Uncertainty of Carbon Economy Using the Faustmann Model

Rasoul Yousefpour and Andrey L. D. Augustynczik*

*Chair of Forestry Economics and Forest Planning, University of Freiburg,
Tennenbacherstr. 4, 79106 Freiburg, Germany;
rasoul.yousefpour@ife.uni-freiburg.de*

ABSTRACT

Forest growth predictions are used to build expectations about the future economic performance of management decisions. Faustmann land expectation value (LEV) is a widely used criterion in forestry to evaluate a diversity of decision parameters, such as rotation age and thinning regimes. Most of the predictions and, consequently, expectations are based on empirical knowledge, assuming a steady state in climate and a deterministic forest growth approach. However, the climate may change to potentially different degrees in the coming decades, causing a dynamic and uncertain forest growth and carbon budget. Moreover, carbon economy in forestry, defined as opportunity cost of in situ carbon sequestration, can hardly be analysed using empirical models and calls for process-based forest biomass production models. Process-based models include numerous parameters and processes that embody some degree of uncertainty. The uncertainty of these parameters and climate state propagates over time to the final decision about carbon economy and optimal management solutions. Here we quantify this uncertainty using Bayesian inference and apply twelve different climate change scenarios to evaluate the forecasts of the process-based forest model 3-PG, to predict the growth of European beech (*Fagus Sylvatica*) in central european conditions as an example. The results show a strong influence of the model's parameters uncertainty on the final decisions about timber based and carbon economy. The uncertainty triples if different climate change scenarios are applied as a source of deep uncertainty where no probability can be

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assigned to any scenario. To deal with deep uncertainty, a robust decision-making approach has been applied to find solutions with minimum regret or maximum value at risk regarding all scenarios. We conclude that communicating uncertainty is a fundamental issue for forestry economics under changing climate conditions, especially if carbon sequestration is an asset. The key message for designing global forest governance policy in the uncertain times of climate change will be the necessity to take into account both the uncertainty on the demand side, that is, socio-economic developments and regional population needs for forest ecosystem services such as wood, but also the uncertainty of the supply side and the inherent ecological uncertainties in predicting the forests' growth, resources, and climatic conditions.

Keywords: Bayesian statistics, Robust Decision-making, Deep uncertainty, Climate change, Compromise programming, Carbon economy, COP21, Forest Policy Design

1 Introduction

Forestry economics is a multi-disciplinary area of research and, among others, integrates forest growth and yield science together with economic calculus to evaluate the performance of management decisions. Faustmann Land Expectation Value (LEV) is a widely used criterion for forest evaluations (Amacher *et al.*, 2011) and needs quantified forest growth predictions to build expectations about future economic outcomes and find optimal decisions. LEV includes rotation age, thinning outcomes, discount rate, establishment and other costs simultaneously in the calculations and can be used to find optimal levels of these factors (e.g., Olschewski and Benitez, 2010; Brazee, 2017; Petuccoa and Andrés-Domenech, 2018).

Traditionally, forest growth and yield data are derived from empirical knowledge gained over time and by establishing permanent forest measurement plots (Pretzsch, 2000). There are long term observations of forest empirical growth parameters such as diameter, height, volume in permanent plots established all over the world for example, Germany (Schober, 1975), USA (Curtis and Marshall, 2005), Sweden (Eriksson, 1976) to build growth and yield tables. The deriving main assumptions behind these empirical studies are steady state in climate and deterministic growth and yield predictions over time (Trasobares *et al.*, 2016). Both assumptions may have held in the past and a wide range of statistical tools have been developed to improve and optimize the procedure (Ashraf *et al.*, 2015).

However, climate is expected to change to different forecasted degrees in the coming decades (IPCC, 2013). As the predictions are based on scenarios developed to integrate driving assumptions about future population growth, energy consumption, land use and land cover change, there is an inherent deep uncertainty about assigning any probability to these scenarios (Van Vuuren *et al.*, 2017). Therefore, it is crucial, on the one hand, to account for climate change in forest growth and yield predictions (Yousefpour *et al.*, 2012; Trasobares *et al.*, 2016; Ashraf *et al.*, 2015) and, on the other hand, to account for the deep uncertainty about future states of the climate (R. and Hanewinkel, 2016; Kim *et al.*, 2017; Radke *et al.*, 2017).

The consideration of uncertainty in ecological-economic systems is a key factor in designing sound policy mechanisms and support decision-making. Bryan *et al.* (2018) highlight the importance of uncertainty analysis for ecosystem services modelling, reporting that uncertainty may have implications to management recommendations, may help stakeholders to assess confidence levels and evaluate the level of uncertainty related to model outputs, and shed light on other important information relevant to decision-making, for example, identifying model instabilities and limits in which model assumption break. Augustynczyk *et al.* (2018) report that the inclusion of uncertainty in a conservation planning model modifies optimal management responses and conservation actions. Fer *et al.* (2018) use an uncertainty analysis to select parameter for the calibration of two ecosystem models. Similarly, the method of identification of parameters causing the most uncertainty on model outcomes may also be applied for planning data collection by focusing on the most important parameters.

Accounting for climate change in forest growth modelling requires process-based modelling approaches (Mäkelä *et al.*, 2000). These models are sensitive to changes in climate properties such as temperature and precipitation in a daily, monthly MLR or at least yearly basis (Coops *et al.*, 1998). The process of photosynthesis is sensitive to environmental conditions, that thus affect biomass production and carbon allocation to different tree compartments, for example, leaves, flowers, branches, stem, and roots (e.g., Sands and Landsberg, 2002). To run these models, however, numerous parameters should be carefully set, adding to the level of uncertainty of the model's outcomes. As the traditional knowledge base about some of these parameters, e.g. carbon allocation to tree compartments and soil water holding capacity, is very weak, inverse calibration attempts can assist to obtain estimates of these parameters in terms of probability distribution, e.g. through Bayesian inference (Hartig *et al.*, 2014).

Moreover, attention to ecosystem services other than timber production is growing in society (Costanza *et al.*, 1997). This challenges forests and their management modelling and asks for novel approaches to quantify co-production of non-timber ecosystem services (Quine *et al.*, 2013). These newly

addressed ecosystem services, such as carbon sequestration in wood, may rather be directly related to the level of net primary production or at least biomass production (Backeus *et al.*, 2006). Therefore, empirical models may fail to truly account for such services or quantify them only indirectly by using a set of allometric equations to approximate the service production levels (Temesgen *et al.*, 2015; Duncanson *et al.*, 2015). Also in this sense, a recent study by Littell *et al.* (2011) and Vauhkonen and Packalen (2018) concluded that involving uncertainties in analyses produces important information on the joint impacts of changes in climate and management practices.

This study uses empirical and process-based approaches to compare their results, regarding both timber production and in situ carbon sequestration as a climate mitigation action. Moreover, we use a Bayesian calibration method to propagate uncertainty of models' parameters and climate change scenarios to the final economic performance of management decisions. We illustrate the contribution of different sources of uncertainty, that is, models' parameters and climate change, solely and in combination. We use a compromise programming approach for a deterministic (minimum weighted average deviation from maximum level of timber and carbon economy) and two robust decision-making cases (two indicators using a regret minimization and a maximum weighted Value-at-Risk (VaR) as objectives). Using the optimization outcomes, we compute the opportunity costs incurred by carbon sequestration-oriented management strategies at different sequestration levels. Moreover, we identify parameters with the highest uncertainty, shows the contribution of these parameters and climate change scenarios to the final outcomes, and illustrates the differences among expectations derived from deterministic and process-based forest growth predictions.

We apply the study framework using a process-based model, 3-PG, for the growth prediction of European beech (*Fagus Sylvatica*) in central European conditions to showcase the above mentioned issues. 3-PG is a widely used forest growth model and encompasses crucial forest processes (Sands and Landsberg, 2002). European beech is the most abundant broadleaved species in central Europe and the potential natural vegetation in large areas of the region (Bohn *et al.*, 2003; Christensen *et al.*, 2005). In addition, Yousefpour *et al.* (2018) report that European beech is among the least costly species for *in situ* carbon sequestration in Europe, due to its low wood price, being the first species to be allocated to carbon sequestration in a Climate-Smart Forestry setting. We use this example to determine the uncertainty effect on carbon economy, i.e. the opportunity cost of carbon sequestration-oriented forest management, in terms of the foregone LEV in management strategies aiming for an optimal combination of timber production and in situ carbon sequestration. The outcomes of this study serve as an example to emphasise the necessity of including uncertainty analysis in designing forest policies. Global commitments for carbon sequestration in forest resources as supplier of

woody materials should consider these uncertainty in addition to the effect of future socio-economics developments (e.g., population growth) to provide a robust expectation base.

2 Material and Methods

2.1 Forest Growth Modelling

To illustrate the implications of using traditional empirical models for forest growth analysis, we apply forest growth and yield tables from Germany (MLR, 1993) to generate the business as usual management strategy (BAU) as a base for comparisons. These tables are still widely in use for forest planning purposes and estimation of future growth rates (Staupendahl, 2006). The figures in these tables are mean values about diameter, height, volume state and increment over time, specified for different site classes and management intensities (low, moderate, and high thinning).

Process-based models produce the same amount of information as in Table 1 and, moreover, additional information about biomass production and potentially other ecosystem services. As the climate properties vary over time, the figures may cause changes in forest growth patterns and processes. We used the widely used process-based model 3-PG (Sands and Landsberg, 2002). This model is driven by monthly mean values of minimum and maximum temperature, precipitation, number of frost days, solar radiation and atmospheric CO₂ concentration. The NPP produced in each month is then allocated to leaves, roots, and stem biomass. Forest parameters, namely stand DBH, height and wood volume are then obtained through allometric relationships. Figure 1

Table 1: Weighting scheme for Land Expectation Value (LEV) and carbon sequestration.

Policy	Carbon weight	LEV weight
1	1	0
2	0.9	0.1
3	0.8	0.2
4	0.7	0.3
5	0.6	0.4
6	0.5	0.5
7	0.4	0.6
8	0.3	0.7
9	0.2	0.8
10	0.1	0.9
11	0	1

Figure 2: Climate forecasts for the study area, in terms of the yearly average for maximum temperature (a), minimum temperature (b), yearly precipitation sum (c) and atmospheric CO₂ (d).

processes, the wood harvesting rate as the only forest management aspect in climate modelling (IAMs) is dependent on local population growth (Van Vuuren *et al.*, 2017). There are however novel efforts to improve forestry representation of global IAMs and ESMS Sohngen and X., 2016; Yousefpour *et al.*, 2018. For local climate predictions, it is essential to downscale the figures to the scale of local case study area. We used twelve different climate change scenarios realized by three different ESMs with a spatial resolution of $0.5 \times 0.5^\circ$, namely HadGEM2-ES, IPSL-CM5A-LR and NORESM1-M, bias-corrected by ISI-MIP, driven by the Representative Concentration Pathway (RCP) 2.6, 4.5, 6.0, and 8.5. Figure 2 shows the main climate variables used in our analysis.

2.3 Bayesian Calibration

Recent advances in computation science may support detailed analysis of model calibration uncertainty. The parametrization of process-based models remain an important challenge in forest growth modelling, since it involves

the calibration of numerous parameters inherently uncertain and onerous data collection, requiring inverse calibration approaches (Hartig *et al.*, 2012). In addition to the possibility to obtain a direct estimation of parameters uncertainty, Bayesian inference provides a natural framework for updating parameter and forecast distributions, combining existing information on parameter values with data and information generated through the inverse estimation (Hartig *et al.*, 2014). Moreover, Bayesian inference allows the computation of posterior probability density functions (PDF) of parameters instead of best estimates in the process of calibration, typically applying MCMC (Markov Chain Monte Carlo) methods (Hartig *et al.*, 2012; Van Oijen *et al.*, 2005). A main advantage of this approach is the opportunity to quantify the contribution of uncertain parameters alone and in combination with others to the final outcomes of the model. In this context, we used the posterior distribution of parameters provided by the calibration of the model 3-PG for beech stands, provided by Augustynczyk *et al.* (2017) to forward uncertainty to economic outcomes and carbon sequestration estimates. The distribution of model results was therefore related to the parameter uncertainty and the sensitivity of interest variables to these parameters.

In order to identify the parameters causing the most uncertainty in the model's outcomes, we performed a sensitivity analysis applying a random forest regression, using the R package random Forest (Breiman, 2001; Liaw and Wiener, 2002). We regressed the model's outcomes in terms of the LEV and carbon sequestration against the vectors of posterior samples, allowing identification of the parameters causing the most variation in the model outcomes, applying the mean decrease in impurity (MDI) as importance criteria.

2.4 Economic Calculus

We use Faustmann LEV (Equation 1) for evaluating 26 management strategies simulated by 3-PG (see Section 2.1 above). LEV includes all cash flows regarding benefits from thinning and harvesting (B) and costs of activities including regeneration (C) and prolong them using an interest rate (i) and rotation age (R).

$$LEV = \frac{\sum_{t=0}^R B_t(1-i)^{R-t} - \sum_{t=0}^R C_t(1-i)^{R-t}}{(1+i)^R - 1} \quad (1)$$

We used LEV to calculate the economic performance of management strategies for timber production and carbon economy (hereafter referred to as LEV). We used a compromise programming approach to find optimal and robust decisions regarding both objectives (LEV and carbon sequestration). Figure 3 shows how a compromise solution can be found for two objectives. For the

Figure 3: Compromise programming approaches to find pareto frontier for two objectives and search for the optimal solution based on normalized weights decided for each objective (Adapted from André and Romero, 2008).

LEV calculation, we follow Hanewinkel *et al.* (2013) and Knoke *et al.* (2005), applying a 2% interest rate to discount timber revenues, a standard approach in Germany (Hanewinkel *et al.*, 2010). The establishment costs were retrieved from Hanewinkel *et al.* (2010) and net wood prices from Hanewinkel *et al.* (2013).

To analyse different policies favoring LEV to carbon sequestration or vice versa, we developed a set of varying weighting systems as in Table 1. Weights for policies 1–11 sums up to 1 (100%) and combines weights for timber (LEV) and carbon. Accordingly, policies 1 and 11 favor purely carbon sequestration and wood production, respectively.

We used three different models to find (i) a deterministic optimal solution (Equations 2–5), (ii) a discrete robust solution (Equations 6–14), and (iii) a robust solution considering all uncertainties (Equations 15–18). A description of data, variables and sets used in the optimization models is provided in Table 2.

2.4.1 Deterministic Model

In the deterministic model, we emulate what managers assume, having perfect information regarding future climate development and model’s parameters and

Table 2: Description of optimization sets, variables and data.

Set	Description
CC	Climate change scenarios
M	Management regimes
Data	Description
w_1	Normalized weight for LEV
w_2	Normalized weight for carbon sequestration
LEV_{ij}	Land expectation value (LEV) generated by management i under climate change scenario j
CAR_{ij}	Carbon sequestered by management i under climate change scenario j
$Varlev_i$	Value-at-Risk of the LEV obtained under management i
$Varcar_i$	Value-at-Risk of the carbon sequestered under management i
$MaxLEV_j$	Maximum LEV obtained under climate change scenario j
$MaxCAR_j$	Maximum carbon sequestration obtained under climate change scenario j
$MaxVarlev$	Maximum Value-at-Risk for LEV
$MaxVarcar$	Maximum Value-at-Risk for carbon sequestration
Variables	Description
x_{ij}	Binary variable that takes value 1 case management i is selected for the solution under climate trajectory j or value 0 otherwise
LEV_{j-}	Deviation for LEV under climate change scenario j compared to the maximum LEV
CAR_{j-}	Deviation for carbon sequestration under climate change scenario j compared to the maximum carbon sequestration
$RLEV_{\min}$	Minimum LEV regret (loss in LEV) across all climate change scenarios for management i
$RLEV_{\max}$	Maximum LEV regret (loss in LEV) across all climate change scenarios for management i
$RCAR_{\min}$	Minimum carbon sequestration regret (loss in carbon sequestration) across all climate change scenarios for management i
$RCAR_{\max}$	Maximum carbon sequestration regret (loss in carbon sequestration) across all climate change scenarios for management i
$Varlev_-$	Deviation for the Value-at-Risk of LEV compared to the maximum Value-at-Risk of LEV
$Varcar_-$	Deviation for the Value-at-Risk of carbon sequestration compared to the maximum Value-at-Risk of carbon sequestration

disregarding any uncertainty. Hence, this model finds the optimal management response for each climate change scenario using the parameter's best estimates to compute forest growth and dynamics. Accordingly this model finds the optimal decision regarding LEV and carbon sequestration as outlined below.

$$\text{Min } Z = \sum_{j \in CC} \sqrt{w_1 LEV_{j-}^2 + w_2 CAR_{j-}^2} \quad (2)$$

s.t.

$$\sum_{i \in M} LEV_{ij} x_{ij} + LEV_{j-} = \text{Max} LEV_j \quad \forall j \in CC \quad (3)$$

$$\sum_{i \in M} CAR_{ij} x_{ij} + CAR_{j-} = \text{Max} CAR_j \quad \forall j \in CC \quad (4)$$

$$x_{ij} \in \{0, 1\} \quad \forall i, \forall j \quad (5)$$

Equation 2-5 describes the optimization model for the deterministic case. The efficient combinations of LEV and carbon sequestration were obtained by minimizing their respective deviations compared to their maximal levels, under different weighting schemes (Equation 2). The distance between the actual LEV and carbon sequestration for a given management regime, compared to the ideal point was evaluated on the Euclidean norm. Constraints Equation 3 assigns to the variable LEV_{j-} the deviation in LEV for each climate change scenario j , compared to the maximum LEV ($\text{Max} LEV_j$). Constraint Equation 4 assigns to the variable CAR_{j-} the deviation in carbon sequestration for each climate change scenario j , compared to the maximum LEV ($\text{Max} CAR_j$). Constraint (Equation 5) enforces that the decision variables x_{ij} take binary values.

2.4.2 Robust Discrete Model

The robust discrete model considers a case, where managers are assumed to hold perfect knowledge (certainty) of model's parameters, but uncertainty in climate development. Therefore, in these model we considered the parameter's best estimates to forecast forest development, but searching for a management solution that performs well, regardless of the future climate outcome:

$$\text{Min } Z = \sqrt{w_1 0.5(RLEV_{\min} + RLEV_{\max})^2 + w_2 0.5(RCAR_{\min} + RCAR_{\max})^2} \quad (6)$$

s.t.

$$\sum_{i \in M} LEV_{ij} x_{ij} + LEV_{j-} = \text{Max} LEV_j \quad \forall j \in CC \quad (7)$$

$$\sum_{i \in M} CAR_{ij} x_{ij} + CAR_{j-} = \text{Max} CAR_j \quad \forall j \in CC \quad (8)$$

$$11x_{i1} \geq \sum_{j \neq 1} x_{ij} \quad \forall i \in M \quad (9)$$

$$RLEV_{\min} = \min_{j \in CC} \{LEV_{j-}\} \quad (10)$$

$$RLEV_{\max} = \max_{j \in CC} \{LEV_{j-}\} \quad (11)$$

$$RCAR_{\min} = \min_{j \in CC} \{CAR_{j-}\} \quad (12)$$

$$RCAR_{\max} = \max_{j \in CC} \{CAR_{j-}\} \quad (13)$$

$$x_{ij} \in \{0, 1\} \quad \forall i, \forall j. \quad (14)$$

Equations 6–14 were applied to obtain robust management regimes towards climate uncertainty. The objective function (Equation 6) minimized the sum of relative regrets on LEV and carbon sequestration, compared to the ideal point. In this model, we selected a single management regime that would guarantee some performance across all climate change trajectories. In this setting, the regret represents the loss in LEV and carbon sequestration by choosing the robust management rather than the deterministic optimum in each climate change trajectory. We weighted equally the best regret (closest to the deterministic optimal solution) and the worst regret (farthest to the deterministic optimal) across all climate trajectories, balancing optimality and robustness. Similar to the deterministic solution, the distance to the ideal point was defined on the Euclidean norm when defining optimal combinations of LEV and carbon sequestration levels. Similar to Equations 3 and 4, constraints Equations 7 and 8 assign to variables LEV_{j-} and CAR_{j-} the deviations in terms of LEV and carbon sequestration for each climate change scenario. Constraint Equation 9 ensures that the same management regime is selected across all 12 climate change scenarios. Constraint Equations 10 and 11 compute the minimum and maximum LEV deviation (regret) across all climate change scenarios and assign them to variables $RLEV_{\min}$ and $RLEV_{\max}$. Similarly, Equations 12 and 13 compute the minimum and maximum carbon sequestration deviation across all climate change scenarios and assign them to variables $RCAR_{\min}$ and $RCAR_{\max}$. Constraint (Eq. 14) enforces that the decision variables x_{ij} take binary values.

2.4.3 Robust Model

The robust model considers a case, where managers take into account the uncertainty related to both climate development and a model's parameters. Here, the outputs in terms of profitability and carbon sequestration are described by a joint probability distribution, taking into account model's parameters and climate change uncertainty. The model then searches for a solution that maximizes the worst-case of this distribution, here computed based on the 5%

quantile of the distribution (VaR at 5% confidence level).

$$\text{Min } Z = \sqrt{w_1 \text{VaRlev}_-^2 + w_2 \text{VaRcar}_-^2} \quad (15)$$

$$\sum_{i \in M} \text{VaRlev}_i x_{ij} + \text{VaRlev}_- = \text{MaxVaRlev} \quad (16)$$

$$\sum_{i \in M} \text{VaRcar}_i x_{ij} + \text{VaRcar}_- = \text{MaxVaRcar} \quad (17)$$

$$x_{ij} \in \{0, 1\} \quad \forall i, \forall j \quad (18)$$

Based on the different weighting schemes for LEV and carbon, we computed the marginal costs of carbon using the maximum LEV as a base. Therefore, carbon costs were defined as the rate between the LEV loss and the carbon sequestration increase at a given weighting scheme (carbon cost = $\Delta \text{LEV} / \Delta C$ sequestration) (Yousefpour *et al.*, 2018). We solved the three optimization models using the software Lingo 17 (Lindo Systems, 2018). We applied a time preference of 2% for timber revenues and the carbon sequestration, in order to account for the timing when sequestration occurs and fluctuations over time. In this sense, the sequestration levels were expressed in Present Tons Equivalent (PTE) per hectare, that is in terms of the discounted carbon sequestration.

3 Results

3.1 Simulation of Management Strategies

Our simulation results showed that climate change is expected to display a positive impact on forest productivity. Figures 4a display the standing wood volume for the BAU management scenario (rotation age = 150 years). We observed an increased standing volume especially for RCP 6.0 trajectories, as a result of the CO₂ fertilization effect. Figure 4b displays the same result for the maximum LEV regime, considering the robust solution towards climate. The optimum solution displayed a shorter rotation (130 years) and increased thinning volume, compared to the BAU management. When parameter uncertainty was taken into account, the robust solution showed the same thinning intensity, but a shorter rotation (120 years) compared to the robust case when only climate was considered. Moreover, we perceived that the optimal management shifted to a thinning from above scheme, harvesting larger trees earlier, in order to anticipate revenues. Ignoring the uncertainty of climate and parameters resulted in the maintenance of larger standing stock and longer rotation period.

As expected, the management regime that maximized *in situ* carbon sequestration in all cases (deterministic, robust towards climate and robust

Figure 4: Simulation results for the evolution of the standing volume of the stands for the business-as-usual management (a), robust towards climate (b) and robust towards climate and parameter uncertainty (c). The robust management regimes represent the Land Expectation Value maximization solution.

Figure 5: Simulation results for the evolution of the standing volume for the carbon sequestration maximization solution.

towards climate, and parameter uncertainty) had no thinning interventions and longer rotation age, equal to 150 years (Figure 5). Similar to the BAU and LEV maximization solutions, productivity was increased under climate change and the stocking of the stand, in terms of wood volume and above ground biomass, was nearly 50% higher than the BAU levels.

3.2 Economic Performance of C Compromise Solutions

The integration of different sources of uncertainty and different weighting schemes were determinant for the outcomes in terms of LEV, carbon sequestration and optimal management regime applied. Figures 6, 7, and 8 show the carbon sequestration, LEV and carbon cost obtained for the deterministic and robust towards climate optimal solutions, respectively. The solid lines represent the deterministic optimal and the dashed lines represent the robust solution under varying preference for carbon sequestration and LEV. We observed that the carbon sequestration nearly doubled from the maximum LEV management to the maximum carbon sequestration management (Figure 6), with concurrent LEV reduction, yielding a carbon cost up to 200 €/PTE (Figure 8). It is noteworthy that for low preferences for carbon and productive

Figure 6: Carbon sequestration for the deterministic and robust towards climate optimal solutions. The solid lines represent the deterministic solution and the dashed lines show the robust solution. The dotted horizontal line shows the result for the BAU management and current climate.

Figure 7: Land Expectation Value for the deterministic and robust towards climate optimal solutions. The solid lines represent the deterministic solution and the dashed lines show the robust solution. The dotted line shows the result for the BAU management and current climate.

Figure 8: Carbon cost for the deterministic and robust towards climate optimal solutions. The solid lines represent the deterministic solution and the dashed lines show the robust solution.

climate trajectories, a negative carbon cost may occur, since slightly lower management intensity may promote the stand capitalization above the interest rate and opportunity costs of not harvesting more, outperforming the robust optimal solution of LEV maximization.

The outcomes for the robust solution towards climate and parameter uncertainty are displayed in Figures 9, 10, and 11. We perceived a substantial increase in the ranges of LEV, carbon sequestration and carbon costs when parameter uncertainty was added. In Figure 9 we observed an increasing uncertainty in carbon sequestration with higher weight for carbon over LEV. Similarly, the LEV range increased for the maximum LEV policy. We perceived a large uncertainty in carbon costs for low preference for carbon (Figure 11), especially under policy 2 (0.9 weight for LEV and 0.1 for carbon sequestration). Under this policy, the uncertainty range encompassed a negative carbon cost, since there is a small probability that the management selected under policy 2 outperforms, in terms of LEV, the management selected under policy 1 (weight 1 for LEV and 0 for carbon sequestration).

3.3 Sensitivity Analysis

We computed the parameter importance for the forest model's outcomes in terms of the LEV and carbon sequestration, applying a random forest

Figure 9: Carbon sequestration for the robust solution towards climate parameter uncertainty. The shaded area represent the ranges in carbon sequestration, the solid line represents the mean value and the dashed line show the Value-at-Risk (5% quantile). The dotted horizontal line shows the result for the BAU management and current climate.

Figure 10: Land Expectation Value (LEV) for the robust solution towards climate parameter uncertainty. The shaded area represent the range in LEV, the solid line represents the mean value and the dashed line show the Value-at-Risk (5% quantile). The dotted line shows the result for the BAU management and current climate.

Figure 11: Carbon cost for the robust solution towards climate parameter uncertainty. The shaded area represent the range in carbon cost and the solid line represents the mean.

regression and computing the mean decrease in impurity (MDI). Figure 12 shows the 3PG model parameters that caused most variation in the LEV and carbon sequestration obtained (for a description of the model parameters see Appendix). Identifying these key sources of uncertainty may provide essential information for future data collection and improved forest growth forecasts. Once the parameters causing the most variation in forest profitability and carbon sequestration are identified, we can apply a targeted data collection to inform these parameters and decrease their uncertainty on average. Thereby, we may reduce the ranges related to forest profitability and carbon sequestration forecasts.

The critical parameters for the variation in LEV and carbon sequestration were similar for the robust solution searching for the highest LEV (Figure 12a) and for the highest carbon sequestration (Figure 12b). The most important parameters for the LEV and sequestration forecast were the maximum allocation to roots (pRn), canopy quantum efficiency (α), modifier of quantum efficiency at an atmospheric $[CO_2]$ of 700 ppm ($f\alpha_{700}$), optimum temperature for growth (T_{opt}), maximum stem mass per tree at a 1000 trees/ha density ($wS \times 1000$) and fraction of stem pool per tree on each dying tree (mS). We observed that the first four parameters, closely related to growth rates, were included among the five most important parameters for both the maximum LEV and maximum carbon sequestration solutions. The parameter $wS \times 1000$ included in the maximum LEV management, related to tree dimensions and

Figure 12: Parameter importance for the Land expectation Value (LEV) forecast (a) and for the carbon sequestration forecast (b), considering the robust solution towards climate and parameter uncertainty.

stand assortment, was replaced by the parameter mS in the maximum carbon sequestration analysis, as mortality became increasingly important for the objective function.

The application of a time preference for carbon sequestration displayed an important impact on the carbon sequestration levels, and affected the trade-off between carbon and LEV as well (Table 3). The discounting had a strong impact on the sequestration levels and when no time preference was considered, the sequestration tripled. Concurrently, the carbon cost reduced drastically, four times lower than the discounted scenario. In addition, the lower urgency for sequestration allowed selecting management regimes with higher profitability for intermediate preference schemes, evidenced by the higher LEV obtained under no time preference for carbon sequestration.

4 Discussions and Conclusions

Carbon economy is an emerging issue in forestry (e.g., Asante *et al.*, 2011; Susaeta *et al.*, 2014; Yousefpour *et al.*, 2018). Uncertainty regarding carbon accounting and applying econometric approaches to determine carbon costs are crucial to assess possible impacts of carbon markets and policy mechanisms for

Table 3: Solutions results for the optimal solution with an equal weighing of timber and carbon values. For the climate and parameter robust solution, the expected values are displayed inside the parenthesis.

Optimal solution	Discounting scheme					
	Timber 2% and Carbon 2%	Rotation age	Number of thinnings	Timber 2%, Carbon 0%	Rotation age	Number of thinnings
Deterministic						
Carbon sequestration (t/ha)	75–87*	120	7	268–360	150	10
LEV (timber, €/ha)	6302–7572			6756–8455		
Carbon Cost (€/t)	128–148†			23–28		
Climate Robust						
Carbon sequestration (t/ha)	75–86*	120	7	268–360	150	10
LEV (timber, €/ha)	6215–7691			6756–8455		
Carbon Cost (€/t)	128–146†			22–30		
Climate and Parameter Robust						
Carbon sequestration (t/ha)	58–100 (76)*	120	7	190–453 (282)	150	10
LEV (timber, €/ha)	3940–8897 (6030)			4043–9478 (6412)		
Carbon Cost (€/t)	104–157 (133)†			22–30 (25)		

*Carbon sequestration in PTE/ha

† Carbon cost in €/PTE

its implementation. Traditionally developed empirical forest yield projection models fail to analyze the sensitivity of carbon budget to climate conditions and ignore the fact that future climate may realize differently. Process-based models are mostly developed and applied to overcome this flaw. However, communicating uncertainty of not very well observed and known model parameters beside climate change adds to the complexity of interpreting the carbon accounting and economic outcomes. We illustrated a case for European beech and applied 3-PG to quantify the magnitude of the uncertainty of climate change and models parameters. Results show that where the BAU strategy expects a constant and low carbon sequestration and cost, and is indifferent to the policies regarding timber and carbon value, any consideration of uncertainty and policies favoring timber or carbon to another one may change the figures substantially (Figures 6–10). This is in line with recent findings, for example of Vauhkonen and Packalen (2018) stating that future management may realize a higher harvest volume (7%–9% depending on the harvest target) than BAU in Finland.

The degree of uncertainty may react to the applied forest policy regarding carbon. Uncertainty propagates to a higher degree if the parameters not being a direct outcome of a well-defined process and related to main processes outcomes by allometric functions or fixed proportions are weighed higher in the decision-making process. For example, as biomass production is a direct outcome of photosynthesis in 3-PG and timber production is secondary (generated applying allometric functions to allocate biomass to tree compartments), the degree of uncertainty is much higher if timber production weights more than carbon in forest policy making (Figure 10, LEV versus Carbon preference 2 and 4). Moreover, models' parameter uncertainty could be reduced by collecting novel data to establish more informed processes.

Analyzing the effects of other sources of uncertainty exist in the literature, for example economic factors on carbon price (Reeson *et al.*, 2015), rotation age (Susaeta *et al.*, 2014), and energy forestry (Di Cerato *et al.*, 2013). Regardless of the source of uncertainty analyzed in the literature, the effects on forest decisions is substantial and asks for changes in BAU strategies. This is in line with our results that the optimal management scheme requires implementation of a different set of silvicultural interventions compared to BAU. We highlight that the robust optimization (RO) approach applied here allows the inclusion of multiple sources of uncertainty in the decision-making problem, without the requirement to assign probabilistic weights to different possible states of the world. This makes RO a powerful tool to account for deep uncertainty, not only on climate development, but on socio-economic conditions as well.

Any time preference about storing more carbon in forests, changes dramatically the carbon budget and economic figures. As shown in Table 4, using a social discount rate of 2% (*versus* 0%) quintuples the carbon cost for forestry disregarding uncertainty. This is because preferring an immediate carbon

sequestration asks for cancellation of timber production and decreases LEV (always discounted by 2%). Moreover and whenever uncertainty is accounted for, the expected economic outcome from forest management decisions is slightly decreased, on average. Van Kooten *et al.* (1995) show that a higher discount rate leads to a higher optimal rotation age, a similar effect as applying a high carbon price in carbon taxing and subsidy policies. They argue that a higher discount rate may disqualify forest resources from being an efficient sink for carbon.

Here we analyze the impacts of climate and model parameter uncertainty on economic output of forest management in terms of the LEV and the opportunity costs to store carbon *in situ*. The establishment of carbon offsets depends on an adequate compensation to forest owners for modifying their management strategies for climate mitigation purposes. Here we compute marginal carbon costs that can act as a basis for compensation schemes and provide an analysis on how uncertainty in environmental conditions, sequestration levels and modelling approaches may modify this cost. In this sense, an important question is how to realize mitigation strategies in practice. After sequestration targets are established, policy mechanisms may be applied to modify forest owners' management strategies and realize sequestration goals. Typical policy mechanisms for increase carbon sequestration in the literature include subsidies for carbon sequestration and taxes on wood income (e.g., Guthrie and Kumareswaran, 2009; Van Kooten *et al.*, 1995). This may be included in the owners utility function, e.g. in the Hartman framework (Hartman, 1976), in order to define the optimal management schemes including carbon benefits.

In our approach, we did not consider substitution effects of carbon sequestered in forest products. In this sense, there was a clear trade-off between carbon sequestration and wood production. Nevertheless, the inclusion of this substitution effect may reduce the trade-off between wood production and carbon sequestration. Moreover, the maintenance of highly stocked stands may lead to large losses when disturbance risk is taken into account (Seidl *et al.*, 2014). The interactions between carbon sequestration, disturbance risk and multiple uncertainty sources deserves further consideration.

4.1 Uncertainty in Forest-Climate Policy Design

Transparent communication of uncertainty with stakeholders and policy-makers is crucial to avoid unrealistic expectations about the performance of forest ecosystems. This is of high priority regarding an increasing pressure on forests to realize the international CO₂ sequestration goals and wood sector to decarbonize the forest utilization activities as agreed in COP₂₁. Global vegetation and integrated assessment models (DGVM, IAM, respectively) simulate the future potentials of forest resources to meet the demanded targets.

However, they usually ignore the forest management dynamics in response to changing environmental conditions and the uncertainty inherent in modelling these responses. Recent efforts identify the gap and try to establish a dynamic forest management module in DGVMs (e.g., Yousefpour *et al.*, 2018) or analyze the sensitivity of forest and wood sector to changing climatic conditions in the future (e.g., Sohngen and X., 2016). Kim *et al.* (2017) recommend using an ensemble of climate simulations to generate robust estimates of greenhouse gas mitigation by forest resources and overcome three source of uncertainty: emissions scenarios, the global system climate response, and natural variability in climate vegetation modelling. Finally, Littell *et al.* (2011) argue that adaptive management provides a unique hedge against uncertainty and inform decision makers not only about uncertainty of climate and ecosystem models but also setting objectives, establishing monitoring systems and assessing the results. Developing futuristic scenarios about governance and utilization of global forest resources should therefore not only take into account the uncertainty (possible outcomes) of socio-economic factors affecting demand side (e.g., population growth and demand on wood production in Van Vuuren *et al.*, 2017), but also ecological factors uncertainty under changing environmental conditions from supply side (Yousefpour *et al.*, 2018).

Appendix – Description of calibrated parameters

Parameter	Description	Parameter	Description
pFS2	Foliage: stem partitioning ratio @ D=2 cm	mF	Fraction mean single-tree foliage biomass lost per dead tree
pFS20	Foliage: stem partitioning ratio @ D=20 cm	mR	Fraction mean single-tree root biomass lost per dead tree
aS	Constant in the stem mass v. diam. relationship	mS	Fraction mean single-tree stem biomass lost per dead tree
nS	Power in the stem mass v. diam. relationship	SLA0	Specific leaf area at age 0
pRx	Maximum fraction of NPP to roots	SLA1	Specific leaf area for mature leaves
pRu	Minimum fraction of NPP to roots	tSLA	Age at which specific leaf area = $(SLA0+SLA1)/2$
gammaFx	Maximum litterfall rate	k	Extinction coefficient for absorption of PAR by canopy
gammaF0	Litterfall rate at t = 0	fullCanAge	Age at canopy cover
tgammaF	Age at which litterfall rate has median value	MaxIntcptn	Maximum proportion of rainfall evaporated from canopy
gammaR	Average monthly root turnover rate	LAImaxIntcptn	LAI for maximum rainfall interception
Topt	Minimum temperature for growth	alpha	Canopy quantum efficiency
Tmax	Optimum temperature for growth	Y	Ratio NPP/GPP
Tmin	Maximum temperature for growth	MinCond	Minimum canopy conductance

Parameter	Description	Parameter	Description
fCalpha700	Assimilation enhancement factor at 700 ppm	MaxCond	Maximum canopy conductance
fCg700	Canopy conductance enhancement factor at 700 ppm	LAIgcx	LAI for maximum canopy conductance
m0	Value of 'm' when FR = 0	CoeffCond	Defines stomatal response to VPD
fN0	Value of 'fNutr' when FR = 0	BLcond	Canopy boundary layer conductance
fNn	Power of (1-FR) in 'fNutr'	fracBB0	Branch and bark fraction at age 0
MaxAge	Maximum stand age used in age modifier	fracBB1	Branch and bark fraction for mature stands
nAge	Power of relative age in function for fAge	tBB	Age at which $\text{fracBB} = (\text{fracBB0} + \text{fracBB1})/2$
rAge	Relative age to give fAge = 0.5	rhoMin	Minimum basic density - for young trees
gammaNx	Mortality rate for large t	rhoMax	Maximum basic density - for older trees
gammaN0	Seedling mortality rate (t = 0)	tRho	Age at which $\text{rho} = (\text{rhoMin} + \text{rhoMax})/2$
tgammaN	Age at which mortality rate has median value	aH	Constant in the stem height relationship
ngammaN	Shape of mortality response	nHB	Power of DBH in the stem height relationship
wS × 1000	Max. stem mass per tree @ 1000 trees/hectare	FR	Fertility rating

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