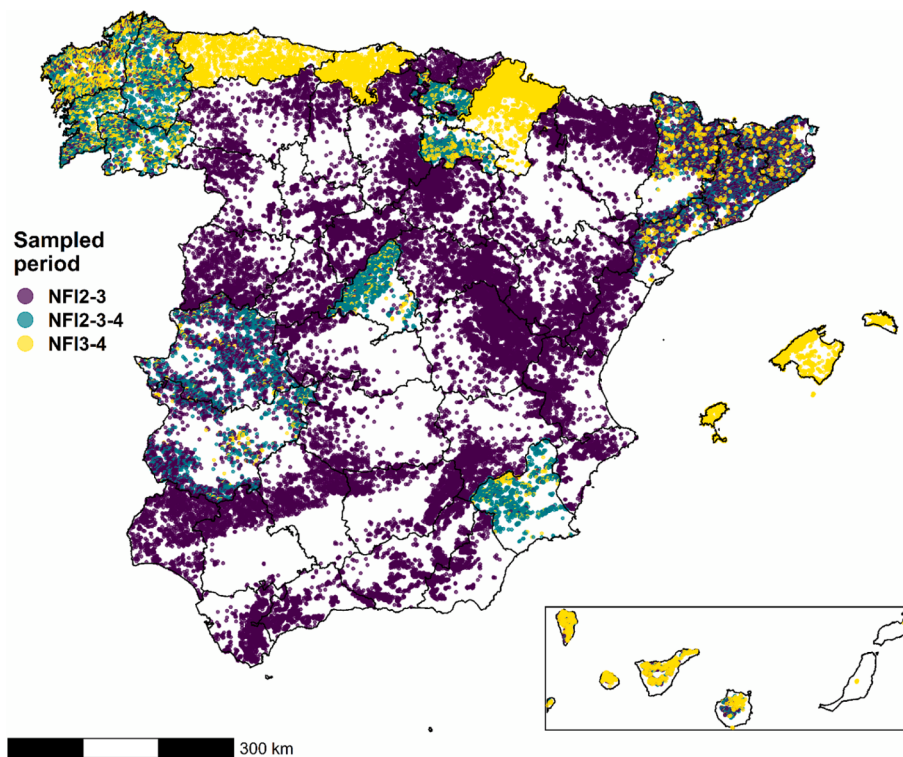


Fig. 1. Location of the national forest inventory (NFI) plots included in the models. The data included 50 359 and 21 987 plots selected for the NFI2-NFI3 and NFI3-NFI4 periods resulting in 838,620 and 514,460 tree measurements, for the same periods respectively.

(Fick and Hijmans 2017), which does not account for interannual variation. We modified the mean annual temperature to $Temp15sq$, being $(T - 15)^2$, to ensure a unimodal relationship with the response variables. The monthly PET was calculated from monthly temperature and monthly potential radiation values using the Hargreaves method, available in the R package 'SPEI' (Beguería and Vicente-Serrano 2013). Monthly PET values were aggregated at the annual scale and averaged over the NFI2-3 and NFI3-4 periods. Finally, the *moisture index* ($PPET$) was estimated by the ratio of the mean annual P to mean annual PET as a suitable measure of average drought intensity during each period.

Preliminary results indicated that the explanatory factors initially included were not sufficient to model the observed variation in plot basal area, with apparent spatial autocorrelation in the residuals and poor model performance in some areas. Hence, we considered the addition of the 50 Spanish provinces as well as the regions of provenance as dummy spatial explanatory variables to improve model fit and decrease the spatial autocorrelation of the residuals. The regions of provenance are defined as areas where ecological features are meant to be homogeneous. These regions were considered only for those species where provenance maps were available and generated following an agglomerative procedure (see definition and maps in Alía et al. 2009).

2.3. Diameter and height increment models

We adjusted the observed diameter and height increments to represent 10-yr increments using the actual time span between repeated plot measurements. Since height was measured with a lower precision in the NFI2 compared to NFI3 and NFI4, we used the NFI3-4 period only for the calibration of HI models, which entailed that the available records were not enough to properly fit models for some species or species groups (we required a minimum sample size of 200); for solving this, static height models were fitted as well for all species and species groups.

Given the sampling design of the Spanish NFI, we first fitted log-linear mixed models for each species considered, with plot identity and measurement period as random effects. Models were fitted using the

package 'lme4' (Bates et al. 2015) from the R statistical software v 4.0.2 (R core team, 2020). Starting from a pure random effect model, we tested specific combinations of transformations of tree-related variables, according to previous experience with similar models (Trasobares et al. 2004a), which allowed avoiding multicollinearity problems. We then considered the sequential addition of stand explanatory variables. Finally, once the model included tree and stand variables, we considered the addition of static and dynamic environmental factors. The models took the general form:

Diameter increment:

$$DI = e^{(x\beta + \mu_p + \mu_t + \varepsilon)} \quad (1)$$

Height increment:

$$HI = e^{(x\beta + \mu_p + \mu_t + \varepsilon)} \quad (2)$$

where X is the final combination of variables with their respective coefficients, and μ_p and μ_t represent the between-plot and the between-inventory effect, respectively, whereas ε stands for the remaining residual, assuming a normal distributed error with mean = 0. The variables were tested using the ANOVA tests of the package 'lmerTest' (Kuznetsova et al. 2017). The final combination of variables for each model had to be significant at the 0.05 level, contribute to the explanatory power of the model, and the resulting model should show no systematic bias in the predictions. In addition, we required the coefficients to be biologically consistent (Trasobares et al. 2004b, 2016): the overall effect of the initial d (respectively, h) on diameter (resp. height) increment had to be unimodal, whereas the coefficient of competition (G or BAL) had to be negative, and that of the extracted trees (BAL_{ext}) positive, for a 10-year period. Concerning the environmental predictors, $SWHC$, and $PPET$ were required to have positive coefficients, whereas $slope$ and $Temp15sq$ were required negative, the first having a negative effect on growth and the latter to ensure a convex relationship.

After fitting log-linear mixed models, we considered the addition of spatial predictors to address the part of the variation not explained by

the models. To preserve the modelling structure of the tree, stand and environmental variables already included we fitted generalized linear models (GLM) with Gamma response and log link function to the same observed data, using the prediction of the log-linear model in the log-space without random effects, X , as an offset (i.e., a constant). In this case, we started the selection of spatial explanatory variables with a full model, from which province and region of provenance dummy variables were sequentially eliminated by backward selection using chi-square likelihood ratio tests.

2.4. Survival models

We aimed to model tree mortality related to stand density and structure, known as *background* or *regular* mortality, as opposed to *disturbance-induced* or *irregular* mortality (i.e., due to insect outbreaks, wildfires, wind or extreme drought). Hence, we defined a threshold of 10% reduction in basal area between NFI surveys as indicator of disturbance-induced mortality, and plots exceeding this value were excluded from the mortality calibration dataset.

As for the increment models, tree and stand explanatory variables were first selected and environmental variables were added according to maximum-likelihood ratio tests; also in this case, the model coefficients were evaluated for biological consistency. In addition to these predictors, a tree viability variable was included, based on past growth (based on Bigler and Bugmann 2004; Trasobares et al. 2016; Hülsmann et al. 2018), for those areas where NFI4 was completed and presented enough observations (we defined a minimum threshold of 400 records and 10 observed deaths). The variable was defined as:

Past tree growth:

$$\ln DI_{prev} = \frac{\ln(DI_{prev} + 1)}{\ln(d + 1)} \quad (3)$$

where we calculate the logarithm of the diameter increment in the NFI2-3 period (defined as DI_{prev}) divided by the logarithm of the tree diameter at the NFI3 (defined as d) representing the relative growth rate.

A version of the base model and an alternative including past tree growth were fitted using GLM with binary response (marking the tree as dead = 0 and alive = 1) and a logit link function.

2.5. Local ingrowth models

We developed models to predict the density amount of regeneration and the average mean diameter of local ingrowth (new tree records of > 7.5 dbh recorded in the sub-plot of 5-m radius). The models for the density amount of ingrowth were developed in two steps (Bravo et al. 2008): in the first step aimed at predicting the incidence of ingrowth in the second survey for species present in the initial survey (y_{new}), and in the second, to predict the density amount of ingrowth (N_{new}). The incidence of ingrowth was addressed with a binomial GLM with logit link, where the predicted variable took the values $y_{new} = 1$ when there were new trees (incidence of ingrowth, or $N_{new} > 0$) and $y_{new} = 0$ otherwise. The density amount of ingrowth (N_{new}) was modelled using those records where local recruitment was observed, using a GLM with gamma response and logarithm link function. Finally, the diameter of those new trees (N_{new}) was modelled after a GLM with gamma response and logarithm link function.

The variable selection was similar to the growth and survival models, starting with tree and stand explanatory variables and environmental variables being added according to chi-square likelihood ratio tests; the model coefficients were also in this case evaluated for biological consistency (the final set of variables used as predictors for the models developed are listed in Appendix C).

2.6. Ingrowth models including new species

We developed a second set of ingrowth models to predict the density and average diameter of ingrowth corresponding to species already present or those present in the neighbourhood, similarly to García-Valdés et al. (2013). The set of explanatory variables and equations were the same as those used to model local ingrowth, except that $N_{sp,i}/N_i$ – the local relative abundance of the species in the target plot i – was replaced by a variable incorporating the relative abundance of the species in its neighbourhood Ω :

$$\left[\frac{N_{sp}}{N} \right]_{\sigma, \Omega} = \max \left(\frac{N_{sp,i}}{N_i}, \frac{\sum k(d_{ij}, \sigma) \cdot \frac{N_{sp,j}}{N_j}}{\sum k(d_{ij}, \sigma)} \right) \quad (4)$$

where d_{ij} is the distance between the target plot i and a neighbour plot j , the ratio $N_{sp,j}/N_j$ is the relative abundance of the species in the neighbour j and $k(d_{ij}, \sigma) = \exp\left(-\left(d_{ij}/\sigma\right)^2\right)$ is a kernel function of the distance between i and j given a scale parameter σ . Ω was defined as the set including the target plot and its 57-nearest neighbours, which given the 1-km spacing between plots corresponds to all plots within a radius of 3 km around the target plot. Observed data to model the incidence of ingrowth now included a larger number of zeros, corresponding to species present in the neighborhood but not being recruited in the target plot. Logistic models were fit for the presence of ingrowth as before, but testing different values of σ (0.5, 1, 2 and 4 km) and keeping the one providing the lowest Akaike Information Criterion (AIC). The same strategy was used to fit models for the density amount of ingrowth. Models for the diameter of recruits did not include any neighbourhood effects.

2.7. Static height models

We fitted height models for all species to ensure the availability of height estimates for species or provinces where height increment models were unavailable; as well for calculating height of ingrowth trees. Data for calibration of static height models was taken from the NFI3 and NFI4, but not from the NFI2, where height estimates were considered of lower precision. Following Trasobares et al. (2004b), we fitted the following non-linear equation based on Hossfeld (Peschel 1938):

Tree height:

$$H = \frac{b_0 + b_1 \cdot PPET + b_2 \cdot SWHC + b_3 \cdot Rad + b_4 \cdot elevation}{1 + \left(\frac{C_1}{d} \right) + \left(\frac{C_2}{d^2} \right)} \quad (5)$$

where the factors included in the numerator determine maximum tree height, whereas the denominator accounted for diameter-height relationships. Model fitting was done using non-linear mixed-effects models (R package 'nlme'; Pinheiro et al., 2021) with plot as random factor in the numerator intercept (b_0 being an intercept a plus the μ_{plot} with mean 0). The model selection was done by considering all possible sub-models and keeping the one minimizing the AIC. As in growth models, dummy variables for province and region of provenance were tested as replacement of the random factor, by using estimates of the fixed part of the numerator and denominator as constants in a non-linear model fitted by least squares, where the additional dummy variables were kept in the numerator only if AIC values decreased. Only the combination of dummy variables previously selected for diameter increment models were tested.

2.8. Model evaluation and performance

We evaluated the performance of each type of model on each species or group on the same data used for the model calibration. The

performance of the models for diameter increment, height increment, static height, ingrowth and diameter of recruits were evaluated using the average bias (defined as predicted minus observed) and root mean squared error (RMSE) statistics, expressed in the original units or as percentage of the mean predicted value. To detect any obvious dependencies or patterns that indicate systematic discrepancies, the models were evaluated quantitatively by examining the magnitude and distribution of residuals for all possible combinations of variables included as well as the spatial distribution of the residuals along the territory. The performance of the *DI* model was evaluated in terms of diameter increment at the tree level and basal area increase at the stand level. The performance of survival and ingrowth incidence models was estimated using the Area Under the Curve (AUC) statistics. For the diameter increment models for *P. sylvestris*, *P. nigra*, *P. halepensis* and *Quercus* sp. we could assess the model performance with an accurately measured independent dataset, consisting of 44 plots, and 3,342 tree measurements in Catalonia.

In addition, biological consistency in stand dynamics predictions was evaluated calculating long-term simulations for all main species. For any given input forest plot, the projection cycle (10-yr step) consisted of the following steps: (i) adding the diameter increment predicted for 10-yr to the diameter of each tree record; (ii) adding the height increment predicted for 10-yr to the height of each tree record, if the tree species has an available model; (iii) multiplying the initial tree density by the survival probability estimated for 10-yr; (iv) estimating local ingrowth (as the product of $P_{ingrowth}$ and $N_{ingrowth}$) and ingrowth diameter, for the species initially present in the plot; (v) estimating the ingrowth of new species and ingrowth diameter for species initially absent in the plot but present in its neighbours; and (vi) estimating the height for recruited trees and all the trees for which height increments could not be calculated using the static height model.

We evaluated the ability of the projection cycle to predict observed forest dynamics for the NFI2-3 and NFI3-4 periods. Since the three NFI surveys had been used for model calibration, we lacked independent evaluation data representing all the stand dynamics processes (growth, survival, ingrowth). Hence, we used the same plots employed for the model calibration. Mortality predictions for the NFI3-4 period included the diameter increment in the former period as predictor when the model was available for the target species. In plots with observed forest management, the mortality model was not applied, hence assuming silvicultural treatments had included the extraction of declining or dead trees. Height increment models were not employed in the full cycle performance evaluation. For the comparison between observed and predicted stand structures, we modified the final observed diameters so that diameter increments corresponded to 10-yr periods (depending on the province remeasurement periods may be longer or shorter) and truncated negative growth values to zero. Observed tree cuts were used to calculate BAL_{ext} and included this explanatory variable in model predictions. We excluded from the final state of observed data those tree records corresponding to recruitment of trees between 7.5 and 12.5 cm outside the 5-m radius subplot.

To understand the sources of uncertainties, we first evaluated the predictive performance of the projection cycle in terms of stand basal area changes corresponding to: (a) growth of surviving trees; (b) growth and mortality of the original trees; (c) new tree records (from either local or colonization ingrowth). After that, we evaluated the bias and accuracy of the projection cycle to predict the final values and 10-yr variation of: (d) stand basal area; (e) total biomass (including roots, stem, branches and leaves), and (f) stem volume including bark. Finally, the biomass calculations were conducted using available allometric equations (based on: Montero et al. 2005; Diéguez-Aranda et al. 2009; Ruiz-Peinado et al. 2011, 2012).

2.9. Forest projection system

A forest projection system based on the previous set of models and

applicable to forest plot data compatible with the NFI plot sampling protocols was developed. The system includes functions to run the fitted models, in either a deterministic or stochastic way, for an input set of forest plots (Fig. 2), in order to simulate the forest dynamics both at stand level or aggregated for a target area (e.g., a region or province), under a given climatic and management scenario. For that, first, the function determines the dominant species and the area represented by each NFI plot. Since the input includes the annual extraction demand (in volume) for a set of species, the initialization proceeds by classifying plots between non-managed (e.g., whether dominated by a species subject to no demand or part of a protected area) and managed according to the prescription rules of the species dominating the plot. For any given simulation step, the function first executes the projection cycle of non-managed plots. Then, it processes sets of plots dominated by each species with defined wood volume demand, which includes processing management treatments (i.e. cuts) and forest dynamics. The order of processing managed plots depends on the difference between the Hart-Becking index (Hart 1928; Becking 1954) and a corresponding parameter threshold included in the silvicultural prescriptions of the species.

2.10. Scenario analysis: Catalonia

Finally, we run the full forest projection system at a regional level to conduct an evaluation of the forest dynamics in Catalonia (NE Spain) under a given climate and management scenarios. The region was chosen as an example of application, based on the availability of data for the definition of the scenarios and assessment. For the simulations, climate projections were obtained from the Euro-CORDEX project (Kotlarski et al. 2014), available at Earth System Grid Federation (<http://esgf.lln.gov>). Specifically, we downloaded daily climate data generated by global circulation models CNRM-CERFACS-CNRM-CM5 and MPI-ESM for an historical reference period (1976–2005) and projection period (2006–2100) under emission scenarios RCP 4.5 and 8.5, regionalized to Europe at 11 km resolution using regional climate models CCLM4-8-17 and RCA4 (the latter coupled to both CNRM and MPI global models). Empirical quantile mapping methods, available in ‘meteoland’ package (De Cáceres et al. 2018), were used to downscale projected temperature and precipitation from 11 km to the plot scale and correct for model systematic biases. To this aim, daily weather data interpolated from observed weather station records was used as reference for the historical period. Mean annual temperature, precipitation and PET values corresponding to 10-yr periods were obtained by first aggregating daily data to the annual scale and then averaging across year periods (2006–2010; 2011–2020; ...; 2091–2100).

We illustrated the capabilities of the projected forest dynamics under two simplified management scenarios: *Business as usual* (BAU), where current wood demand and silvicultural practices are assumed unaltered for the remaining of the century and *Climate-smart forestry and circular bioeconomy* (CSFB), simulating a progressive increment of managed area coupled to a change in silvicultural prescriptions (aimed at decreasing drought and wildfire impacts and favouring wood products leading to lower CO₂ emissions) and increase in the share of demand for construction timber (longer life span, higher economic added value) vs demand for packing/boards (Nabuurs et al. 2018). Timber demand (as m³ of wood including bark) under BAU was calculated for each of the four Catalan provinces and each species using two sources: annual reported cuts (sawmill wood) between 2005 and 2010 (MAPA 2019) and firewood biomass records (Observatori Forestal, 2021) transformed to volume assuming 1 kg dm⁻³ density for green wood. Current overall wood demand in Catalonia was equal to 850 784 m³/yr, representing around 20% of current forest growth. The silvicultural prescriptions by species under BAU and the changes in prescriptions under CSFB scenario included a shift towards thinning from below for conifers managed using irregular models and a + 5 cm increase in the diameter leading to final cuts for species managed using regular models.

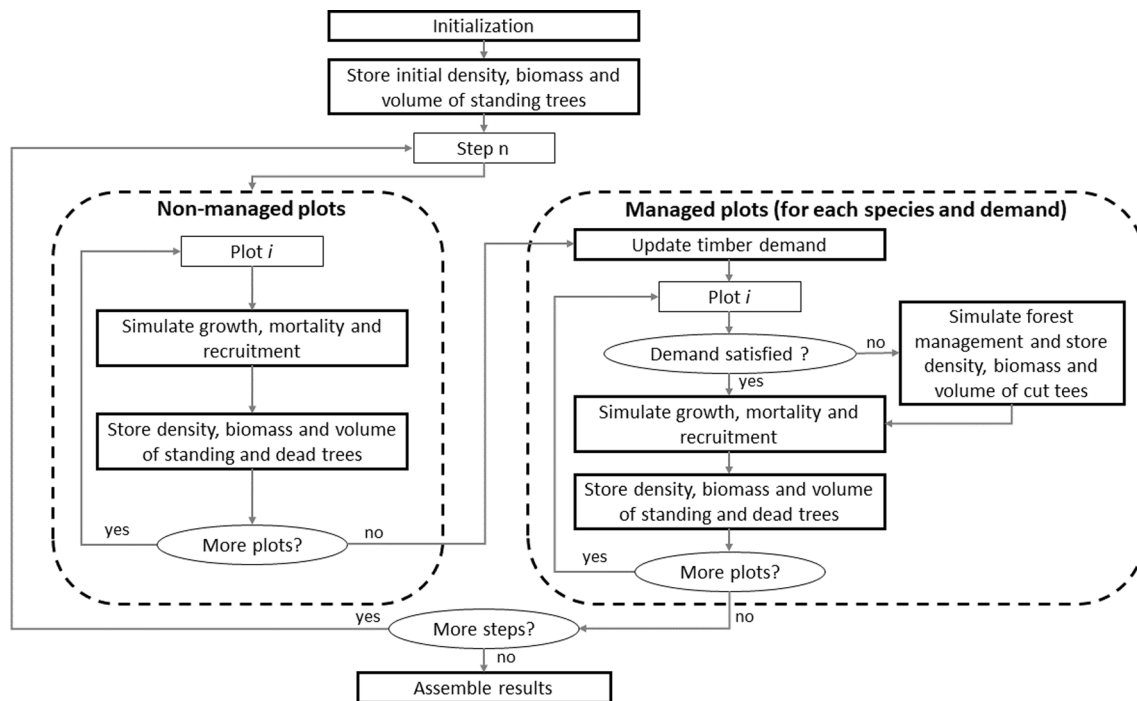


Fig. 2. Flow diagram of the simulation algorithm to define demand-based scenarios based on the fitted models.

The simulations were run on 9 901 forest plots under each climate and management scenario and starting with the forest structure and composition based on the NFI3. The forest dynamics were simulated using the deterministic application of diameter increment, survival, ingrowth (local and colonization) and static height models (see Fortin and Langevin 2012), and included stochastic wildfire impacts, as an example of disturbance, following the models by González et al. (2006, 2007). Strata from the National Forest Map were used to scale NFI plot-based results to areal-based values. Based on this, we evaluated forest dynamics at the regional level during the 21st century in terms of volume of standing trees, annual rates of stand growth, dead trees, extracted trees, and fire impact.

3. Results

3.1. Model evaluation

The residuals of the growth models showed no trends when displayed as a function of predictors or predicted growth. Diameter increment (10-yr) models were overall unbiased ($+0.07$ cm; $+2.2\%$) and had a root mean squared error (RMSE) of 1.9 cm (60.8%). By species, model biases were all below 4% in all cases, except for *Eucalyptus* spp. (8.7%), whereas RMSE values in percentage (RMSE%) ranged between 45% and 85% . At the stand level, basal area increments per species were unbiased (-0.03 m²·ha⁻¹; -1.0%) and RMSE was 1.73 m²·ha⁻¹ (50.2%), with RMSE% varying across species between 39% and 90% .

The validation using the independent data for *P. sylvestris*, *P. nigra*, *Pinus halepensis* and *Quercus* sp. confirmed the good performance of the models. The RMSE% values at the individual-tree level decreased from an average of 61.3 to 50.8 when using the independent dataset, while for the case of the basal area, changes at the stand level RMSE% decreased from 50.7 to 29.8 , respectively. In both cases, the estimated bias in percentage was negligible, irrespective of the data used (whether NFI or independent).

Height increment models were overall mildly biased (-0.069 m; -3.7%) and had a RMSE of 1.49 m, larger in relative terms (79%) compared to diameter increment models. RMSE % varied across species between 55% and 100% . Overall, the prediction capacity of survival

models not including previous growth was moderate (AUC = 0.749) but varied across species between 0.590 and 0.841 . Survival models including previous growth could be fitted for 16 out of 27 species/groups, and their predictive capacity was overall higher (AUC = 0.816) than models not including this predictor, varying across species between 0.703 and 0.906 . Local ingrowth incidence models were moderate to good, with AUC values ranging between 0.685 and 0.887 , whereas those including new colonizations had higher AUC, between 0.731 and 0.949 . Local ingrowth models had biases below 3% in all cases while RMSE % values ranged between 53.9% and 116% . Ingrowth models including new colonization were also unbiased but had slightly larger RMSE% values. Ingrowth diameter models were essentially unbiased and had small RMSE% values, ranging between 11% and 67% . RMSE% in models predicting (static) height as a function of diameter and environmental variables ranged between 13.7% and 38.0% depending on the target species.

The full projection cycle had variable performance to predict stand basal area changes depending on the subset of tree records considered (Table 1). When considering diameter increases of surviving trees only, biases were negligible and RMSE were 1.6 m²·ha⁻¹ and 2.1 m²·ha⁻¹ for NFI2-3 and NFI3-4, respectively, equivalent to 48.9% and 49.8% in relative terms. When considering growth and mortality of initial trees (this includes the incorporation of trees of dbh > 12.5 cm into large subplots), biases were still small but RMSE % increased to 107% and 177% , respectively. Ingrowth was predicted with relatively small (< 11%) biases, but large RMSE values were observed, with higher RMSE % in the case of colonization of new species. Taking into account all processes together, the full projection cycle had generally a low systematic bias in terms of basal area changes (~ 0.2 m²·ha⁻¹), but RMSE for stand basal area was 3.5 m²·ha⁻¹ and 4.7 m²·ha⁻¹ for NFI2-3 and NFI3-4, respectively, equivalent to 96% and 140% in relative terms (Table 2). This higher RMSE compared to those of Table 1 is explained by the compounding of errors derived from growth, mortality and ingrowth processes (see also Fig. 3). When comparing plot-averaged predicted vs observed basal area changes depending on the species dominating the plot we did not observe large disagreements (Fig. 4). The same comparison when averaging predictions across Spanish provinces indicated that significant biases occurred only in a few cases (Fig. 3b).

Table 1

Performance of the full projection cycle in terms of predicting basal area changes due to different processes: (a) basal area increase due to diameter increment of surviving trees; (b) basal area change due to growth and mortality processes (includes observed incorporation of trees with dbh > 12.5 cm in subplots of > 5 radius); (c) basal area increase due to local ingrowth (within the 5-m radius subplot); (d) basal area increase due to ingrowth of new species (within the 5-m radius subplot). Bias % and RMSE % result from dividing Bias and RMSE, respectively, by the mean predicted value.

Variable	NFI period	Mean Obs.	Mean Pred.	Bias	Bias (%)	RMSE	RMSE (%)	R ² (%)
(a) BA incr. growth (m ² /ha)	2–3	+3.40	+3.29	−0.11	−3.3	1.61	48.9	78.7
	3–4	+4.13	+4.20	+0.08	+1.8	2.09	49.8	70.6
(b) BA change growth/mort. (m ² /ha)	2–3	+3.03	+2.86	−0.17	−6.1	3.05	106.7	48.8
	3–4	+2.36	+2.24	−0.12	−5.3	3.97	177.3	64.0
(c) BA incr. local ingrowth (m ² /ha)	2–3	+0.62	+0.64	+0.03	+3.9	1.21	189.4	20.6
	3–4	+0.91	+0.84	−0.07	−8.1	1.64	195.0	19.9
(d) BA incr. coloniz. ingrowth (m ² /ha)	2–3	+0.134	+0.137	+0.003	+2.2	0.62	452.5	4.5
	3–4	+0.216	+0.240	+0.024	+10.2	0.90	372.4	3.9

Table 2

Performance of the full projection cycle in terms of predicting the variation and final value of stand basal area, total biomass and wood volume. Bias % and RMSE % result from dividing Bias and RMSE, respectively, by the mean predicted value.

Variable	NFI period	Mean Obs.	Mean Pred.	Bias	Bias (%)	RMSE	RMSE (%)	R ² (%)
Final BA (m ² /ha)	2–3	14.81	14.57	−0.24	−1.6	3.48	23.9	90.6
	3–4	19.80	19.64	−0.16	−0.8	4.65	23.7	87.4
BA change (m ² /ha)	2–3	+3.87	+3.63	−0.24	−6.5	3.48	95.9	46.2
	3–4	+3.48	+3.32	−0.16	−4.9	4.65	140.1	57.0
Final biomass (Mg CO ₂ /ha)	2–3	108.0	108.2	+0.24	+0.2	29.2	26.9	89.7
	3–4	163.8	164.1	+0.36	+0.2	44.8	27.3	88.2
Biomass change (Mg CO ₂ /ha)	2–3	+29.7	+29.9	+0.24	+0.8	29.2	97.4	42.5
	3–4	+34.7	+35.0	+0.36	+1.0	44.8	127.8	50.3
Final volume (m ³ /ha)	2–3	81.0	83.6	+2.56	+3.1	29.1	34.8	88.4
	3–4	130.7	134.7	+4.06	+3.0	45.9	34.1	83.4
Volume change (m ³ /ha)	2–3	+24.6	+27.1	+2.56	+9.4	29.1	107.3	52.0
	3–4	+28.3	+32.3	+4.06	+12.6	45.9	141.8	47.1

Negligible biases occurred when predicting biomass changes (+0.24 and + 0.36 MgCO₂·ha^{−1} for NFI2-3 and NFI3-4, respectively, corresponding to + 0.8% and + 1% in relative terms), but small positive biases appeared when translating stand structures into wood volume changes (+2.56 and + 4.06 m³·ha^{−1}, respectively, corresponding to + 9.4% and + 12.6% in relative terms). RMSE% of biomass and volume changes were similar to those of basal area changes (Table 2).

The long-term simulations demonstrated biological consistency in terms of increase and decrease in the number of trees, basal area, volume and steady state stand occupation levels typical for each of the species (Fig. 5 and Fig. 6 illustrates the values corresponding to *Pinus halepensis* and *Fagus sylvatica*, respectively, in two alternative provinces; for the rest of species, see Appendix D and for the full evaluation of all the models fit, see Appendix E).

3.2. Scenario analysis

The three combinations of global and regional climate models project similar average temperature trends during 21st century (Fig. 7), with smaller increases (+1.7 °C) under the milder RCP4.5 scenario and a larger increase (+4.2 °C) under the harsher RCP8.5, with differences between scenarios becoming more apparent in the second half of the century. In terms of precipitation, variation between consecutive 10-yr is stronger and patterns differ across climate combinations. Nevertheless, climate projections do not indicate strong decreases in mean annual precipitation until 2075, when significant decreases are predicted under RCP8.5. PET values are slightly higher for climate model combinations CNRM/RCA4 and MPIESM/RCA4 than for CNRM/CCLM, leading to slightly lower moisture index values for the first two model combinations. During the second half of the century an increase in aridity is predicted, being stronger under RCP8.5.

Forests in Catalonia are expected to steadily increase in standing volume throughout the 21st century, regardless of the climate or management scenario (Fig. 8), from around 100 m³·ha^{−1} up to 220 m³·ha^{−1}

under the BAU scenario, and 200 m³·ha^{−1} under the CSFB scenarios (see Appendix F). Nevertheless, forest growth rate is progressively reduced from 2.5 m³·ha^{−1}·yr^{−1} to 0.5 m³·ha^{−1}·yr^{−1} due to overall increased stand density/competition leading to a decrease in diameter increments and survival (Fig. 8c-d). We observed a relatively small difference between climatic scenarios, although forest growth is expected to be more severely reduced by the end of the century under RCP8.5 than under RCP4.5, resulting in lower standing volumes. Tree mortality increases under all management scenarios but is lower under CSFB compared to BAU. The extraction rate is around 22%, at the beginning of the century, and remains relatively constant throughout most of the century under BAU, but the decrease in forest growth leads to higher extraction rates (up to 60%) towards the end of the century. Under the CSFB scenarios extraction rates reach 40–50%, as expected, in 2050. However, the demand specified under the CSFB scenario cannot be completely fulfilled afterwards (Fig. 8e).

4. Discussion

Forests in Spain cover large and various geographical areas, with diverse climatic, topographic, edaphic and management conditions leading to highly diverse forests (Sanchez de Dios et al., 2019). The models presented in this study, and their integration into a forest projection system, allow coping with this complexity and provide suitable and necessary tools for forest simulation with wide applications in forest management and planning. The ambition is exhaustive, representing the broad gradient in conditions (i.e., forests ranging from Atlantic to Mediterranean, plus the Canary Islands) with models that are climate- and management-sensitive, and include the 27 most common species and species groups in the country.

The data used to fit the models were based on NFI records from several measurement periods. The use of NFI data for modelling forest dynamics presents well-known drawbacks, since they are not specifically designed for the development of growth and yield models and the

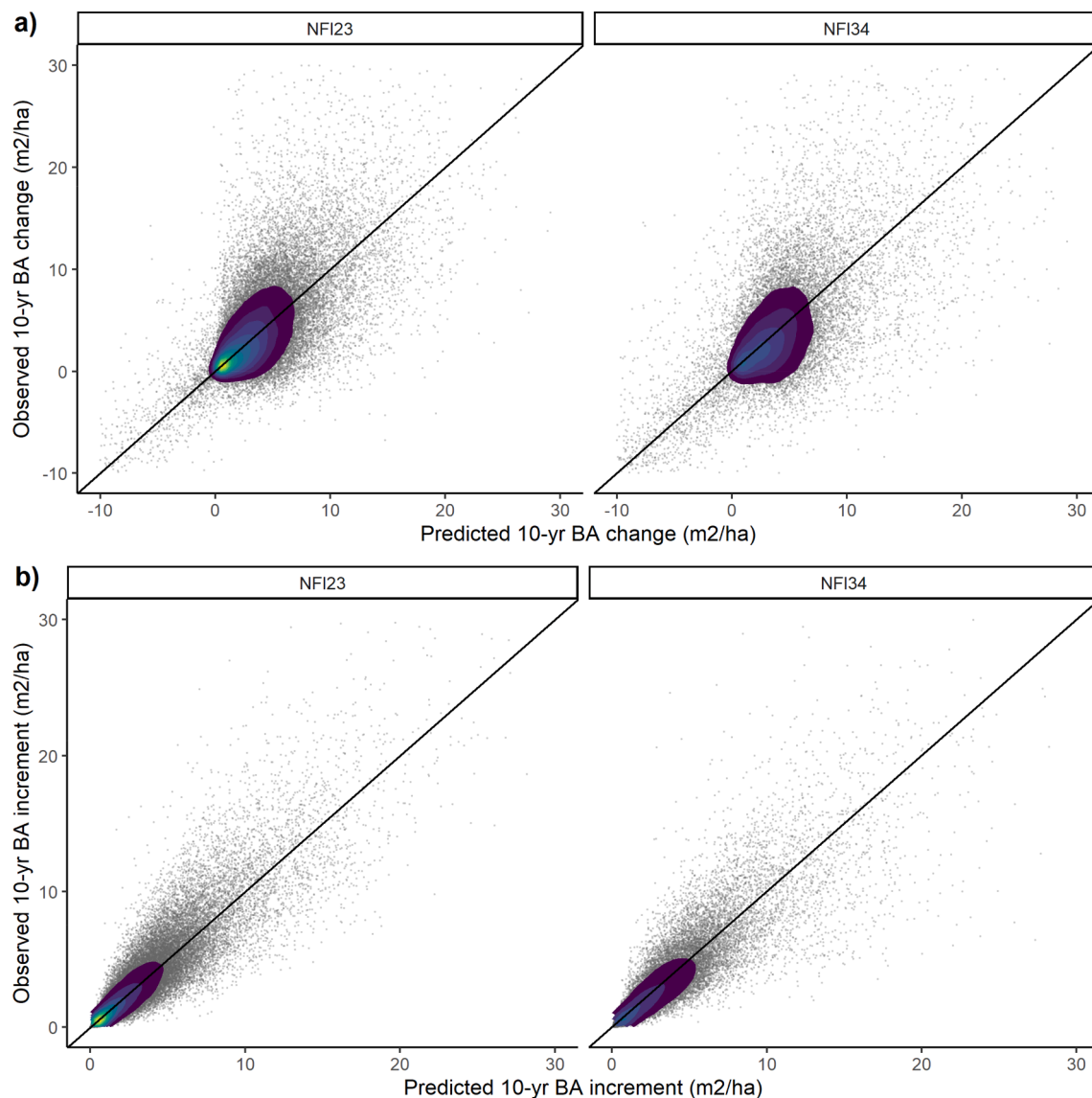


Fig. 3. Predicted vs. observed basal area (BA) changes during the two study periods (NFI2-3 and NFI3-4): (a) basal area changes derived from the full projection cycle (b) basal area changes derived from diameter increments of living trees. (Contours represent the density of points.)

sampling protocols present biases and limitations (see Weiskittel et al. 2011). However, the large amount of data available largely compensated for any measurement error, which was in fact confirmed by the error assessment based on the independent diameter increment observations. In this sense, the Spanish NFI is perhaps the largest dataset of direct forest measurements in Europe, presenting one of the densest and largest geographical coverages (Tomppo et al. 2010), and being regarded as the most important forestry project, performed along several decades and based on an extensive field data collection (Alberdi et al., 2017), which is a unique, robust, and reliable basis for empirical modelling. In fact, the present study is one of the first addressing all available records along three consecutive surveys, although it must be noted that the last survey had fewer plots than the previous ones and it was not yet available for all the provinces.

The models followed an individual tree approach, largely based on previous regional studies for specific species (see Trasobares et al. 2004a, 2016; Trasobares and Pukkala 2004) but differing in the scope and ambition. Among the improvements, it should be stressed that the models are explicitly multi-specific, addressing both mixed and pure stands, cover the whole territory, have been calibrated using all available data for three consecutive NFI surveys, the regeneration considers

the species colonization dynamics from neighbouring plots and the predictions address explicitly climatic explanatory variables; these allow performing simulations under climate change scenarios in combination with management alternatives.

The overall modelling structure is regarded as a solid approach to characterize growth under variable stand conditions and management practices (Weiskittel et al. 2011). Alternative approaches can be better suited for some of the intended goals. For instance, the use of process models in forestry has demonstrated the potential to simulating growth and yield under alternative climatic scenarios (e.g. García-Gonzalo et al. 2007), the use of more complex and spatially explicit simulators has been used to address forest stands under climate change with focus on the ecosystem services (e.g. Cristal et al. 2019), and finally, machine learning approaches are becoming more popular, resulting on high levels of prediction accuracy (e.g. Jevšenak and Skudnik 2021). However, the use of regression individual-tree models still presents important benefits: (1) their simplicity facilitates the use and application, since it only requires sharing the model parameters to be implemented, (2) integrate better the management/silviculture effects than process-based models and are calibrated for the region, and (3) the use of a hierarchical model structure addressed possible autocorrelation biases,

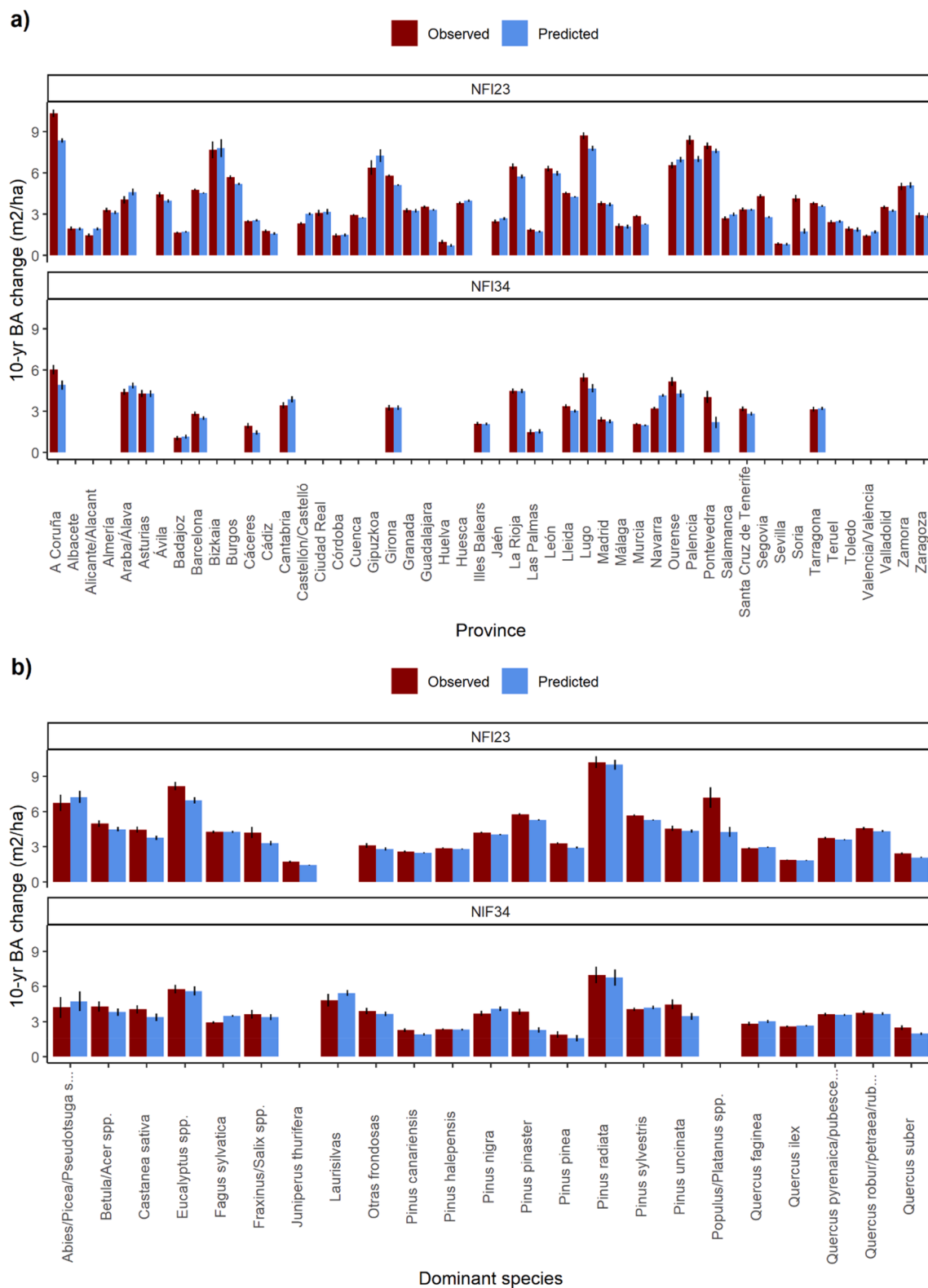


Fig. 4. Mean predicted and observed basal (BA) area changes (a) by Spanish provinces and (b) by species dominance, for the two study periods (NFI2-3 and NFI3-4). Error bars represent 1 X SE (calculated as the plot-level values standard deviation, standardized by the square root of the number of plots) of the mean value.

enabled a straightforward integration of the spatial variation, and allowed to incorporate the various environmental and climatic effects, resulting in reasonably good levels of biological consistency and accuracy. It must be taken into account that the purpose in the long-term simulations was not to derive concrete ecological or predictive

conclusions, but rather observe the behaviour of the variables with respect to the species ecology (e.g., to identify possible violations of biological limitations such as excessive growth, heights or diameters beyond biological maxima, etc... as in [Trasobares et al, 2004a](#)). The results were overall satisfactory at this level, although in some cases, the

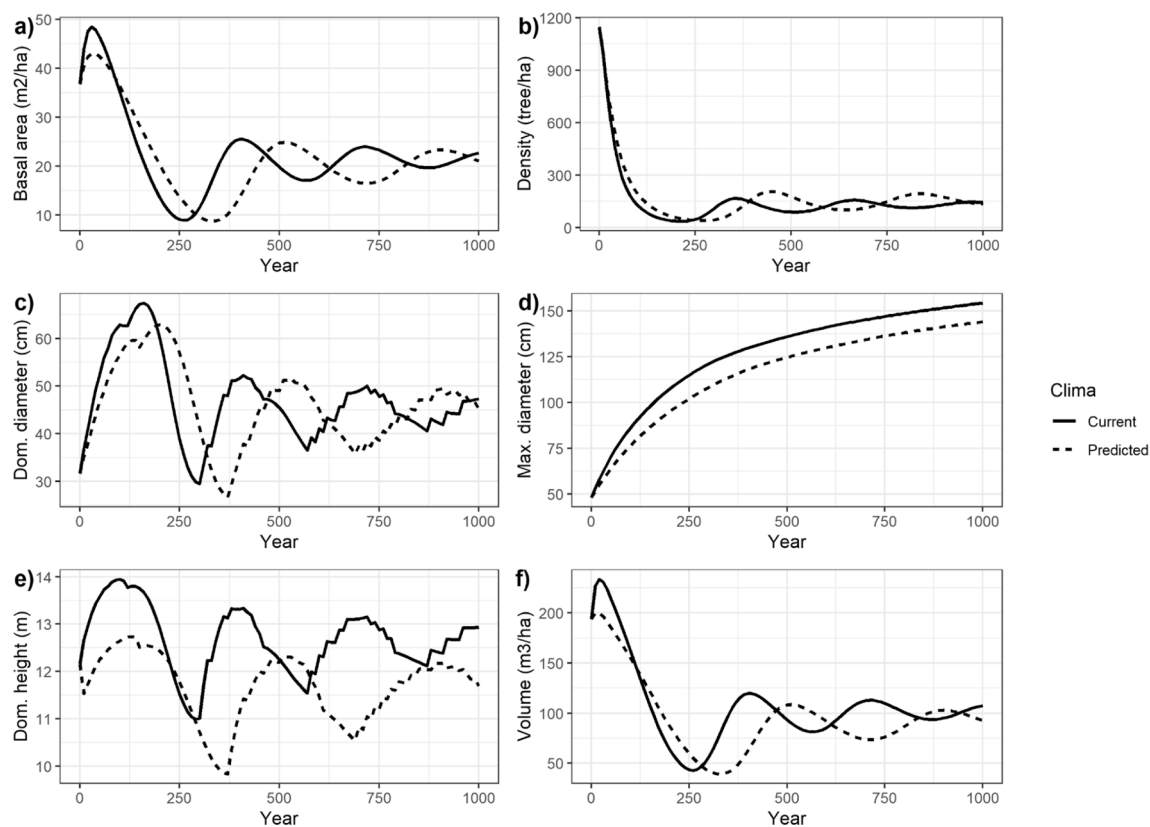


Fig 5. Long-term modelled stand dynamics for *Pinus halepensis* for current climatic conditions (*current*) and alternative climatic conditions (temperature + 2.0°C and precipitation -25%, *predicted*). The stand is located in the province of Girona, region of provenance nr. 1.

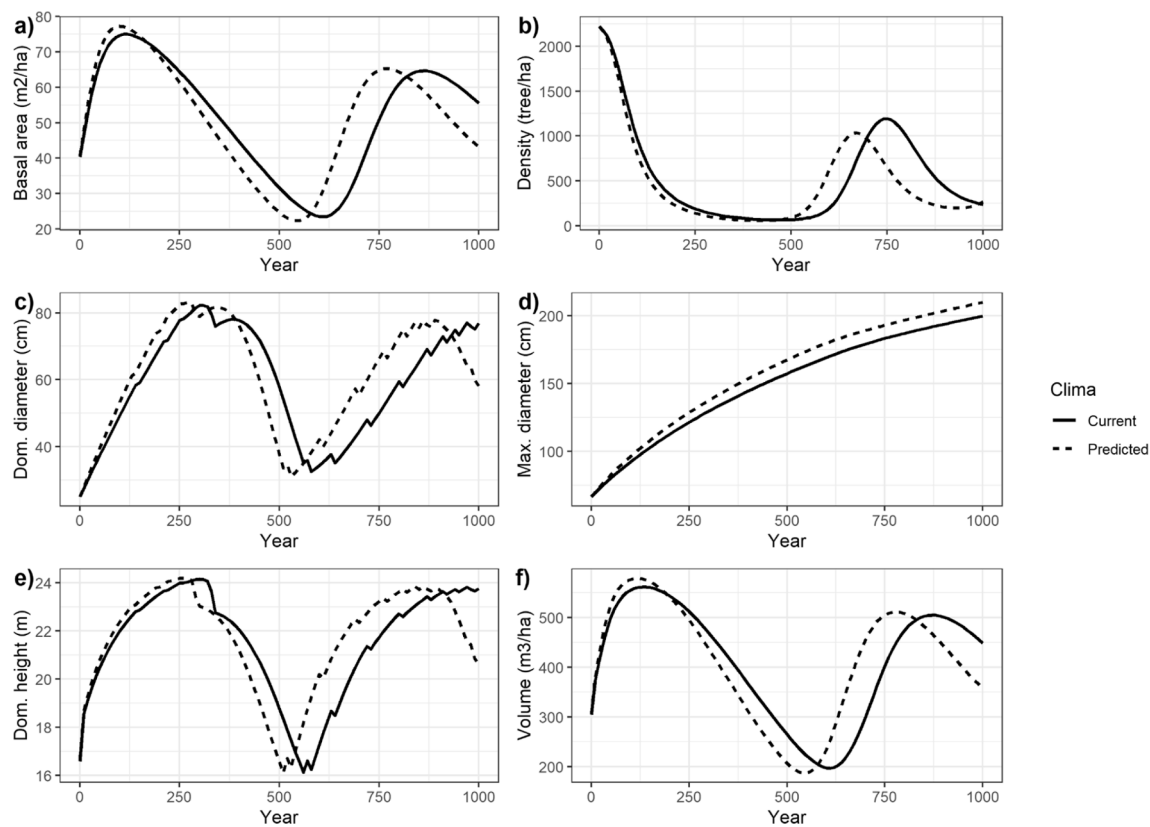


Fig 6. Long-term modelled stand dynamics for *Fagus sylvatica* for current climatic conditions (*current*) and alternative climatic conditions (temperature + 2.0°C and precipitation -25%, *predicted*). The stand is located in the province of La Rioja, region of provenance nr. 17.

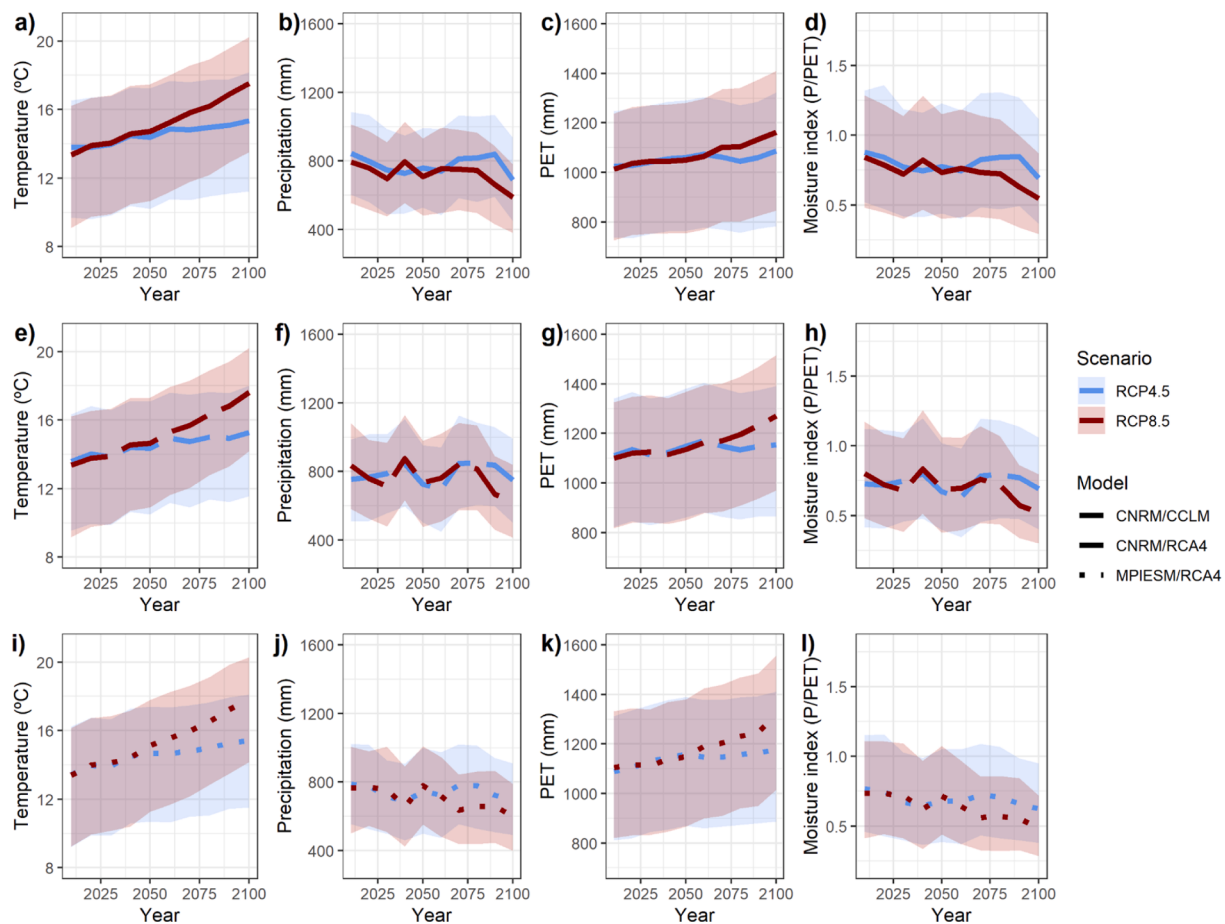


Fig. 7. Temperature, precipitation, PET and moisture index series in 10-yr steps for forest plots in Catalonia under climate change scenarios RCP4.5 and RCP8.5, as given by three combinations of global circulation model and regional climate model: CNRM/CCLM (a-d), CNRM/RCA4 (e-h) and MPIESM/RCA4 (i-l). Lines indicate mean values across plots whereas the limits of shaded areas correspond to 10% and 90% quantiles.

simulation indicated possible limitations in the ingrowth and survival models.

At the same time, there are obvious drawbacks derived from the approach and data. Survival models may be biased in some cases due to the fact that dead (or close to death) trees are often removed if the area is periodically managed. Concerning the ingrowth models, they are limited to the number of trees that enter the smallest dbh class during a 10-year period, which is, however, sufficient if simulations use a fixed plot size. The NFI variable radius subplot design implies variable probability of tree detection within the plot, which may result in biased model calibration. Since this approach allows efficiently sampling uneven forest structures and better represent large trees, we consider it as beneficial for modelling purposes; although, it also supposes a limitation for the application of our models to forest plot data sampled using other designs or with significantly different size (Salas-González et al. 2001).

The forest projection tool integrating all the models developed allows predicting variation in several forest goods and services, such as wood production, carbon sequestration and water provisioning if coupled to other existing tools (De Cáceres et al. 2015; Rocas-Díaz et al. 2021). This may also allow performing forest policy analysis and allows exploring the consequences of several policies on the provision of the ecosystem services (Naaburs et al. 2018). The ingrowth models, for instance, may have additional applications concerning habitat suitability or to model changes in biodiversity (McRae et al. 2008). Considering the climatic gradients and compositional variability of forests in Spain, the diversity of management practices, as well as the results obtained by similar approaches in other countries (Monserud and Sterba 1996; Hynynen et al. 2002; Antón-Fernández et al. 2016), we

consider the performance of the full projection cycle as satisfactory. Predicted diameter increments result in a RMSE around 50% in basal area changes (29.8% using accurate independent data in Catalonia), and biases that are relatively small in most provinces. The complete projection cycle is still relatively unbiased for basal area changes, but relative RMSE increases due to the accumulation of errors coming from the mortality and ingrowth models (Weiskittel et al. 2011). The model bias slightly increases when translating the stand structure and composition into volume estimates, because errors in diameter increments and height estimates become compounded. All in all, the model performance is, overall, satisfactory for evaluations across the national level. Model applications at the level of Autonomous communities (such as shown here for Catalonia) or of individual provinces is acceptable, thanks to the inclusion of region spatial predictors based on province and provenance; additional modeling efforts (e.g., the use stand dominant height – relationships) may be conducted on regions where plantations are frequent, such as in the north-west of the country.

The scenarios evaluated for Catalonia illustrate the sensitivity of the projection system to climatic variation, indicating a lower weight of climatic scenarios with respect to management scenarios. Some authors argue that the changes in environmental conditions may not always be fully described, at least with enough resolution, with the fixed coefficients of empirical models (Kramer et al. 2008; Fontes et al. 2010). In addition, the temporal resolution of the models (10-year periods) may be a limitation for representing with enough detail the effects of climatic extreme events such long drought periods (García-Valdés et al. 2021). Also, this approach might have limitations to correctly represent a true change in climatic conditions at a given location, and rather simulate a

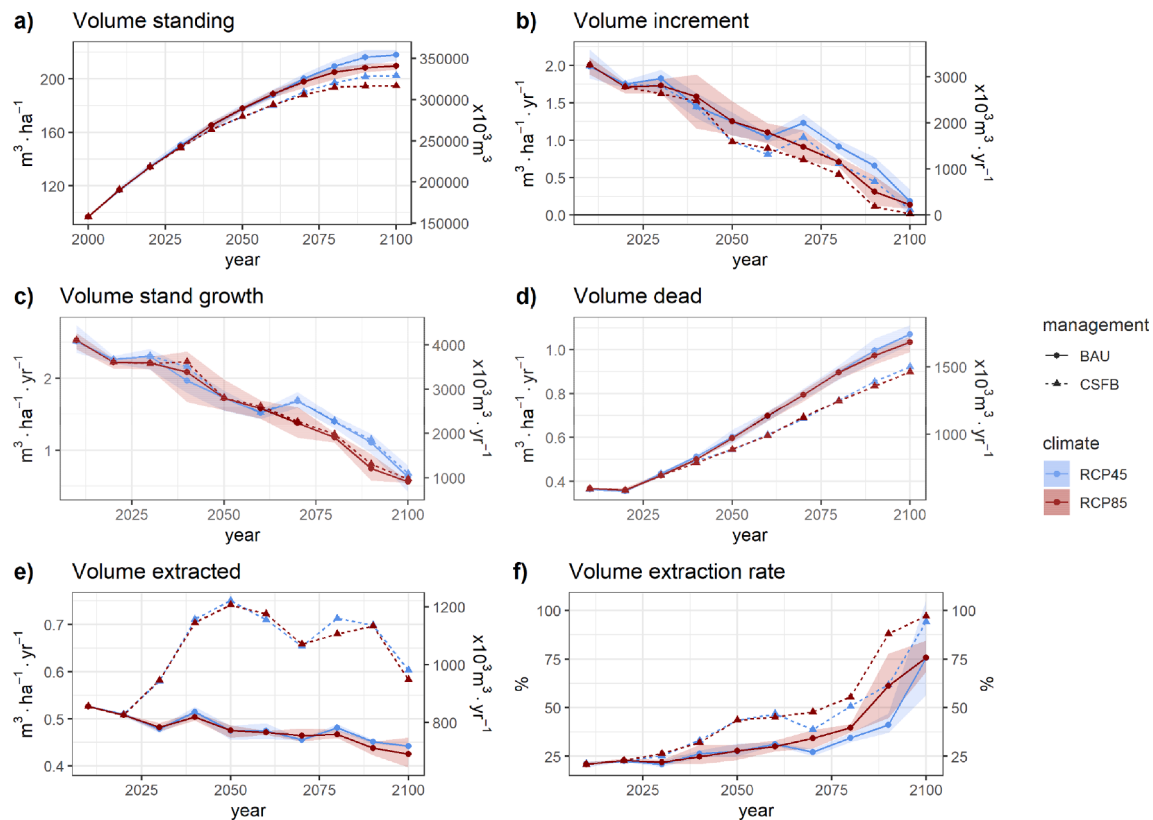


Fig. 8. Simulation results in terms of wood volume including bark (m^3) for SNFI plots in Catalonia under combinations of two climate scenarios (RCP4.5 and RCP8.5, refs. + 1.7 °C and + 4.2 °C, respectively) and two management scenarios (*Business as usual*, BAU, and *Climate-smart forestry and circular bioeconomy*, CSFB), for a) standing volume, b) annual volume increment, c) stand growth, d) dead trees, e) volume extracted and f) extraction rate. Shaded areas indicate the interval of predictions obtained with the three climate model combinations whereas lines correspond to mean values.

“spatial relocation” of the tree. However, the use of other explicit spatial-dependent variables in the models, the use of local parameters, and the inclusion of two measurement periods in most of the plots, addresses, at least partially, this concern. In addition, the use of a unimodal distribution to represent temperature effects (following García-Valdés et al., 2013) was conceived to avoid collinearity with the drought variables and, at the same time, adding a penalty on colder climate, while avoiding excessive modelling complexity. An explicit species-dependent parameter in this variable could help improve the models, although the beta parameter associated to the variable already accounts for part of the variability due to the species, and perhaps would be a modest improvement in the aggregated predictions at scenario level. Being aware that process-based models may be better suited to evaluate the effect of climatic changes, we believe that the models calibrated here encompass a climatic variation (i.e., aridity gradient) that is broad enough to justify a rather robust evaluation of climatic scenarios. The use of climate means in empirical tree growth models at multiannual resolutions is further supported by the fact that short-term negative growth responses to climatic extremes are often followed by periods of increased growth (Pretzsch et al. 2013).

We consider the models and forest projection system presented here as tools to be continuously refined, as done for similar systems in other countries (Barreiro and Tomé 2017). In particular, we expect the performance of some models to increase after the completion of the NFI4, particularly for survival models including past growth and height increment models (Hülsmann et al. 2018), which we did not consider in the evaluation of the full projection cycle for this reason. The completion of NFI4 will also allow evaluating the performance of the full projection cycle using an evaluation data set independent of that used for model calibration (Rohner et al. 2018). We envisage other potential improvements such as: (a) exploring the inclusion of interaction between climate

and competition in mortality models (Ruiz-Benito et al. 2013; Condés and del Río 2015); (b) exploring alternative statistical approaches for ingrowth (Zell et al. 2019) or the effect of long-distance dispersal events; (c) allowing the calculation of decomposition rates on snags and stumps to include their effect on carbon emissions (Melin 2014); (d) accounting for other perturbations such as pathogens, insect attacks, storms or extreme drought (Hanewinkel et al. 2004; Schütz et al. 2006; Martín-Alcón et al. 2010; Seidl et al. 2011); or (e) including the interaction between climate change and the frequency and intensity of wildfires (Duane et al. 2019). It is also important to remark that thanks to the robustness of the data, the models may as well provide interesting potential for application in other countries or regions.

Regarding the potential use of the forest projection system, this article presents how the system may be used to analyze the impact of different management and climate scenarios on the provision of ecosystem services. This is a first step to contribute to evaluating large scale policy and climate scenarios and to identify possible synergies and trade-offs among ecosystem services related to those scenarios, incorporating the models into decision support systems (García-Gonzalo et al. 2015). In this sense, the system presented in the current article may be adapted to simulate management alternatives for each stand at landscape or regional level, to provide a basis for broad-scale policies, as the predictions can be used to analyse how forests may respond to alternative management regimes (Crookston and Dixon, 2005), to assess emissions under different scenarios (Nunery and Keeton 2010), to generate indicators for decision and planning (Schwenk, et al 2012), or to spatialize the results to link fuel models to the forest dynamics variables, to generate long-term landscape-level assessment of fire hazard (Finney et al 2007), among others.

5. Conclusions

The results of this study present environmentally driven models for forest stand dynamics based on distance-independent individual-tree growth and yield models. In total, 182 models are fit to predict diameter increment, height increment, total height, survival and ingrowth in stands, incorporating static and dynamic environmental variables. The models show a good performance in terms of biological consistency and predictive power. These individual models can be effectively used for individual studies at stand or landscape level, presenting a set of tools that can be used according to specific multi-objective planning needs.

In addition, the models are integrated into a full forest projection system to perform simulations of forest dynamics and resulting changes in the provision of ecosystem services, including in these projections the effects of climate and forest management. The resulting models and projection system provide a solid basis for the simulation of stand to country climate-sensitive forest scenarios for Spain and neighbouring regions (e.g., Portugal), and can be the basis of future applications in forest management and planning.

CRedit authorship contribution statement

Antoni Trasobares: Conceptualization, Methodology, Formal analysis, Data curation, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Blas Mola-Yudego:** Data curation, Methodology, Writing – original draft, Writing – review & editing. **Núria Aquilué:** Data curation, Visualization, Software, Writing – review & editing. **José Ramón González-Olabarria:** Methodology, Writing – review & editing. **Jordi García-Gonzalo:** Methodology, Writing – review & editing. **Raúl García-Valdés:** Methodology, Formal analysis, Writing – review & editing. **Miquel De Cáceres:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.foreco.2021.119909>.

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