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Productivity of *Fagus sylvatica* under climate change – A Bayesian analysis of risk and uncertainty using the model 3-PG

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ABSTRACT

To assess the long-term impacts of forest management interventions under climate change, process-based models, which allow to predict transient dynamics under environmental change, are arguably the most suitable tools available. A challenge for using these models for management decisions, however, is their higher parametric uncertainty, which propagates to predictions and thus into the decision-making process. Here, we demonstrate how this problem can be addressed through Bayesian inference. We first conduct a Bayesian calibration to generate an estimate of posterior parametric uncertainty for the process-based forest growth model 3-PG for *Fagus sylvatica*. The calibration uses data from twelve sites in Germany, together with a robust (Student's t) error model. We then propagate the estimated uncertainty together with economic uncertainty to forest productivity and Land Expectation Value (LEV), allowing us to evaluate alternative management regimes under climate change. Our results demonstrate that parametric and economic uncertainty have strong impacts on the variation of predicted forest productivity and profitability. Management regimes with increased thinning intensity were overall most robust to economic, climate change and parametric model uncertainty. We conclude that estimating and propagating economic and model uncertainty is crucial for developing robust adaptive management strategies for forests under climate change.

1. Introduction

European beech (*Fagus sylvatica* L.) is the most abundant broad-leaved tree species in Central Europe (Bohn et al., 2003; Ellenberg, 1996). Due to its high shade tolerance, it would naturally dominate large parts of the region, particularly in Germany (Christensen et al., 2005). In the recent past, markedly during the last 200 years, large areas originally dominated by beech forests were replaced by faster growing conifer species, e.g. Norway Spruce (*Picea abies*) and Scots Pine (*Pinus sylvestris*), with the aim of reestablishing forests on degraded land, increasing forest profitability and supplying wood for the forest industry (Spiecker, 2003). The focus of forest management, however, has shifted during the past decades towards a multipurpose approach. A consequence of this change in values is an increasing interest in recovering the naturalness of European forests. Efforts are thus being made to adopt close-to-nature management systems, increase the complexity of forest stands and promote the natural vegetation (Brunet et al., 2010). The restoration of natural forest composition is also motivated by the objective to recover forest biodiversity and ecosystem functioning in degraded forests ecosystems (Burton and Macdonald, 2011). For example, the forest administration of Baden-Württemberg describes beech-dominated forests as an especially valuable forest type, due to its perceived closeness to nature and connectivity function. Therefore, the long-term goal of the forest administration is to increase the proportion of this type of forests (LFBW, 2014).

One of the most important management recommendations for forest restoration and rehabilitation is restoring the species composition and stand structure of natural forests (Halme et al.,

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2013). At the same time, however, when planning an increase of the share of *Fagus sylvatica*, it is crucial to take into account future climate development (Ravenscroft et al., 2010). Climate change is predicted to affect important forest processes, such as carbon assimilation, water balance, nutrient cycling, species distributions and disturbance regimes (Davis et al., 2017; Laflower et al., 2016; Pan et al., 2011; Seidl et al., 2014; Tarancón et al., 2014). Hence, it is crucial for managers and decision-makers to evaluate the behavior of beech stands under climate change, assess the suitability of forest policies targeted at increasing the share of this species, and avoid risks that might lead to a loss of ecosystem functioning or profitability.

Arguably the most suitable tool to assess the impacts of novel climatic conditions on forest ecosystems are process-based forest models. The advantage of these models over more empirical or statistical models is that they are built on explicit processes and interactions in forest ecosystems that describe not only demography and stand structure, but also carbon, water and nutrient cycles (Busing et al., 2007; Friend et al., 1997; van Oijen et al., 2005). As such, they should be better suited to predict forest responses to environmental changes (e.g. alterations in atmospheric CO_2, precipitation regimes, air temperature, nitrogen deposition, etc.), as well as transient dynamics (Hartig et al., 2012). Because of these advantages, many studies have applied process-based forest models at different spatial and temporal scales for evaluating forest responses to climate change (e.g. Koca et al. 2006; Morin and Thuiller, 2009; Rollinson et al., 2017), risks related to climatic changes (e.g. Allen et al., 2010; Cailleret et al., 2014; Soja et al., 2007) forest productivity (e.g. González-García et al., 2016) or shifts on species distribution (e.g. Morin et al., 2007; Snell et al., 2014).

For forest management, one of the most important outputs of these models is productivity in biomass and wood volume. Productivity is not only decisive for the commercial value of the forest (Liang et al., 2016), but typically also correlates with other important ecosystem services (Bonan, 2008; de Groot et al., 2002; Tilman et al., 2012). Forest managers can use productivity estimates to plan and evaluate different management options and adjust management plans accordingly (Temperli et al., 2013). To predict productivity under environmental changes, process-based models are of particular interest, because they allow deriving key variables, such as stem volume, stem biomass and carbon sequestration. Although stand-level forest growth models are typically simpler than fully-fledged physiological gap models, they still commonly use numerous parameters that determine the behavior of a range of interacting processes in the model. Not all of these parameters are well-known, and it can be expected that parameters may also vary regionally with provenances and growing conditions (Moran et al., 2016). The resulting parametric uncertainty should be propagated to the models' predictions, meaning that a sensible economic analysis will have to consider that a range of possible model outcomes exists, and each of those could lead to very different management implications. For developing robust management plans, it is therefore crucial to quantify and account for this parametric model uncertainty (Reyer et al., 2016).

One of the best-developed frameworks for estimating and propagating parametric model uncertainty is Bayesian inference. In a nutshell, Bayesian inference is a statistical method that allows expressing, estimating and propagating uncertainty, represented by probability distributions, for each variable of interest in a model, including parameters and model predictions (Hartig et al., 2012; Lichstein et al., 2010). As such, it provides a natural way to compute parametric model uncertainty and subsequently forward it into economic models of forest profitability, e.g. net present value (NPV) or land expectation value (LEV) (Cyert and DeGroot, 1987; Dorazio and Johnson, 2003). As an additional advantage, the Bayesian framework also seamlessly allows including uncertainty in input and drivers of the model. This means that climate change uncertainty, one of the main issues faced by forest managers, can be integrated with parametric model uncertainty in the planning process (Hallegatte et al., 2012; Pasalodos-Tato et al., 2013). Applying this framework in combination with risk analysis enables the selection of robust forest management alternatives, which perform well regardless of future climate paths (Hadka et al., 2015).

Currently, one of the most broadly applied physiology-oriented process-based model is 3-PG (Three Physiological Principles Predicting Growth), developed initially by Landsberg and Waring (1997). 3-PG predicts stand productivity based on photosynthetically active radiation (PAR) and canopy quantum efficiency. The canopy quantum efficiency is constrained by environmental factors, such as temperature, water availability, vapor pressure deficit, stand age and fertility (Almeida et al., 2004b; Landsberg et al., 2001a). The Net Primary Productivity (NPP) is obtained as a constant rate of the Gross Primary Productivity (GPP), and the carbon is allocated to different tree components, according to specific ratios (Amichev et al., 2011). Promoted by its easy accessibility, flexibility and the limited number of parameters, 3-PG has been applied to assess forest productivity of a variety of species and sites (e.g. Fontes et al., 2006; Landsberg et al., 2003; Minunno et al., 2010; Nightingale et al., 2008). Moreover, the model has been successfully calibrated for temperate forest species applying a Bayesian approach (e.g. Minunno et al., 2010; Xenakis et al., 2008).

Considering the importance of developing robust management scenarios for beech forests, the main goals of this study are: (1) To calibrate 3-PG for beech stands in Germany and evaluate the fit of the model and accuracy of the model's predictions; (2) evaluate the impacts of uncertainty on forest productivity and profitability under climate change and (3) to identify robust management regimes towards climate, economic and parametric model uncertainty.

The calibration was performed with a data set composed of intensively monitored permanent inventory plots. The data provided various standard inventory variables, including stand density, stand diameter at breast height (DBH), stand height, standing volume; and site parameters, including climate and soil characteristics. We applied allometric equations for deriving foliage, root and stem biomass of each plot. For the calibration, we used Bayesian inference, to estimate parameters uncertainty from direct information (prior) and indirect information (model outputs). We then forwarded the parametric uncertainty to posterior model predictions (e.g. for stand biomass and volume). We used the results to evaluate the impacts of parametric model uncertainty on the profitability of beech stands under climate change, in terms of Land Expectation Value (LEV), Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) of alternative management regimes.

2. Material and methods

2.1. The 3-PG model

The 3-PG model is based on two main sets of calculations: (1) defining the biomass increment and (2) allocating the growth to different tree compartments, determining the growth pattern of the stand (Landsberg et al., 2001b). These calculations are performed in five submodels (Forrester and Tang, 2016): (1) a carbohydrate assimilation submodel, computing the gross primary productivity (GPP) based on the photosynthetically active radiation (PAR) intercepted by the forest stand and the canopy quantum efficiency. The canopy quantum efficiency is constrained by environmental factors, such as vapor pressure deficit (VPD), water availability and temperature. The Net Primary Productivity (NPP) is then calculated based on a fixed rate of the GPP (Almeida et al., 2004a); (2) the second submodel allocates the NPP into different tree compartments, starting with roots, followed by stem and foliage. The allocation of NPP to roots is driven by site fertility and water availability, while the allocation to stem and foliage follows allometric relationships (Landsberg and Waring, 1997); (3) a tree mortality submodel following the -1.5 self-thinning law and an age and stress dependent factor (Bryars et al., 2013); (4) a soil water balance submodel describing the water availability based on the initial soil water, monthly precipitation, evaporation and transpiration. Transpiration is calculated based on the Penman–Monteith equation and the evaporation accounts for the water interception by the canopy (Waring et al., 2014); (5) a submodel to calculate stand variables of management interest, e.g. stand height, basal area, volume, stem biomass, among others (Esprey et al., 2004).

The model operates on a monthly time step. It requires as input basic climatic variables (vapor pressure deficit, number of frost days, precipitation and solar radiation), stand structure (age, number of tress per hectare, foliage biomass, roots biomass and stem biomass), indication of site fertility and management history (age of thinning, thinning intensity, number of stems per hectare of remaining stand) (Almeida et al., 2004b; Landsberg et al., 2005).

3-PG was initially developed for simulating stands of evergreen forest plantations. Therefore, its original form does not consider deciduous species. Two approaches were applied to include the ecology of deciduous dynamics into 3-PG. The first approach, applied by Potithep and Yasuoka (2011), interrupts the functioning of trees during the winter months. The second approach, developed by Forrester and Tang (2016), models the stand development of deciduous species through the inclusion of two additional parameters into the model, namely the month of leaf fall and the month of leaf production. Between the months of leaf fall and leaf production, the leaf biomass is reduced to zero and no photosynthetic active light is absorbed, thus setting the GPP to zero. In the month of leaf production, the same leaf biomass lost in the month of leaf fall is recovered, with the complete allocation of NPP to leaf biomass, until the leaf biomass is recovered. Subsequently, the remaining NPP partitioning follows as usual. In this study, we used the approach proposed by Forrester and Tang (2016) because it describes more accurately the process involved in the leaf fall and leaf production in a beech stand.

2.2. Data

We calibrated the 3-PG model based on data from 12 intensively monitored plots in Germany. Sites 1–6, 13 and 14 are located in Southern Baden-Württemberg and were inventoried twice, with a 13-year interval between measurements. Data regarding stand density, DBH, height and volume was recorded, as well as climate and soil parameters. Sites 7–12 and 15–17 are part of the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests) level II plots in Germany (ICP, 2010) and were inventoried every 3–5 years. Table 1 reports the initial characteristics of each plot, including stand age, tree number, stand diameter (DBH), stand height and standing volume for the sites used for calibration. The plots included in our study had different monitoring periods, ranging from 8 to 43 years, generating in total 56 observations for each of the previously mentioned variables. For initialization, the model requires monthly climate data, soil data and initial values for stem, root and foliage biomass. For sites 1–6 and 12–14 the climate and soil data were measured *in situ*. For the remaining sites, the climate data was retrieved from the German Weather Service (DWD), based on spatially interpolated data reported for the whole country in a 1 km × 1 km grid and soil information was retrieved from the Soil Maps and Databases from the Federal Institute for Geosciences and Natural Resources (BGR). For all sites, the leaf, root and stem biomass were calculated using allometric equations, compatible with the DBH and height range of the dataset, reported in Wutzler et al. (2008) (details in Appendix A).

2.3. Bayesian calibration

2.3.1. The Bayesian framework

Bayesian inference of process based forest growth models has gained attention during the past decade, with applications to a broad range of models and tree species (e.g. Hartig et al., 2014; van Oijen et al., 2013). The Bayesian approach provides a framework for estimating parametric uncertainty in terms of probabilistic distributions, thus enabling a direct quantification of parameter uncertainty (e.g. van Oijen et al., 2005). Bayes theorem states that the best estimate (posterior uncertainty $p(\theta|y)$) for a parameter vector θ given data y is given by:

$$p(\theta|y) = \frac{p(\theta)p(y|\theta)}{p|y} \tag{1}$$

Here, $p(\theta)$ expresses our prior beliefs on possible parameter values. These prior beliefs are modified via the likelihood function $p(y|\theta)$, which calculates the probability density of observing the data, conditional on the model's parameters. It can be shown mathematically that the additional term $p(y)$ can be expressed as the integral over $p(\theta)p(y|\theta)$, and therefore factors out when estimating the posterior uncertainty $p(\theta|y)$. The estimation of the distribution $p(\theta|y)$ is usually done by Markov Chain Monte Carlo (MCMC) algorithms, a class of stochastic algorithms that use a sampling scheme to construct an approximation of $p(\theta|y)$.

2.3.2. Prior distribution

A far as we know, no previous attempts were performed for calibrating 3-PG for beech stands. Thus, no quantitative prior knowledge regarding parameter values was available. Therefore, we applied bounded uniform distributions for the parameter values (see Appendix B). The minimum and maximum values for the parameters were defined based on the ranges (maximum-minimum) of the other 28 species that were previously calibrated for 3-PG and 3-PGmix (Forrester and Tang, 2016). The minimum value for each parameter was defined as the minimum value recorded for the defined parameter, minus half of the range for this parameter. Similarly, the maximum value was obtained through the maximum value recorded, plus half of the range. Exceptions were applied to parameters limited to values between 0 and 1, and for the maximum age parameter. For the maximum age parameter, due to the known possibility of considerably old beech stands compared to the usual age range of species already parametrized for 3-PG, we applied a wider prior. Moreover, the month of leaf fall was defined in accordance to Gressler et al. (2015) as October, and the month of leaf production established in accordance to Menzel et al. (2015) as April.

2.3.3. Likelihood function

As in regression models, outliers can be problematic for a Bayesian analysis, because they can exert a strong influence on the parameter estimates. To make the calibration more robust against this problem, we applied a well-know approach from robust statistical inference, which is modeling the residual error as a Student's t distribution with sampled degrees of freedom $\varepsilon \sim t_{\nu}(0, \sigma_i^2)$ (Lange et al., 1989). The Student's t distribution can be interpreted as a scaled mixture of normal distributions and approximates the

Table 1
Initial state of the stands used for calibration. The table shows the characteristics of the stands used for calibration, including tree number, stand age, stand diameter (DBH), stand height, standing volume and number of observations.

Site	Latitude	N/ha	Age	DBH (cm)	H (m)	Volume (m^3/ha)	Obs. number
Training dataset							
1	48.0	512	70	25.6	24.7	321.0	2
2	48.0	452	70	26.8	26.7	330.4	2
3	48.0	613	70	23.5	25.8	352.0	2
4	48.0	579	80	21.3	19.1	195.7	2
5	48.0	524	80	23.0	22.9	244.0	2
6	48.0	610	80	20.5	19.8	190.6	2
7	50.1	292	123	36.3	31.7	534.7	4
8	51.2	740	77	24.7	22.9	474.4	3
9	51.4	156	141	52.3	35.2	406.9	3
10	51.7	229	168	42.2	28.2	489.2	5
11	51.7	199	114	36.0	26.8	383.4	11
12	51.8	245	120	37.4	25.2	342.0	18
Validation dataset							
13	48.0	427	70	27.8	28.7	386.8	2
14	48.0	676	80	20.8	21.0	236.1	2
15	51.5	227	136	43.0	31.8	632.7	5
16	51.6	168	111	44.7	30.8	481.8	13
17	53.4	867	77	16.6	18.11	242.4	3

normal distribution when $v \to \infty$. Conversely, with small v, the distribution is heavy tailed, which means that the occurrence of outliers in the data set has smaller effects on the likelihood value. The Student t likelihood is

$$p(y|\theta) = \Pi_{i=1}^{N} \frac{\Gamma(v+1)/2}{\Gamma(v/2)\sqrt{v\pi\sigma}} \left[1 + \frac{1}{v}\frac{1(\hat{y}_i - y_i)^2}{\sigma_2}\right]^{-(v+1)/2} \quad (2)$$

where Γ: gamma function; v: degrees of freedom of output variable; y_i: i-th observation of output variable; $\hat{y}_i$: i-th simulated value of output variable; and σ_i^2: variance of output variable. For the calibration, we parameterized v (Eq. (3)) as

$$v = 1 - N * \text{In}(1 - u) \quad (3)$$

which maps the degrees of freedom from 1 to ∞, where N is a constant, related to the probability of having outliers in the dataset (Kruschke, 2014), defined in our case as 50. We then estimated the parameter u with a uniform prior distribution from 0 to 1.

2.3.4. Posterior estimation

In order to estimate the posterior, we applied the Differential Evolution Markov Chain Monte-Carlo algorithm (henceforth: DE-MCzs). The DE-MCzs combines characteristics of conventional MCMC methods with the ideas of differential evolution optimization algorithms (Ter Braak and Vrugt, 2008). As discussed in Ter Braak and Vrugt (2008), the DEMCzs method automatically adjusts scale and orientation of the proposal distribution and uses a snooker updater, which leads to an increased efficiency compared to "conventional" MCMC methods. In order to accelerate convergence, chains were initialized with a Nelder-Mead pre-optimization, implemented in the Bayesian Tools R package (Hartig et al., 2017).

Convergence of the MCMCs was assessed through the Gelman-Rubin diagnostic. The Gelman-Rubin diagnostic was proposed by Gelman and Rubin (1992) and computes the potential scale reduction factor $\sqrt{\hat{R}}$, the square root of between-chain and within-chain variance. Thus, the scale reduction factor is an indication of whether the chains still look different from each other, with a value of 1 indicating that they look identical, at least regarding their variance. To evaluate convergence, we computed two chains with the DEMCzs algorithm, and required that $\sqrt{\hat{R}} < 1.1$ for assuming that the chains are converged, i.e. they are provide a sufficient approximation of the target distribution.

2.4. Goodness of fit

In Bayesian inference, goodness-of-fit is usually evaluated via posterior predictive simulations, meaning that new data is simulated from the model with parameters from the estimated posterior distributions, and the resulting simulations are compared to the observed data. From such posterior predictive simulations, one can calculate standardized residuals, which essentially ask where the observed data fall within the range of posterior predictive simulations. To apply this methodology, we simulated new data based on 1000 draws from the parameter posterior distribution, and assessed the frequency of obtaining simulated values that were smaller/larger than observed data.

Additionally, we evaluate percentage bias and Normalized Root Mean Squared Error (NRMSE) on both calibration and validation data. The percentage bias (PBIAS) measures the average bias of model's predictions in percent. A positive value indicates model underestimation, whereas negative values indicate model's overestimation of the variables of interest. The NRMSE measures the model accuracy, indicating the estimation error of interest variables. For computing the accuracy metrics, we simulated 1000 draws from the posterior distribution of the parameters and computed the NRMSE and PBIAS based on the average response.

To account for the uncertainty introduced by the allometric equations into the model's projections, we computed the variance of the leaf, root and stem biomass at stand level applying the functions provided by Wutzler et al. (2008) at each month of our predictions. Subsequently, we generated 1000 random draws from a uniform distribution and computed for each draw, the respective quantile of a normal distribution with zero mean and standard deviation based on each month's corresponding variance, finally adding these random draws to our model's predictions.

2.5. Impacts of climate and parametric model uncertainty on forest LEV

To assess the impacts of parameter uncertainty on forest profitability, we computed the LEV under changing climate for different management regimes. The basis of our simulations was the management regime described in the yield table for *Fagus sylvatica* used in Baden-Württemberg, considering an intermediary productivity class (yield class, determined as the mean annual volume increment at base age 100 years, equal to 6 m^3/ha/year). For the implementation of management interventions in the model, we

Table 2
Management regimes, defined by rotation length and thinning intensity. The numbers are the identifiers for each management regime with the respective thinning intensity (column) and rotation length (row).

Rotation length	Thinning intensity			
	BAU	Decreased	Increased	No thinning
120	1	6	11	16
130	2	7	12	17
140	3	8	13	18
150	4	9	14	19
160	5	10	15	20

derived the number of trees and the biomass of harvested trees compared to the average tree in the stand from the yield table. We initialized the model with the values reported in the yield table for a 40-year-old stand with thinning interventions every 10 years. We applied five options for rotation length (120,130, 140, 150 and 160 years) in combination with four thinning intensity options (no thinning, business-as-usual (BAU), increased thinning intensity and decreased thinning intensity) generating in total 20 alternative management regimes (Table 2). The management for decreased and increased thinning intensity was defined by increasing and decreasing the biomass fraction of thinned trees in relation to the biomass of the average tree in the stand and the number of remaining trees by 30% compared to the values applied in the BAU management (Fig. 1). The number of trees under the no-thinning management resulted from the natural development of the stand, i.e. governed by the occurrence of natural mortality due to environmental pressures and density dependent mortality according to the -1.5 thinning rule. This rule is a log-log relationship between size and density that describes the mortality of crowded even-aged stands, commonly displaying slope of -1.5 (Weller, 1987).

For the further analysis, we calculated model outputs for the amount of wood extracted from the stand by thinning and final harvesting, for a climatically typical stand located in Tuttlingen 48.0N, 8.75 E (Baden-Württemberg, Germany), under 12 climate change trajectories, as a combination of the ISI-MIP Regional Climate Model – RCM and 3 Global Climate Models - GCM (HadGEM2-ES, IPSL-CM5A-LR and NorESM1-M), considering the representative concentration pathways (RCP) 2.6, 4.5, 6.0 and 8.5.

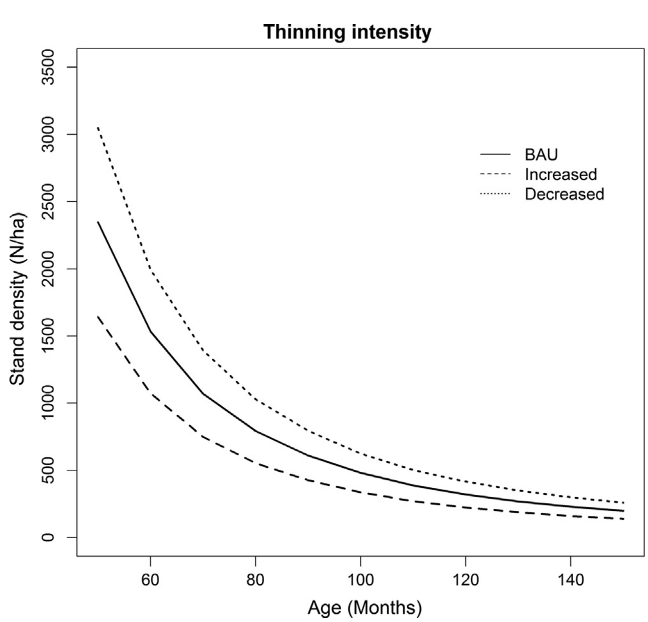

Fig. 1. Prescribed number of remaining trees according to stand age for different thinning schemes.

To forward parametric model uncertainty, we generated 1000 draws from the posterior distribution for each of the 12 climate change trajectories, added the variability introduced by the allometric equations and computed the posterior predictive distribution for Land Expectation Value (LEV) of the 20 management regimes.

To account for economic uncertainty, we fitted a lognormal distribution of real wood prices for each assortment class during the period 2004–2016 in Baden-Württemberg. We then generated, for each posterior draw and thinning period, a random draw from the correspondent distribution with zero mean and added it to the current wood prices. Similarly, we considered three options for discounting schemes, applying a risk free interest rate of 1, 2 and 3%, and subsequently including uncertainty on the risk component of interest rate applied by managers. To this end, at each posterior, a random draw from a normal distribution with expected values equal to 2, 3 and 4% truncated at ±50% of the expected value was considered. We applied a 0.9% standard deviation, according to Brousseau and Durré (2013). This standard deviation refers to consol bonds volatility, which is a suitable proxy to long term interest rates, being thus well suited to long term investments, such as forest investments. Therewith, we examined a range of possible discounting schemes applied by forest managers, according to their risk perception, with interest rates supported on [0.01, 0.03], [0.02, 0.04] and [0.03, 0.05]. Initial maintenance costs were computed according to Hanewinkel et al. (2010) and corrected by the inflation rates. We assumed no planting costs, as beech stands are established through natural regeneration in the region. We defined net wood prices based on harvesting costs reported by Härtl et al. (2013). The price was calculated based on the stand DBH, using the average of the prices of the nearest two assortment classes (see details in Appendix C). Additionally, in order to identify which model parameters had the most influence on the LEV variation, we regressed posterior predictive LEV values for management alternatives 5, 10, 15 and 20 with a 160-years rotation length against the respective posterior parameter, using a random forest algorithm (R package randomForest, see Breiman, 2001; Liaw and Wiener, 2002).

2.6. Robust optimum management regimes under uncertainty

To identify the most suitable management regime under climate and parametric model uncertainty, we evaluated the robustness of each management regime by empirically computing the mean LEV, the Value-at-Risk (VaR) and the Conditional Value-at-Risk (CVaR) for all management alternatives under the 12 climate trajectories.

The VaR is commonly applied in portfolio optimization (Ben-Tal et al., 2009). By seeking the highest VaR we consider the management regime with highest LEV at a given α-level confidence, defined in our case as 95%. Thus, for a given management regime, we expect that in 95% of the cases we will obtain a LEV superior to the VaR. The management regime with highest CVaR, also referred to as expected shortfall, yields the lowest probability of catastrophic outcomes, thus we search for the highest average value of the (1-α)-quantile of the LEV distribution. In our case we defined the management regime with the highest value yielded by the average of the lowest 5% LEVs based on our simulations. Therewith, we established the most robust management option considering model, economic and climate change uncertainty.

3. Results

3.1. Calibration results

The calibration converged to the target distributions after 6 million iterations of the DEMCzs algorithm. Only the potential scale reduction factor of alpha (canopy quantum efficiency) was with 1.28 still slightly higher than our convergence criterion, but due to computational limitations, we accepted this result as a sufficient approximation of the posterior.

The marginal posterior distribution of model parameters are presented in Table 3 (for parameters description see Appendix D). The data was more informative for parameters related to allometric relationships and carbon partitioning, e.g. constant and slope of stem mass and diameter relationship (aS and nS), while there was considerable uncertainty for parameters related to stand mortality, e.g. fraction mean single-tree foliage, mean single-tree root and mean single-tree stem biomass lost per dead tree

Table 3
Posterior parameter estimates, summarized by their quantiles.

Parameter	Quantile				
	2.50%	25%	50%	75%	97.50%
pFS2	0.030	0.031	0.033	0.036	0.048
pFS20	0.050	0.051	0.052	0.055	0.062
aS	0.238	0.292	0.322	0.351	0.391
nS	2.141	2.174	2.200	2.229	2.287
pRx	0.301	0.313	0.331	0.356	0.430
pRn	0.029	0.039	0.048	0.057	0.072
gammaFx	0.016	0.018	0.019	0.021	0.025
gammaF0	0.000	0.001	0.002	0.003	0.003
tgammaF	16.740	48.400	80.790	114.900	146.800
gammaR	0.000	0.000	0.000	0.000	0.001
Topt	10.280	12.330	14.640	17.670	24.180
Tmax	25.810	30.260	33.960	37.000	39.710
Tmin	-9.848	-8.485	-6.834	-4.713	-0.184
fCalpha700	1.020	1.234	1.433	1.660	1.873
fCg700	0.023	0.228	0.451	0.701	0.966
m0	0.001	0.011	0.018	0.024	0.029
fN0	0.206	0.251	0.296	0.346	0.453
fNn	0.550	0.981	1.270	1.577	1.956
MaxAge	203.500	233.500	265.600	301.800	344.800
nAge	1.932	3.039	3.545	3.957	4.292
rAge	0.555	0.689	0.796	0.922	1.216
gammaNx	0.006	0.062	0.110	0.172	0.311
gammaN0	0.001	0.007	0.014	0.022	0.029
tgammaN	21.620	36.420	51.230	65.010	78.590
ngammaN	0.027	0.303	0.644	1.024	1.452
wSx1000	244.900	324.500	394.200	459.700	531.200
mF	0.012	0.107	0.207	0.302	0.391
mR	0.007	0.066	0.127	0.188	0.243
mS	0.009	0.069	0.128	0.189	0.244
SLA0	10.580	15.130	20.100	24.900	29.500
SLA1	12.560	19.190	22.880	26.120	29.510
tSLA	3.734	10.020	16.330	22.860	29.270
k	0.407	0.459	0.504	0.550	0.595
fullCanAge	10.640	16.260	22.320	28.760	35.150
MaxIntcptn	0.326	0.366	0.382	0.392	0.399
LAImaxIntcptn	0.742	4.636	6.302	7.765	9.637
alpha	0.031	0.039	0.047	0.056	0.068
Y	0.442	0.457	0.473	0.492	0.508
MinCond	0.001	0.008	0.015	0.023	0.029
MaxCond	0.020	0.025	0.028	0.029	0.030
LAIgcx	2.070	2.599	3.092	3.545	3.957
CoeffCond	0.000	0.003	0.007	0.013	0.030
BLcond	0.007	0.011	0.013	0.016	0.021
fracBB0	0.690	0.869	0.930	0.970	0.997
fracBB1	0.003	0.040	0.087	0.137	0.193
tBB	22.010	29.020	32.480	35.410	38.130
rhoMin	0.261	0.309	0.342	0.380	0.460
rhoMax	0.480	0.538	0.576	0.612	0.672
tRho	66.410	111.300	128.100	140.600	149.100
aH	4.341	5.143	5.496	5.767	5.980
nHB	0.421	0.432	0.445	0.464	0.511
FR_1	0.118	0.160	0.202	0.257	0.339
FR_2	0.174	0.312	0.395	0.493	0.588
FR_3	0.123	0.215	0.278	0.350	0.462
FR_4	0.133	0.203	0.261	0.328	0.435
FR_5	0.167	0.241	0.301	0.367	0.502
FR_6	0.128	0.202	0.260	0.333	0.469
FR_7	0.110	0.172	0.222	0.281	0.407
FR_8	0.358	0.437	0.466	0.486	0.499
FR_9	0.096	0.135	0.166	0.206	0.277
FR_10	0.176	0.241	0.298	0.377	0.475
FR_11	0.041	0.086	0.112	0.144	0.220
FR_12	0.021	0.099	0.149	0.205	0.317

(continued on next page)

Table 3 (*continued*)

Parameter	Quantile				
	2.50%	25%	50%	75%	97.50%
sigmaDBH	2.270	2.610	2.799	2.985	3.418
sigmaH	1.282	1.939	2.125	2.304	2.677
sigmaWF	0.066	0.100	0.126	0.162	0.280
sigmaWR	0.378	0.498	0.574	0.659	0.854
sigmaWS	2.516	3.425	4.027	4.734	6.460
sigmaVol	5.623	8.002	9.520	11.080	14.690
uDBH	0.119	0.359	0.569	0.770	0.972
uH	0.021	0.204	0.455	0.691	0.961
uWF	0.000	0.002	0.006	0.011	0.042
uWR	0.000	0.002	0.003	0.006	0.014
uWS	0.000	0.002	0.005	0.008	0.018
uVol	0.001	0.005	0.010	0.017	0.032

(mF, mR and mS). Parameters related to the leaf biomass development and leaf biomass, such as the specific leaf area (SLA0 and tSLA) presented high uncertainty as well, thus indicating the need to collect more informative data regarding leaf development.

The error model estimated heavier tails for leaf biomass, root biomass, stem biomass and stand volume than for DBH and height. For the first four variables, the parameter *u*, controlling the number of degrees of freedom in the Student t likelihood, had median value neighboring 0.05, resulting in small number of degrees of freedom (close to 3 according to Eq. (3)). On the other hand, the same parameter had much higher values for DBH and height (close to 0.5), indicating that outliers were less problematic for these variables.

Model predictions had reasonable NRMSE and bias (Table 4) (for model's predictions see Appendix E). For all output variables except foliage biomass, we observed a trend of slight underestimation, indicated by the positive bias, ranging from 0.88 to 2.40%, with the best results for stand height and poorest results for foliage biomass. Similarly, the highest accuracy of predictions was observed for stand height and DBH, presenting the lowest NRMSE (7.3 and 8% respectively) and the poorest for foliage biomass (14.96%). For the validation data, the results presented higher accuracy, with smaller NRMSE for all output variables except foliage biomass and DBH, whereas the bias increased for all outputs. There was stronger overestimation trend for foliage biomass, equal to 13.57%. Bayesian *p*-values for volume predictions showed a fairly homogenous distribution indicating the suitability of the Student t as error model (details in Appendix F).

Table 4
Goodness of fit of the calibrated model for calibration and validation data, expressed by the percentage NRMSE (Normalized root mean square error) and PBIAS (Percentage bias).

Output variable	NRMSE (%)	PBIAS (%)
Calibration data		
DBH (cm)	7.3	1.19
Stand height (m)	8.0	0.90
Stand volume (m^3/ha)	8.37	0.88
Foliage biomass (tDW/ha)	14.96	−2.88
Root biomass (tDW/ha)	9.05	2.16
Stem biomass (tDW/ha)	8.64	2.40
Validation data		
Output variable	NRMSE (%)	PBIAS (%)
DBH (cm)	9.07	−7.4
Stand height (m)	4.55	1.64
Stand volume (m^3/ha)	6.65	−3.39
Foliage biomass (tDW/ha)	30.21	−13.57
Root biomass (tDW/ha)	5.84	3.09
Stem biomass (tDW/ha)	6.03	−0.69

3.2. Parametric and climate uncertainty impacts on forest profitability

Taking into account the uncertainty set for interest rates supported on [0.01, 0.03], management regime 15, with increased thinning intensity, resulted in the highest expected LEV, whereas the no thinning management (20) displayed the poorest economic outcomes (Fig. 2), with a high probability density around 0. Management 5, considering BAU thinning and management 10 with decreased thinning intensity presented similar results, with a better performance under BAU thinning. In general, the LEV distribution displayed a positive skewness for all rotation ages and thinning intensities.

Climate change, parameter and economic uncertainty affected significantly the forest LEV. The LEV ranged in general from −2000 EUR/ha to over 25,000 EUR/ha, i.e. from unviable (negative LEV) to highly profitable forest management (Fig. 2). Even for the cases of the most profitable management regimes evaluated, we perceived a probability of obtaining a negative LEV. Moreover, BAU management regimes were in general suboptimal considering forest profitability.

Fig. 3a and b shows the LEV distribution of the robust management regimes considering the interest rate uncertainty sets supported on [0.02, 0.04] and [0.03, 0.05] and expected values of 3 and 4%, respectively. Similarly to the results obtained applying the interest rate supported on [0.01, 0.03], the increase in thinning intensity appeared as the most suitable option in terms of profitability. However, it was beneficial to decrease the rotation length to 130 and 120 years when the expected interest rate increased to 3 and 4%, respectively. Additionally, we perceived a strong reduction on the expected LEV with increased interest rates, neighboring 500 EUR/ha for the interest rates with 3% expected value and -1100 EUR/ha when the expected interest rates increased to 4%.

We noticed that the LEV distribution showed a positive skewedness for all uncertainty sets applied to interest rates. This behavior arose both from the effect of interest rate and price uncertainty, given that the price distribution was also positively skewed. In addition, the fact that the LEV increases drastically in absolute terms when the interest rate is reduced, resulting in a heavy right tail, contributed substantially to the shape of the LEV distribution.

The uncertainty in LEV slightly increased with increasing climate change intensity (see details in Appendix G). The LEV increased from trajectories considering RCP 2.6 to RCP 8.5 as result of increasing productivity, mainly due to CO_2 fertilization effects. On the other hand, there was a concurrent increase in the standard deviation as well, indicating that as climate diverge from current conditions (e.g. RCP 8.5), the effects of climate change slightly increase uncertainty.

Looking at the sources of uncertainty by regressing posterior parameters against their outcomes, we found that the parameters

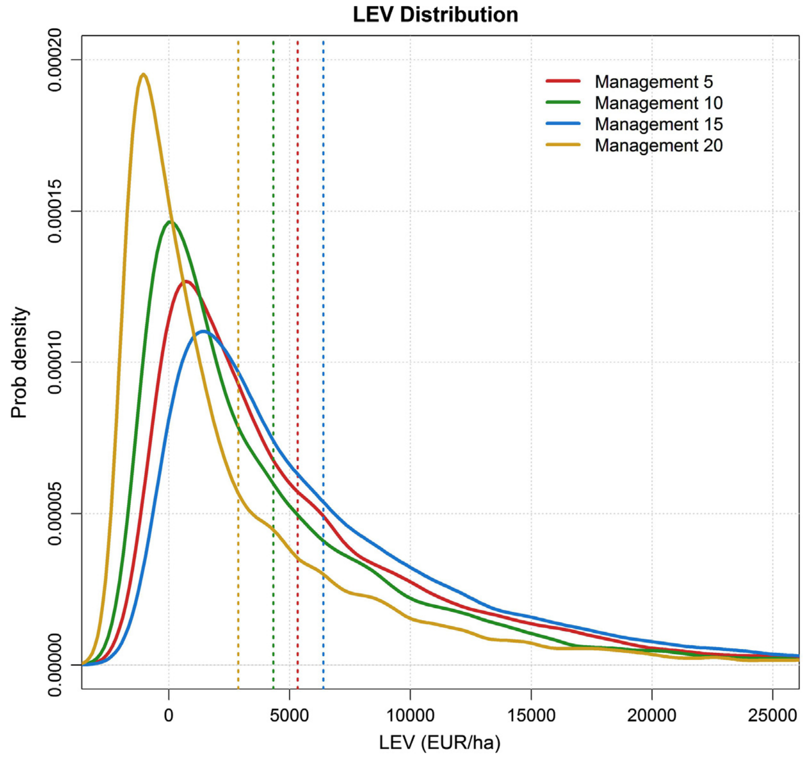

Fig. 2. The figure shows the distribution of the Land Expectation Value (LEV) based on parameter, climate and economic uncertainty. The curves correspond to management regimes 5, 10, 15 and 20, described in Table 3, with its respective mean value (dotted lines), considering the interest rate distribution supported on [0.01, 0.03].

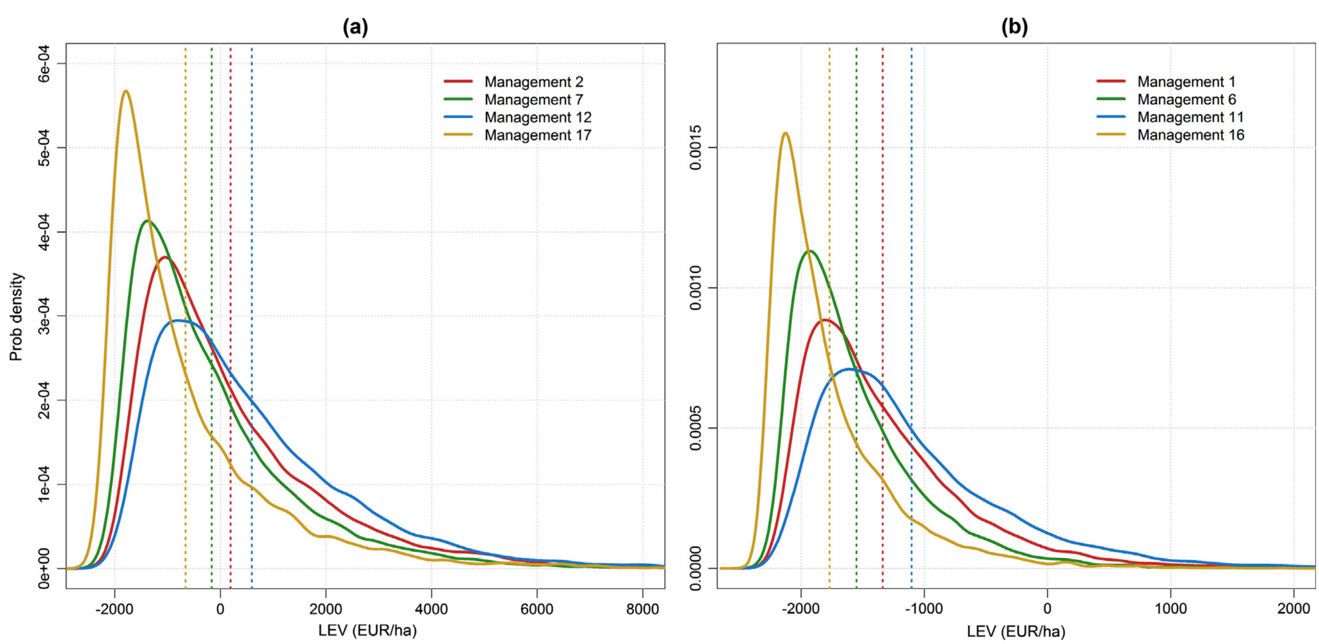

Fig. 3. The figure shows the distribution of the Land Expectation Value (LEV) based on parameter, climate and economic uncertainty. Mean values appear as dotted lines. (a) shows the results for the interest rate distribution supported on [0.02, 0.04] and (b) displays the results for interest rate distribution supported on [0.03, 0.05].

with the highest importance to management uncertainty for management regimes with thinning interventions (Fig. 4a–c) were related to the growth enhancement due to CO_2-fertilization (fCalpha700), the optimum temperature for growth (Topt), the canopy quantum efficiency (alpha) and the maximum allocation of NPP to roots (pRn). The first four parameters are closely related to growth rates, whereas the maximum allocation to root has a direct impact on the carbon allocation to stems. Consequently, the wood volume produced in the stand and the respective LEV are significantly affected. When no thinning interventions were applied, the occurrence of mortality became significant, evidenced by the high importance of parameter mS (fraction mean single-tree stem biomass lost per dead tree), being directly related to the standing volume and the value of the stand at the end of simulation period

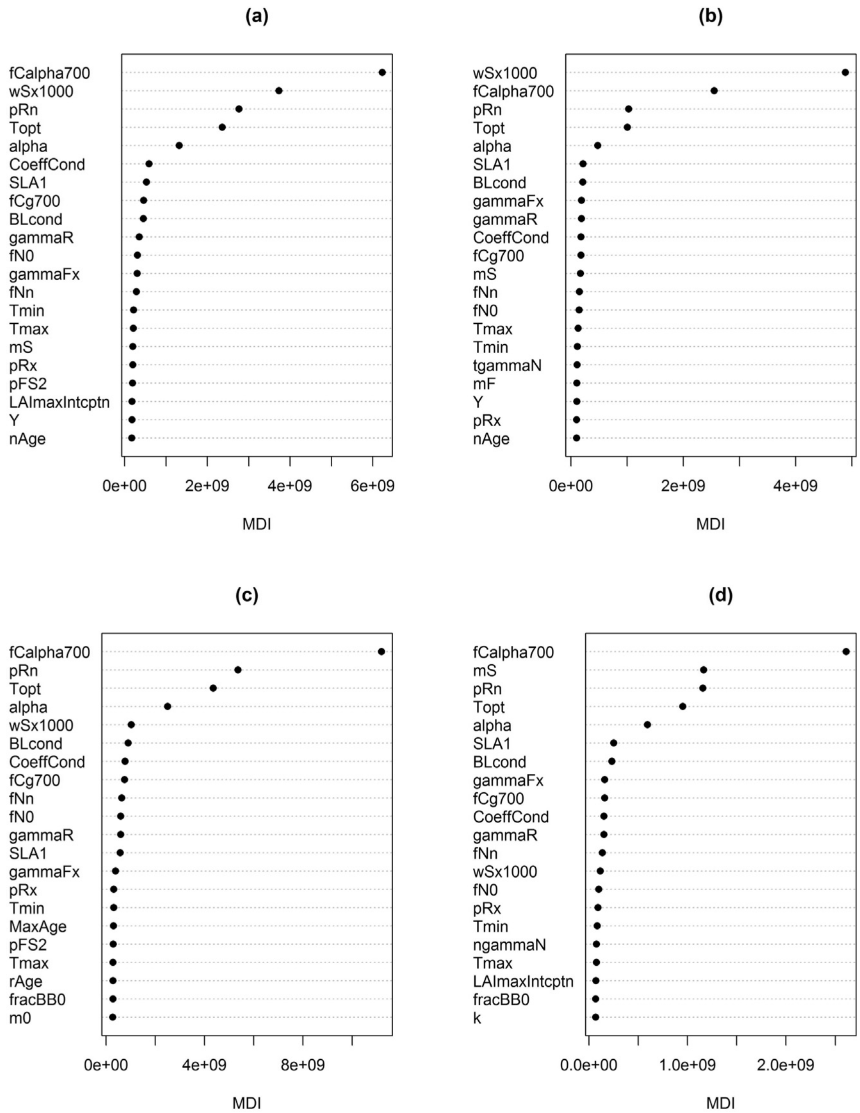

Fig. 4. Importance of the uncertainty of the different parameters to the overall LEV uncertainty, measured as MDI (mean decrease in node impurity). Estimates were obtained by regressing parameter variation against LEV variation using a random forest for managements 5 (a), 10 (b), 15 (c) and 20 (d), considering all climate change trajectories.

(Fig. 4d). For BAU and decreased thinning intensity (Fig. 4a–b), parameter wSx1000, the maximum stem mass per tree (at a density of 1000 trees/hectare), affected strongly the LEV, as the average stand diameter is derived from this quantity, this parameter controls the average tree dimensions. Therewith, stand assortments and value are directly affected.

3.3. Robust optimal management under uncertainty

According to our results, the most robust management regarding climate, economic and parametric model uncertainty was management scenario 15 when the, with increased thinning intensity and a 160-years rotation length. It yielded the highest mean LEV (6394 EUR/ha), VaR (-155 EUR/ha) and CVaR (−597 EUR/ha) (Table 5), thus being the most robust alternative resulting in the lowest probability of poor economic outcomes. On the other hand, the lowest mean LEV was yielded by management 20 (2865 EUR/ha), with no thinning interventions and a 160-years rotation length. In general, with increasing rotation length, the probability of poor results decreased for increased thinning intensity management, with the LEV distribution presenting light shifts to the right and higher VaR. On the other hand, for regimes with no thinning and decreased thinning intensity, increasing rotation length decreased the profitability. Moreover, we observed a stronger impact of thinning intensity on forest profitability compared to the rotation length.

We found fairly high standard deviations for the LEV and consequently low values for the VaR and CVaR. This behavior is likely the combination of the high uncertainty with the choice of the α-confidence level. The uncertainty in prices, interest rate and model parameters led to a high standard deviation of the LEV that allied to the high α-confidence level yielded low VaR and CVaR. We would expect an increase in these values with the decrease in confidence level and uncertainty.

Looking at the most robust alternative, management 15, it was at first view rather unexpected that with increased rotation age the LEV increased. The increase in rotation length obviously led to a prolonged beneficial effect of CO_2 fertilization on the growth response of the stands at later periods of the simulation, and due to the relatively low interest rates applied (ranging from1 to 3%), forest growth rates remained higher than interest rates, counterbalancing the opportunity costs of not harvesting earlier. On the other hand, with lower contribution of early harvestings for management regimes with no thinning and decreased thinning intensity, the LEV decreased with the increase in rotation length.

Table 5
Mean LEV, standard deviation (Sd), Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) for each management regime and for each interest rate uncertainty set. The highest mean, VaR and CVaR for each interest rate set appear highlighted.

Management	Mean (LEV/ha)	Mean (LEV/ha)	Mean (LEV/ha)	VaR (LEV/ha)	VaR (LEV/ha)	VaR (LEV/ha)	CVaR (LEV/ha)	CVaR (LEV/ha)	CVaR (LEV/ha)
Interest rate (%)	1-3	2-4	3-5	1-3	2-4	3-5	1-3	2-4	3-5
1	5504	274	-1317	-466	-1620	-2048	-888	-1782	-2119
2	5221	116	-1396	-496	-1646	-2066	-847	-1779	-2122
3	5444	107	-1415	-540	-1706	-2096	-947	-1839	-2155
4	5406	47	-1442	-532	-1705	-2098	-908	-1852	-2169
5	5330	-3	-1460	-592	-1738	-2121	-995	-1895	-2188
6	5215	-55	-1547	-652	-1740	-2124	-1009	-1869	-2171
7	5183	-183	-1620	-780	-1822	-2166	-1162	-1956	-2215
8	4946	-343	-1693	-866	-1874	-2192	-1218	-1992	-2235
9	4793	-459	-1741	-970	-1939	-2223	-1299	-2042	-2258
10	4319	-625	-1794	-1075	-1985	-2243	-1385	-2088	-2277
11	5677	562	-1104	-282	-1504	-1982	-689	-1672	-2061
12	5969	583	-1119	-221	-1495	-1983	-631	-1662	-2061
13	6392	660	-1100	-201	-1503	-1989	-663	-1696	-2080
14	6305	597	-1130	-222	-1528	-2006	-655	-1701	-2083
15	6394	583	-1144	-155	-1504	-1997	-597	-1689	-2082
16	4840	-389	-1755	-1267	-2019	-2246	-1662	-2141	-2286
17	4242	-691	-1889	-1358	-2071	-2272	-1674	-2160	-2297
18	3782	-929	-1988	-1486	-2130	-2294	-1788	-2206	-2314
19	3450	-1122	-2063	-1594	-2171	-2310	-1813	-2224	-2322
20	2865	-1334	-2132	-1742	-2221	-2325	-1904	-2256	-2333

We highlight that when the interest rate increased, it was beneficial to decrease rotation lengths. For the interest rates supported on [0.02, 0.04], management 12 with a 130 years rotation and increased thinning intensity was the most robust, displaying the highest VaR and CVaR (-1495 EUR/ha and −1662 EUR/ha, respectively). With the increase in interest rates to the uncertainty set supported on [0.03, 0.05], a further reduction in rotation length to 120 years was the most robust solution (management 11). Moreover, we perceived that when interest rates increased, the selection of robust management regime varied when different robust metrics were considered. For both sets applying increased interest rates, the management with highest expected LEV differed from the management with highest VaR and CVaR (Table 5), indicating the importance of taking the tails of LEV distributions into account when deciding upon management alternatives.

If we had disregarded parametric model and economic uncertainty, we would have concluded that the optimum management regime for the interest rate uncertainty set supported on [0.01, 0.03] would be management 11, 12 or 13, depending on the climate change trajectory (Table 6, results refer to the model outputs generated with the median value of each model parameter and presents the highest LEV management for each climate change trajectory). Compared to the robust management regime, the optimum solutions would result in a higher degree of risk, with a decrease of 82% in the VaR value for management 11, 43% for management 12 and 29% for management 13.

In general, our results demonstrate a substantial influence of all sources of uncertainty on the LEV (Fig. 5). The contribution of interest rate uncertainty was dominant when we applied the uncertainty set supported on [0.01, 0.03], causing the LEV to range from 0 to 20,000 EUR/ha. Price uncertainty and parametric model uncertainty had a smaller but still important impact on the total uncertainty. With the increase in interest rates in Fig. 5b and 5c, the contribution of interest rate uncertainty to total uncertainty reduced, whereas the contribution of price and parametric model uncertainty increased. The LEV distribution showed a positive skewedness, especially for interest rates, due to the stronger influence of the lower half of the interest rate distributions on LEV, compared to the upper half.

Although model uncertainty contributed to smaller extent compared to price and interest rate, especially when small interest rates were applied (Fig. 5a), it showed an important effect on LEV (ranging from 0 to 10,000 EUR/ha) and on the selection of robust management alternatives. Taking into account only the economic uncertainty, the robust management would be management 12 (details in Appendix H), which presented considerably lower VaR and CVaR values when parametric model uncertainty was included in the analysis (Table 5).

4. Discussion

We used the process-based forest model 3-PG to investigate the impact and relative importance of uncertainty in model parameters, drivers (climate change trajectories) and economic parameters on the predicted profitability of beech forests. Uncertainties were estimated using Bayesian inference and then propagated to

Table 6
Deterministic and robust solution for each of the 12 climate change trajectories (CC), with its respective Representative Concentration Pathway (RCP), Global Climate Model (GCM), Optimum management regime, the robust management regime and the reduction in Value-at-Risk of the deterministic solution compared to the robust solution for the interest rate uncertainty set [0.01, 0.03].

CC	RCP	GCM	Optimum	Robust	VaR difference (%)
1	2.6	HadGEM2-ES	11	15	−82
2	2.6	IPSL-CM5A-LR	11	15	−82
3	2.6	NorESM1-M	12	15	−43
4	4.5	HadGEM2-ES	12	15	−43
5	4.5	IPSL-CM5A-LR	12	15	−43
6	4.5	NorESM1-M	12	15	−43
7	6.0	HadGEM2-ES	11	15	−82
8	6.0	IPSL-CM5A-LR	12	15	−43
9	6.0	NorESM1-M	13	15	−29
10	8.5	HadGEM2-ES	11	15	−82
11	8.5	IPSL-CM5A-LR	13	15	−29
12	8.5	NorESM1-M	13	15	−29

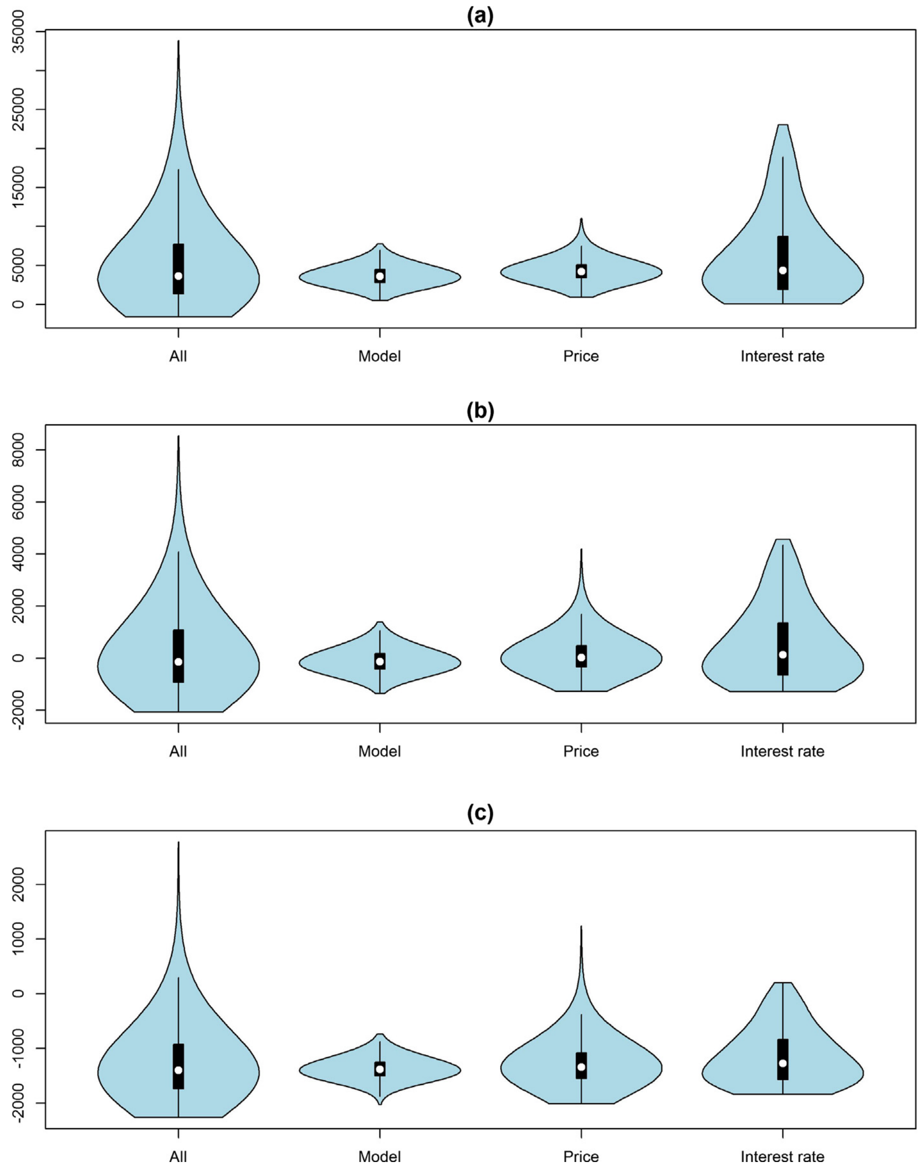

Fig. 5. Contribution of difference sources of uncertainty to the total uncertainty for the robust management 14, under climate change trajectory 1 (Table 6). Figures (a), (b) and (c) correspond to the uncertainty sets to interest rates supported on [0.01, 0.03], [0.02, 0.04] and [0.03, 0.05], respectively.

estimates of forest productivity and profitability. Our main findings are that all three uncertainties strongly impact forest profitability, and that neglecting them can lead to the selection of risky management options in the future. Our study thus both, highlights the importance of including uncertainty in the decision-making process, and provides a blueprint to operationalize such a goal. In what follows, we discuss the results of the study in more detail.

4.1. Calibration of the model and estimation of parametric uncertainty

In our calibration, the data proved informative especially for parameters directly related to stand structure, such as the intercept and slope of allometric equations for diameter and height. Higher uncertainties remained in parameters related to the canopy development. Some calibrated values markedly deviated to previous 3-PG calibrations for other species: The foliage and stem partitioning ratios for young and mature stands (pSF2 and pFS20) obtained in our study (presenting median values equal to 0.034 and 0.055) were substantially lower compared to usual values that range from 0.2 to 0.9 (e.g. Headlee et al., 2013; Nightingale et al., 2008). On the other hand, the obtained values for these parameters are compatible with the calibration for other deciduous species, e.g. Potithep and Yasuoka (2011), who used values equal to 0.03 and 0.03, respectively. The calibrated specific leaf area for mature leaves was substantially higher compared to other species (median values equal to 18), in line with other reported values for beech in the literature (e.g. Bartelink, 1997; van Hees, 1997).

Although the predictions for stand volume were reasonable, we observed that the model response after strong thinning interventions was not adequate, as it underestimated the volume in this case for the majority of sites (details in Appendix D). This behavior may arise due to the high growth responsiveness of beech even at advanced age and to limitations in the 3-PG canopy cover model, particularly after disturbances. As Forrester and Tang (2016) note, the model applies a canopy cover value between 0 and 1 that accounts for reduction on the canopy cover after disturbance, but does not account for the increased light absorption due to reduced shading from neighbor trees. In this sense, the light absorption by the canopy may be underestimated, resulting in an underestimation of the growth rates after thinning interventions.

Foliage biomass estimates were less accurate compared to the other outputs. Paul et al. (2007) found a similar pattern evaluating growth predictions yielded by 3-PG for two species in Australia, obtaining poor model efficiency for the prediction of foliage biomass, with much higher efficiency for DBH and stem biomass. Foliage biomass is usually less well explained by other predictors, such as DBH, compared to volume or stem biomass, presenting in general lower coefficients of determination (Muukkonen, 2007; Zianis et al., 2005). The predictions obtained through the calibration showed NRSME values close or below 10% for the output variables, whereas the bias remained below 4%, with exception of the leaf biomass, with substantially higher NRMSE and bias (14.96% and -2.88%, respectively). These ranges are compatible with the values found in the literature applying 3-PG to evaluate the growth of other tree species (e.g. Nightingale et al., 2008; Rodríguez-Suárez et al., 2010; Zhao et al., 2009).

4.2. Parametric and climate uncertainty impacts on forest productivity

We observed strong impacts of climate change and parametric model uncertainty on forest profitability in our results. Similarly, Reyer et al. (2016) reported significant impacts of climate and parameter uncertainty on forest NPP in Europe. Lonsdale et al. (2015) obtained predictions for *Pinus sylvestris* in UK applying the model 3-PGN, calibrated using a Bayesian approach, ranging approximately from 500 to 750m3/ha at an age of 100 years, that would roughly result in a 33% difference between the upper and lower bound of the growing stock's net present value (considering a 2% interest rate). Moreover, numerous studies highlight the importance of taking into account parametric model uncertainty when providing productivity and ecosystem development estimates (e.g. Ahlström et al., 2012; Valle et al., 2009; Verbeeck et al., 2006; Zaehle et al., 2005).

Our results demonstrate important impacts of parametric model uncertainty for a process-based model. An open question is if similar results would be expected for empirical models. McRoberts and Westfall (2014) and Berger et al. (2014) analyzed the effects of parameter uncertainty for estimating individual tree volumes for large area estimates, using forest inventory data. The authors found minor impacts of parameter uncertainty on the predictions. These results could be explained from the nature of models applied in these studies. Simple empirical individual tree volume models typically present high coefficients of determination and low parameter variance, resulting in only marginal effects of parameter uncertainty on model predictions.

We found that the most important 3-PG parameters contributing to LEV uncertainty were related to the absorbed PAR and CO_2 fertilization effects, thus with direct impact on forest productivity and wood production. This is in accordance with studies assessing the effects of climate change and CO_2 fertilization on forest productivity applying other process-based models (e.g. Devaraju et al., 2016; Reyer et al., 2014). The parametric model uncertainty reflects the ongoing debate about the limitations of CO_2 fertilization, in particular whether productivity may eventually be limited by other factors, such as nutrient availability (Girardin et al., 2011). In this sense, carbon fertilization effects might result in an overestimation of forest growth and consequently forest profitability. Moreover, for management regimes with no thinning, parameters related to mortality were critical, due to the increase in intertree competition. Hence, the sensitivity of the model to mortality parameters was enhanced. Hülsmann et al. (2016) point to this behavior modeling beech mortality in three European regions, indicating that mortality in beech forests was mainly driven by competition.

4.3. Robust optimal management under uncertainty

The LEV ranges obtained in our study for beech stands are compatible with values reported in the literature (e.g. Griess and Knoke, 2013; Hanewinkel et al., 2013). The optimum management regime disregarding climate, model and economic uncertainty recommended shortening the rotation age (120–140 years) in accordance with Hanewinkel et al. (2010). Similarly, the consideration of higher interest rates also sustained a reduction in rotation length to 130 and 120 years as the most robust option, as the growth rates of the forest were not capable to surpass the interest rates applied and counterbalance the opportunity costs of not harvesting the stands earlier.

In our analysis, the choice of an optimum management regime would imply a higher degree of risk when uncertainty was considered. Härtl et al. (2013), Neuner et al. (2013) and Eyvindson and Kangas (2017) point to similar patterns applying portfolio optimization theory in forest planning problems. The authors report the selection of management regimes different from the nominal optimum when uncertainty and risk is included in the analysis. In addition, increasing interest rates also resulted.

A trade-off between robustness and optimality might appear when considering planning under uncertainty. It may be necessary to sacrifice optimality for less sensitivity to the various sources of uncertainty (Lempert and Collins, 2007). This behavior is reported by numerous studies addressing environmental management under uncertainty (e.g. McInerney et al., 2012; Regan et al., 2005; Singh et al., 2015). However, in our approach, the conservativeness of the response may be adjusted by modifying the confidence level of the VaR and CVaR, in order to accurately represent preferences of managers or decision-makers. A decrease in the α-level approximates the VaR and CVaR to the mean LEV. More risk-averse managers are likely to care about the tails of the distribution, choosing a higher α-level, i.e. focusing on the worst-case scenario, whereas a risk-loving manager is likely to focus on the expected value of the LEV distribution, choosing a lower α-level.

In our study, we directly estimated the probabilities of model parameters, whereas climate change trajectories were deep uncertain. There might be cases where it is not possible to directly estimate any probabilities or distributions have only partial information. In such cases, other robust non-stochastic approaches may be applied as well. One option is the application of robust tractable approximations, obtained by bounding probabilities and allowing to guarantee the performance in worst-case scenarios (Ben-Tal et al., 2009). Another possibility is the application of satisficing or regret approaches proposed by the Robust Decision Making framework. These approaches provide a solid background for decision-making under uncertainty, allowing selecting options that perform well over a wide range of possible scenarios (Hadka et al., 2015).

We highlight that neglecting parameter, climate and economic uncertainty when developing management plans may result in poor outcomes in the future. Therefore, it is crucial to include these analysis in forest management plans. In this sense, the Bayesian framework appears as a natural choice, due to the possibility of obtaining a direct estimation of parameter uncertainty. Although examples of linkages between parametric model uncertainty and decision-making using a Bayesian approach may be found in management of other environmental resources, such as water management (e.g. Hobbs, 1997; Katz, 2002), its application to forest management is very scarce.

Forest management, similarly to the management of other environmental resources, involves a constant process of collecting data, implementing and revising management actions, constantly updating beliefs, which makes the Bayesian paradigm adequate (Dorazio and Johnson, 2003). In this context, we point to the fact that due to the lack of studies calibrating the 3-PG forest model for beech, we applied non-informative priors, obtaining relatively high parameter uncertainty, especially for parameters to which the data was not informative. Future studies could use our posterior results as new priors when new data become available (Hartig et al., 2012). For this purpose, we provide a thinned posterior sample (1000 samples) in the supplementary material. Moreover, beliefs in climate change trajectories may be updated and uncertainty reduced with new information (Yousefpour et al., 2013). Therewith, it is possible to reduce parametric model uncertainty and provide narrower parameter ranges and LEV distributions.

4.4. Limitations

Our parametrization of the process-based model 3-PG was based on wide (uninformative) priors. While the data was informative for several parameters, canopy development was not well constrained. Collecting more data on these parameters could likely further reduce parametric model uncertainty and produce more accurate estimates. Landsberg et al. (2003) suggested that, in order to obtain satisfactory results of growth simulation applying 3-PG, collecting information regarding the leaf area index, litterfall rates and stem mass is recommended.

We considered in our approach the uncertainties related to model parametrization, economy and climate change, which are commonly neglected by managers. These sources of uncertainty are critical for decision-making in forestry. However, we did not consider some other important sources of uncertainty that may also have significant implications for forest management. For instance, wood demand and operational efficiency may have strong impacts on forest profitability and thus could be included when deciding upon management strategies (Pasalodos-Tato et al., 2013). In addition, disturbances such as diseases, pests and changes in wood characteristics may have a significant impact on forest profitability. Beech trees at advanced age are particularly susceptible to the occurrence of red heart, which affect directly wood properties and its value, thus with implications to forest profitability (Zell et al., 2004). In this sense, the 3-PG model may be extended to encompass forest disturbances and wood quality to provide a more holistic analysis of risk.

The selection of the best management regime, as well as the impacts of different sources of uncertainty, was based purely in the economic outcome of the forest in our analysis. Therefore, we observed an overwhelming impact of the interest rate and price uncertainty. However, this might not be the case when multiple ecosystem values are considered, e.g. carbon sequestration, biodiversity and disturbance risk might be strongly affected by climate and model uncertainty. In this sense, future research may focus on robust management alternatives considering multiple-objective forest management, including managers' preferences for different forest ecosystem goods and services, applying multi-criteria decision making (MCDM) tools and evaluating trade-offs between different objectives (e.g. Creutzburg et al., 2016; Schwenk et al., 2012).

5. Conclusions

Forest managers and policy makers often face several sources of uncertainty when designing forest plans (e.g. environmental conditions, prices, operation efficiency), which adds considerable complexity to the management decision and usually creates trade-offs between high-yield and robust strategies. An important source of uncertainty usually neglected by forest managers is parametric model uncertainty, which implicitly represents the uncertainty about the properties of the forest itself. Bayesian inference addresses this problem by providing a framework for quantifying and merging uncertainty at different levels of the modeling process, and propagating it to practical outcomes (e.g. NPV, LEV, and IRR) or other models. Our study demonstrates that this approach, combined with risk analysis, may be successfully applied to analyze the uncertainty of process-based forest models in a forest planning context. We used the framework to select management alternatives that were robust against parametric, economic and climate change uncertainty. We believe that such a systematic quantification of uncertainties is key for designing management plans that will safeguard the provisioning of forest goods and services under climate change, according to societal preferences.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2017.06.061.

References

Allen, C.D., Macalady, A.K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kizberger, T., Rigling, A., Breshears, D.D., Hogg, E.H., Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J.H., Allard, G., Running, S.W., Semerci, A., Cobb, N., 2010. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. For. Ecol. Manage. 259, 660–684.

Almeida, A.C., Landsberg, J.J., Sands, P.J., 2004a. Parameterisation of 3-PG model for fast-growing Eucalyptus grandis plantations. For. Ecol. Manage. 193, 179–195.

Almeida, A.C., Landsberg, J.J., Sands, P.J., Ambrogi, M.S., Fonseca, S., Barddal, S.M., Bertolucci, F.L., meida et al., 2004 b. Needs and opportunities for using a process-based productivity model as a practical tool in Eucalyptus plantations. For. Ecol. Manage. 193, 167–177.

Ahlström, A., Schurgers, G., Arneth, A., Smith, B., 2012. Robustness and uncertainty in terrestrial ecosystem carbon response to CMIP5 climate change projections. Environ. Res. Lett. 7, 044008.

Amichev, B.Y., Hangs, R.D., Van Rees, K.C., 2011. A novel approach to simulate growth of multi-stem willow in bioenergy production systems with a simple process-based model (3PG). Biomass Bioenerg. 35, 473–488.

Bartelink, H.H., 1997. Allometric relationships for biomass and leaf area of beech (Fagus sylvatica L. In Annales des Sciences Forestieres (Vol. 54, No. 1, pp. 39–50). EDP Sciences.

Ben-Tal, A., El Ghaoui, L., Nemirovski, A., 2009. Robust Optimization. Princeton University Press.

Berger, A., Gschwantner, T., McRoberts, R.E., Schadauer, K., 2014. Effects of measurement errors on individual tree stem volume estimates for the Austrian National Forest Inventory. For. Sci. 60, 14–24.

BGR (Bundesanstalt für Geowissenschaften und Rohstoffe). Bodenkundliche Karten und Datenbanken. Available at: <https://www.bgr.bund.de/DE/Themen/Boden/Informationsgrundlagen/Bodenkundliche_Karten_Datenbanken/bodenkundliche_karten_datenbanken_node.html> (accessed 30/02/2016).

Bohn, U., Neuhäusl, R., Gollub, G., Hettwer, C., Neuhäuslová, Z., Schlüter, H., Weber, H., 2003. Map of the Natural Vegetation of Europe – Scale 1:2 500 000. Landwirtschaftsverlag, Münster, Map and Explanatory Text.

Bonan, G.B., 2008. Forests and climate change: forcings, feedbacks, and the climate benefits of forests. Science 320, 1444–1449.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.

Brousseau, V., Durré, A., 2013. Interest Rate Volatility: A consol Rate-Based Measure. ECB Working Paper Series 1505.Brunet, J., Fritz, Ö., & Richnau, G., 2010. Biodiversity in European beech forests–a review with recommendations for sustainable forest management. Ecological Bulletins 53, 77–94.

Brunet, J., Fritz, Ö., Richnau, G., 2010. Biodiversity in European beech forests – a review with recommendations for sustainable forest management. Ecol. Bull. 53, 77–94.
Bryars, C., Maier, C., Zhao, D., Kane, M., Borders, B., Will, R., Teskey, R., 2013. Fixed physiological parameters in the 3-PG model produced accurate estimates of loblolly pine growth on sites in different geographic regions. For. Ecol. Manage. 289, 501–514.
Burton, P.J., Macdonald, S.E., 2011. The restorative imperative: challenges, objectives and approaches to restoring naturalness in forests. Silva Fennica 45, 843–863.
Busing, R.T., Solomon, A.M., McKane, R.B., Burdick, C.A., 2007. Forest dynamics in Oregon landscapes: evaluation and application of an individual-based model. Ecol. Appl. 17, 1967–1981.
Cailleret, M., Heurich, M., Bugmann, H., 2014. Reduction in browsing intensity may not compensate climate change effects on tree species composition in the Bavarian Forest National Park. For. Ecol. Manage. 328, 179–192.
Christensen, M., Hahn, K., Mountford, E.P., Odor, P., Standovár, T., Rozenbergar, D., Diaci, J., Wijdeven, S., Meyer, P., Winter, S., Vrska, T., 2005. Dead wood in European beech (*Fagus sylvatica*) forest reserves. For. Ecol. Manage. 210, 267–282.
Creutzburg, M.K., Scheller, R.M., Lucash, M.S., LeDuc, S.D., Johnson, M.G., 2016. Forest management scenarios in a changing climate: tradeoffs between carbon, timber, and old forest. Ecol. Appl.
Cyert, R.M., DeGroot, M.H., 1987. Bayesian Analysis and Uncertainty in Economic Theory. Rowman & Littlefield.
Davis, R., Yang, Z., Yost, A., Belongie, C., Cohen, W., 2017. The normal fire environment—modeling environmental suitability for large forest wildfires using past, present, and future climate normals. For. Ecol. Manage. 390, 173–186.
De Groot, R.S., Wilson, M.A., Boumans, R.M., 2002. A typology for the classification, description and valuation of ecosystem functions, goods and services. Ecol. Econ. 41, 393–408.
Devaraju, N., Bala, G., Caldeira, K., Nemani, R., 2016. A model based investigation of the relative importance of CO_2-fertilization, climate warming, nitrogen deposition and land use change on the global terrestrial carbon uptake in the historical period. Clim. Dyn. 47, 173–190.
DWD (Deutsche Wetterdienst). Climate data center. Available at: <http://www.dwd.de/EN/climate_environment/cdc/cdc.html> (accessed 25/02/2016).
Dorazio, R.M., Johnson, F.A., 2003. Bayesian inference and decision theory—a framework for decision making in natural resource management. Ecol. Appl. 13, 556–563.
Ellenberg, H., 1996. Vegetation Mitteleuropas mit den Alpen in ökologischer, dynamischer und historischer Sicht: 170 Tabellen, 5, stark veränd. und verb. Aufl. UTB, vol 8104. Ulmer, Stuttgart.
Esprey, L.J., Sands, P.J., Smith, C.W., 2004. Understanding 3-PG using a sensitivity analysis. For. Ecol. Manage. 193, 235–250.
Eyvindson, K., Kangas, A., 2017. Comment on "A simple way to incorporate uncertainty and risk into forest harvest scheduling". For. Ecol. Manage. 386, 86–91.
Fontes, L., Landsberg, J., Tomé, J., Tomé, M., Pacheco, C.A., Soares, P., Araujo, C., 2006. Calibration and testing of a generalized process-based model for use in Portuguese eucalyptus plantations. Can. J. For. Res. 36, 3209–3221.
Forrester, D.I., Tang, X., 2016. Analysing the spatial and temporal dynamics of species interactions in mixed-species forests and the effects of stand density using the 3-PG model. Ecol. Model. 319, 233–254.
Friend, A.D., Stevens, A.K., Knox, R.G., Cannell, M.G.R., 1997. A process-based, terrestrial biosphere model of ecosystem dynamics Hybrid v3. 0. Ecol. Model. 95, 249–287.
Gelman, A., Rubin, D.B., 1992. Inference from iterative simulation using multiple sequences. Stat. Sci., 457–472
Girardin, M.P., Bernier, P.Y., Raulier, F., Tardif, J.C., Conciatori, F., Guo, X.J., 2011. Testing for a CO_2 fertilization effect on growth of Canadian boreal forests. J. Geophys. Res.: Biogeosci. 116, G01012.
González-García, M., Almeida, A.C., Hevia, A., Majada, J., Beadle, C., 2016. Application of a process-based model for predicting the productivity of Eucalyptus nitens bioenergy plantations in Spain. GCB Bioenergy 8, 194–210.
Gressler, E., Jochner, S., Capdevielle-Vargas, R.M., Morellato, L.P.C., Menzel, A., 2015. Vertical variation in autumn leaf phenology of Fagus sylvatica L. in southern Germany. Agric. For. Meteorol. 201, 176–186.
Griess, V.C., Knoke, T., 2013. Bioeconomic modeling of mixed Norway spruce—European beech stands: economic consequences of considering ecological effects. Eur. J. Forest Res. 132, 511–522.
Hadka, D., Herman, J., Reed, P., Keller, K., 2015. An open source framework for many-objective robust decision making. Environ. Model. Software 74, 114–129.
Hallegatte, S., Shah, A., Brown, C., Lempert, R., Gill, S., 2012. Investment Decision Making under Deep Uncertainty – Application to Climate Change. The World Bank.
Halme, P., Allen, K.A., Auniņš, A., Bradshaw, R.H., Brūmelis, G., Čada, V., et al., 2013. Challenges of ecological restoration: lessons from forests in northern Europe. Biol. Cons. 167, 248–256.
Hanewinkel, M., Cullmann, D.A., Schelhaas, M.J., Nabuurs, G.J., Zimmermann, N.E., 2013. Climate change may cause severe loss in the economic value of European forest land. Nat. Clim. Change 3, 203–207.
Hanewinkel, M., Hummel, S., Cullmann, D.A., 2010. Modelling and economic evaluation of forest biome shifts under climate change in Southwest Germany. For. Ecol. Manage. 259, 710–719.
Hartig, F., Dislich, C., Wiegand, T., Huth, A., 2014. Technical Note: Approximate Bayesian parameterization of a process-based tropical forest model. Biogeosciences 11, 1261–1272. http://dx.doi.org/10.5194/bg-11-1261-2014.
Hartig, F., Dyke, J., Hickler, T., Higgins, S.I., O'Hara, R.B., Scheiter, S., Huth, A., 2012. Connecting dynamic vegetation models to data–an inverse perspective. J. Biogeogr. 39, 2240–2252.
Hartig, F., Minunno, F., Paul, S., 2017. BayesianTools: General-Purpose MCMC and SMC Samplers and Tools for Bayesian Statistics. R package version. R package version 0.0.0.9000. <https://cran.r-project.org/web/packages/BayesianTools/index.html>.
Härtl, F., Hahn, A., Knoke, T., 2013. Risk-sensitive planning support for forest enterprises: the YAFO model. Comput. Electron. Agric. 94, 58–70.
Headlee, W.L., Zalesny, R.S., Donner, D.M., Hall, R.B., 2013. Using a process-based model (3-PG) to predict and map hybrid poplar biomass productivity in Minnesota and Wisconsin, USA. BioEnergy Res. 6, 196–210.
Hobbs, B.F., 1997. Bayesian methods for analysing climate change and water resource uncertainties. J. Environ. Manage. 49, 53–72.
Hülsmann, L., Bugmann, H.K., Commarmot, B., Meyer, P., Zimmermann, S., Brang, P., 2016. Does one model fit all? Patterns of beech mortality in natural forests of three European regions. Ecol. Appl. 26, 2463–2477.
ICP, 2010. Manual on methods and criteria for harmonized sampling, assessment, monitoring and analysis of the effects of air pollution on forests. In International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests). Convention on Long-Range Transboundary Air Pollution (LRTAP). UNECE, Hamburg.
Katz, R.W., 2002. Techniques for estimating uncertainty in climate change scenarios and impact studies. Clim. Res. 20, 167–185.
Koca, D., Smith, B., Sykes, M.T., 2006. Modelling regional climate change effects on potential natural ecosystems in Sweden. Clim. Change 78, 381–406.
Kruschke, J., 2014. Doing Bayesian Data Analysis: A Tutorial With R, JAGS, and Stan. Academic Press.
Laflower, D.M., Hurteau, M.D., Koch, G.W., North, M.P., Hungate, B.A., 2016. Climate-driven changes in forest succession and the influence of management on forest carbon dynamics in the Puget Lowlands of Washington State, USA. For. Ecol. Manage. 362, 194–204.
Landsberg, J.J., Johnsen, K.H., Albaugh, T.J., Allen, H.L., McKeand, S.E., 2001a. Applying 3-PG, a simple process-based model designed to produce practical results, to data from loblolly pine experiments. For. Sci. 47, 43–51.
Landsberg, J.J., Waring, R.H., 1997. A generalised model of forest productivity using simplified concepts of radiation-use efficiency, carbon balance and partitioning. For. Ecol. Manage. 95, 209–228.
Landsberg, J.J., Waring, R.H., Coops, N.C., 2001b. The 3-PG forest model: matters arising from evaluation against plantation data from different countries. In: Models for the sustainable management of temperate plantation forests. In: Carnus, J.-M., Dewar, R., Loustau, D., Tomé, M., Orazio, C. (Eds.), Eur For. Inst. Proc., vol. 41, pp. 31-43.
Landsberg, J.J., Waring, R.H., Coops, N.C., 2003. Performance of the forest productivity model 3-PG applied to a wide range of forest types. For. Ecol. Manage. 172, 199–214.
Landsberg, J., Mäkelä, A., Sievänen, R., Kukkola, M., 2005. Analysis of biomass accumulation and stem size distributions over long periods in managed stands of Pinus sylvestris in Finland using the 3-PG model. Tree Physiol. 25, 781–792.
Lange, K.L., Little, R.J., Taylor, J.M., 1989. Robust statistical modeling using the t distribution. J. Am. Stat. Assoc. 84, 881–896.
Lempert, R.J., Collins, M.T., 2007. Managing the risk of uncertain threshold responses: comparison of robust, optimum, and precautionary approaches. Risk Anal. 27, 1009–1026.
LFBW (Landsbetrieb Forst Baden-Württemberg). 2014. Richtlinie Landesweiter Waldentwicklungstypen. <http://www.forstbw.de/fileadmin/forstbw_infothek/forstbw_praxis/wet/ForstBW_Waldentwicklung_web.pdf Stuttgart: Ministerium Ländlicher Raum Baden-Württemberg>.
Liang, J., Crowther, T.W., Picard, N., Wiser, S., Zhou, M., Alberti, G., et al., 2016. Positive biodiversity-productivity relationship predominant in global forests. Science 354, aaf8957.
Liaw, A., Wiener, M., 2002. Classification and regression by randomForest. R News 2, 18–22.
Lichstein, J.W., Dushoff, J., Ogle, K., Chen, A., Purves, D.W., Caspersen, J.P., Pacala, S. W., 2010. Unlocking the forest inventory data: relating individual tree performance to unmeasured environmental factors. Ecol. Appl. 20, 684–699.
Lonsdale, J., Xenakis, G., Mencuccini, M., Perks, M., 2015. A comparison of models for quantifying growth and standing carbon in UK Scots pine forests. iForest-Biogeosci. Forest. 8, 596.
McInerney, D., Lempert, R., Keller, K., 2012. What are robust strategies in the face of uncertain climate threshold responses? Clim. Change 112, 547–568.
McRoberts, R.E., Westfall, J.A., 2014. Effects of uncertainty in model predictions of individual tree volume on large area volume estimates. For. Sci. 60, 34–42.
Menzel, A., Helm, R., Zang, C., 2015. Patterns of late spring frost leaf damage and recovery in a European beech (*Fagus sylvatica* L.) stand in south-eastern Germany based on repeated digital photographs. Front. Plant Sci. 6, 110.
Minunno, F., Xenakis, G., Perks, M.P., Mencuccini, M., 2010. Calibration and validation of a simplified process-based model for the prediction of the carbon balance of Scottish Sitka spruce (*Picea sitchensis*) plantations. Can. J. For. Res. 40, 2411–2426.
Moran, E.V., Hartig, F., Bell, D.M., 2016. Intraspecific trait variation across scales: implications for understanding global change responses. Glob. Change Biol. 22, 137–150.

Morin, X., Thuiller, W., 2009. Comparing niche-and process-based models to reduce prediction uncertainty in species range shifts under climate change. Ecology 90, 1301–1313.
Morin, X., Augspurger, C., Chuine, I., 2007. Process-based modeling of species'distributions: what limits temperate tree species'range boundaries? Ecology 88, 2280–2291.
Muukkonen, P., 2007. Generalized allometric volume and biomass equations for some tree species in Europe. Eur. J. Forest Res. 126, 157–166.
Neuner, S., Beinhofer, B., Knoke, T., 2013. The optimal tree species composition for a private forest enterprise–applying the theory of portfolio selection. Scand. J. For. Res. 28, 38–48.
Nightingale, J.M., Hill, M.J., Phinn, S.R., Davies, I.D., Held, A.A., Erskine, P.D., 2008. Use of 3-PG and 3-PGS to simulate forest growth dynamics of Australian tropical rainforests: I. Parameterisation and calibration for old-growth, regenerating and plantation forests. For. Ecol. Manage. 254, 107–121.
Pan, Y., Birdsey, R.A., Fang, J., Houghton, R., Kauppi, P.E., Kurz, W.A., et al., 2011. A large and persistent carbon sink in the world's forests. Science 333, 988–993.
Pasalodos-Tato, M., Mäkinen, A., Garcia-Gonzalo, J., Borges, J.G., Lämås, T., Eriksson, L.O., 2013. Assessing uncertainty and risk in forest planning and decision support systems: review of classical methods and introduction of new approaches. For. Syst. 22, 282–303.
Paul, K.I., Booth, T.H., Jovanovic, T., Sands, P.J., Morris, J.D., 2007. Calibration of the forest growth model 3-PG to eucalypt plantations growing in low rainfall regions of Australia. For. Ecol. Manage. 243, 237–247.
Potithep, S., Yasuoka, Y., 2011. Application of the 3-PG model for gross primary productivity estimation in deciduous broadleaf forests: a study area in Japan. Forests 2, 590–609.
Ravenscroft, C., Scheller, R.M., Mladenoff, D.J., White, M.A., 2010. Forest restoration in a mixed-ownership landscape under climate change. Ecol. Appl. 20, 327–346.
Regan, H.M., Ben-Haim, Y., Langford, B., Wilson, W.G., Lundberg, P., Andelman, S.J., Burgman, M.A., 2005. Robust decision-making under severe uncertainty for conservation management. Ecol. Appl. 15, 1471–1477.
Reyer, C.P., Flechsig, M., Lasch-Born, P., Van Oijen, M., 2016. Integrating parameter uncertainty of a process-based model in assessments of climate change effects on forest productivity. Clim. Change 137, 395–409.
Reyer, C., Lasch-Born, P., Suckow, F., Gutsch, M., Murawski, A., Pilz, T., 2014. Projections of regional changes in forest net primary productivity for different tree species in Europe driven by climate change and carbon dioxide. Ann. For. Sci. 71, 211–225.
Rodríguez-Suárez, J.A., Soto, B., Iglesias, M.L., Diaz-Fierros, F., 2010. Application of the 3PG forest growth model to a Eucalyptus globulus plantation in Northwest Spain. Eur. J. Forest Res. 129, 573–583.
Rollinson, C.R., Liu, Y., Raiho, A., Moore, D.J., McLachlan, J., Bishop, D.A., et al., 2017. Emergent climate and CO_2 sensitivities of net primary productivity in ecosystem models do not agree with empirical data in temperate forests of eastern North America. Global Change Biology.
Schwenk, W.S., Donovan, T.M., Keeton, W.S., Nunery, J.S., 2012. Carbon storage, timber production, and biodiversity: comparing ecosystem services with multi-criteria decision analysis. Ecol. Appl. 22, 1612–1627.
Seidl, R., Schelhaas, M.J., Rammer, W., Verkerk, P.J., 2014. Increasing forest disturbances in Europe and their impact on carbon storage. Nat. Clim. Change 4, 806–810.
Singh, R., Reed, P.M., Keller, K., 2015. Many-objective robust decision making for managing an ecosystem with a deeply uncertain threshold response. Ecol. Soc. 20, 12.
Snell, R.S., Huth, A., Nabel, J.E., Bocedi, G., Travis, J.M.J., Gravel, D., et al., 2014. Using dynamic vegetation models to simulate plant range shifts. Ecography 37, 1184–1197.
Soja, A.J., Tchebakova, N.M., French, N.H., Flannigan, M.D., Shugart, H.H., Stocks, B.J., et al., 2007. Climate-induced boreal forest change: predictions versus current observations. Global Planet. Change 56, 274–296.
Spiecker, H., 2003. Silvicultural management in maintaining biodiversity and resistance of forests in Europe—temperate zone. J. Environ. Manage. 67, 55–65.
Tarancón, A.A., Fulé, P.Z., Shive, K.L., Sieg, C.H., Meador, A.S., Strom, B., 2014. Simulating post-wildfire forest trajectories under alternative climate and management scenarios. Ecol. Appl. 24, 1626–1637.
Temperli, C., Bugmann, H., Elkin, C., 2012. Adaptive management for competing forest goods and services under climate change. Ecol. Appl. 22, 2065–2077.
ter Braak, C.J., Vrugt, J.A., 2008. Differential evolution Markov chain with snooker updater and fewer chains. Stat. Comput. 18, 435–446.
Tilman, D., Reich, P.B., Isbell, F., 2012. Biodiversity impacts ecosystem productivity as much as resources, disturbance, or herbivory. Proc. Natl. Acad. Sci. 109, 10394–10397.
Valle, D., Staudhammer, C.L., Cropper, W.P., Gardingen, P.R., 2009. The importance of multimodel projections to assess uncertainty in projections from simulation models. Ecol. Appl. 19, 1680–1692.
Van Hees, A.F.M., 1997. Growth and morphology of pedunculate oak (*Quercus robur* L.) and beech (*Fagus sylvatica* L.) seedlings in relation to shading and drought. In Annales des Sciences Forestières 54, 9–18.
van Oijen, M., Reyer, C., Bohn, F.J., Cameron, D.R., Deckmyn, G., Flechsig, M., et al., 2013. Bayesian calibration, comparison and averaging of six forest models, using data from Scots pine stands across Europe. For. Ecol. Manage. 289, 255–268.
van Oijen, M., Rougier, J., Smith, R., 2005. Bayesian calibration of process-based forest models: bridging the gap between models and data. Tree Physiol. 25, 915–927.
Verbeeck, H., Samson, R., Verdonck, F., Lemeur, R., 2006. Parameter sensitivity and uncertainty of the forest carbon flux model FORUG: a Monte Carlo analysis. Tree Physiol. 26, 807–817.
Waring, R.H., Coops, N.C., Mathys, A., Hilker, T., Latta, G., 2014. Process-based modeling to assess the effects of recent climatic variation on site productivity and forest function across western North America. Forests 5, 518–534.
Weller, D.E., 1987. A Reevaluation of the-3/2 Power Rule of Plant Self-Thinning. Ecol. Monogr. 57, 23–43.
Wutzler, T., Wirth, C., Schumacher, J., 2008. Generic biomass functions for Common beech (*Fagus sylvatica*) in Central Europe: predictions and components of uncertainty. Can. J. For. Res. 38, 1661–1675.
Xenakis, G., Ray, D., Mencuccini, M., 2008. Sensitivity and uncertainty analysis from a coupled 3-PG and soil organic matter decomposition model. Ecol. Model. 219, 1–16.
Yousefpour, R., Temperli, C., Bugmann, H., Elkin, C., Hanewinkel, M., Meilby, H., et al., 2013. Updating beliefs and combining evidence in adaptive forest management under climate change: a case study of Norway spruce (Picea abies L. Karst) in the Black Forest, Germany. J. Environ. Manage. 122, 56–64.
Zhao, M., Xiang, W., Peng, C., Tian, D., 2009. Simulating age-related changes in carbon storage and allocation in a Chinese fir plantation growing in southern China using the 3-PG model. For. Ecol. Manage. 257, 1520–1531.
Zaehle, S., Sitch, S., Smith, B., Hatterman, F., 2005. Effects of parameter uncertainties on the modeling of terrestrial biosphere dynamics. Global Biogeochem. Cycles 19, GB3020.
Zell, J., Hanewinkel, M., Seeling, U., 2004. Financial optimisation of target diameter harvest of European beech (Fagus sylvatica) considering the risk of decrease of timber quality due to red heartwood. For. Policy Econ. 6, 579–593.
Zianis, D., Muukkonen, P., Mäkipää, R., Mencuccini, M., 2005. Biomass and stem volume equations for tree species in Europe. Silva Fennica Monogr. 4, 1–63.