This item is the archived peer-reviewed author-version of:

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Reference:

Horemans Joanna, Vinduskova Olga, Deckmyn Gaby.- How random are predictions of forest growth? The importance of weather variability
Revue canadienne de recherche forestière - ISSN 0045-5067 - 51:3(2021), p. 349-356
Full text (Publisher's DOI): <https://doi.org/10.1139/CJFR-2019-0366>

How random are predictions of forest growth? The importance of weather variability

Running head: Weather variability determines forest growth predictions

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Abstract

Quantifying the output uncertainty and tracking down its origins is key to interpreting the results of modelling studies. We perform such an uncertainty analysis on the predictions of forest growth and yield under climate change. We specifically focus on the effect of the inter-annual climate variability. For that, the climate years in the model input (daily resolution) were randomly shuffled within each 5-year period. In total, 540 simulations (10 parameter sets, 9 climate shuffles, 3 global climate models and 2 mitigation scenarios), were made for one growing cycle (80 years) of a Scots pine forest growing in Peitz (Germany). Our results show that, besides the important effect of the parameter set, the random order of climate years can significantly change results such as basal area and produced volume, and the response of these to climate change. We stress that the effect of weather variability should be included in the design of impact model ensembles, and the accompanying uncertainty analysis. We further suggest presenting model results as likelihoods to allow risk assessment. For example, in our study the likelihood of a decrease in basal area of >10% with no mitigation was 20.4%, while the likelihood of an increase >10% was 34.4%.

Keywords

forest model, uncertainty, weather variability, basal area, production

42 **Introduction**

43 Impact and risk assessment in forestry is preferentially studied with the use of process-based
44 models that, in contrast to empirical models, offer the possibility to mechanistically simulate
45 forest functional changes and responses to changing environmental conditions (e.g. Korzukhin,
46 et al. 1996; Matala et al. 2003). Identifying the future consequences of global change and
47 proposed management changes on the growth and functioning of forests is however inherently
48 associated with high uncertainty (Tennoy et al. 2006). Uncertainty has multiple causes, but the
49 overarching reasons are the ignorance about how greenhouse gas emissions will evolve as a
50 function of energy production and consumption, and the incompleteness of the climatic and
51 ecological model systems that predict how the climate changes in response to greenhouse gas
52 emissions, and how forests respond to these changes in climate (Pilkey and Pilkey-Jarvis 2007,
53 Reyer et al. 2014). A conceptual basis for uncertainty management in model-based decision
54 support brought some clarification in this domain (Walker et al. 2003) and more attention is
55 since given to the quantification of the main sources of uncertainty (Uüsitalo et al. 2015).
56 Bayesian calibration techniques, using Markov Chain Monte Carlo (Van Oijen 2005) and other
57 kinds of, Bayesian or non-Bayesian, algorithms (Gaucherel et al. 2008), shed light on parameter
58 uncertainty and its implementation in model simulation and model outcome communication.
59 Model ensembles further tackle the uncertainty arising from the forest models themselves by
60 delivering information about variation in output caused by different model structures and
61 assumptions (e.g. Friend et al. 2013). Although in such ensembles the correct weighting of
62 individual model output, related to the (in)dependency between model structures and parameter
63 choices between different models, is still neglected, the use of model ensembles is a big step
64 forward to the knowledge of realistic forest impact ranges. More uncertainty in forest model
65 outcomes derives from the proposed storylines about future global societies. These future
66 society scenarios are inserted in Integrated Assessment Models of which the outputs are

subsequently used in Global Climate Models (GCMs) and Regional Climate Models (Olesen et al. 2007). Multiple studies have been carried out to quantify the contributions of selected sources of uncertainty to the total variance of forest model outcomes, with widely varying results (Oleson et al. 2007; Nishina et al. 2015; Reyer et al. 2016). Such variance-based analyses allow us not only to interpret the model results in a stochastic way, but can also guide forest impact research towards tackling the domains that have the greatest impact on uncertainty. However, the results in each individual study are highly dependent on the simulation design and the incorporated sources of uncertainty and their levels.

Recently, several studies have emphasized the importance of extreme events such as long heat or drought periods in addition to the ‘average’ changes in climate generally included in climate predictions (Seidl et al. 2011). Indeed, the occurrence of extreme events is predicted to increase as the climate changes. But even without an increase in extreme events (s.a. length of drought periods or heat waves), the day-to-day changes in weather affect the growth of plants (Razavi et al. 2016). For crop models we know that between-year differences can be substantial, due to the specific weather conditions (Powel and Reinhard 2016). It is unlikely that the yield of an annual crop in a very dry and a very wet year would equal the yield of two intermediate years. For trees, the sequence of climate years can have an even larger impact because their growth and reproduction depend on the weather in previous year(s). Yet, in long-term forest studies, these effects are generally assumed to average out. Furthermore, for prediction lead time (the time between the issuance of a forecast and the occurrence of the phenomena that were predicted) within 2 decades, an important part of the total uncertainty in climate predictions could be ascribed to the internal variability of the climate system (Hawkins and Sutton 2009; 2011). This uncertainty attributed to variability in weather is mostly neglected in uncertainty analyses of forest model results or only incorporated indirectly by analyzing the

climate predictions separately (Horemans et al. 2016). Also in the communication of model results, this source of uncertainty is generally overlooked.

The main objective of this paper was to analyze the importance of weather variability on model predictions in relation to other sources of uncertainty by the inclusion of different year to year variability in the climate input for forest growth simulations. Furthermore, we propose a more stochastic way to analyze and communicate uncertainty.

Materials and methods

ANAFORE model

The ANAFORE model is a detailed mechanistic stand-scale model that dynamically simulates stand carbon (C), water and nitrogen fluxes, tree growth, and wood tissue development by following a bottom-up approach: leaf level processes (e.g. photosynthesis and transpiration) are simulated at a half-hourly time step and implemented into a daily-operating tree architecture and C allocation module (see Deckmyn et al. (2008) for a full description). Trees are simulated as cohorts of identical trees, of the same or different species. Concerning the effects of global change, assimilated C is calculated from photosynthesis modelled with the Farquhar (1980) model in combination with the Dewar model (2002) for stomatal conductance: the model is therefore both sensitive to CO₂ concentration and simulates increased water use efficiency under high CO₂ concentrations. Concerning allocation, C is allocated to roots or shoots depending on the most limiting factor (light, water, or nutrients) and the crown width to height ratio depends on the stand density and its effect on light availability. The model needs 140 parameters, and has been calibrated for deciduous and coniferous species through a Bayesian optimization routine (Deckmyn et al. 2008, 2009, 2011; Van Oijen et al. 2013).

Simulation design

The model runs were performed for a virtual *Pinus sylvestris* forest planted in Peitz (using data from the PROFOUND database which includes the longterm monitoring site of Scots pine in Peitz, Germany (Lasch et al. 2019) in 2021 (assumed 1 year old-trees) at a density of 10 000 trees per hectare and growing 79 years (tree age: 80 years), until 2100 on a sandy soil (87-91% sand depending on the soil layer). The management scenario consisted of an initial thinning of maximum 50% in stem number (depending on self-thinning) at 15 years age (to 5000 tree ha⁻¹) and subsequent thinning every 15 years. This initial high density was also used in the parameterization run (Brasschaat) which affected the early-growth parameters so our parameter sets are better suited to high density planting. The amount thinned after the first thinning, equaled half of the increase in basal area since the previous thinning, therefore it depended on forest growth. This closely reflects the management in Brasschaat, the site for which our model was calibrated, which has climate and soil conditions comparable to Peitz. Foresters adjust thinning intensity to the growth intensity.

The climate data for the simulation design, coming from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), included two emission/climate scenarios based on greenhouse gas concentration trajectories (Representative Concentration Pathway or RCP) as defined by the Intergovernmental Panel on Climate Change (IPCC). We used the most stringent mitigation scenario (RCP2.6) and the no-mitigation scenario (RCP6.0). The climate projections were made using three Global Climate Models (GCMs): MIROC5, IPSL-CM5A-LR and GFDL-ESM2M. These data were not locally bias corrected. Nine variations of the predicted climate variability were included, hereinafter called ‘climate shuffles’ or simply ‘shuffles’. They were implemented by changing the order of the different years nine times, but always constricted within a five year time period, so as not to change the impact of long-term trends in the climate projections (year 1 could become year 5 but not year 10). For each shuffle, one permutation was carried out in each of the 5-year periods and these permuted 5-year sequences

were then concatenated in their respective order to form one climate input. This was repeated 9 times to obtain the different climate shuffles.

For our model runs, we used 10 different parameter sets (which each had 140 parameters) derived from the posterior distribution of a previous model calibration by Bortier et al. (2018) who calibrated ANAFORE using forest biomass and flux data from the Scots pine Brasschaat forest (Belgium). For that study, a Bayesian approach (van Oijen 2005) was used to calibrate the model parameters (only parameters describing the tree, all soil parameters were fixed) according to the model fit with measured data of DBH (diameter at breast height), tree height, gross primary production and evapotranspiration from years 1996-2010 (for full description of the calibration see Bortier et al. 2018). For the present study, a Latin hypercube sample of 10 parameter sets was taken from the described posterior parameter distribution, to reduce the required number of runs. A Latin hypercube sample is partially random but takes more samples from the range with the higher likelihood so one gets a more representative sample than with random sampling (McKay et al. 1979). The average variation of the 140 parameters (for values see Bortier et al. 2018) was 11%, and the likelihood of the 10 parameter sets ranged from -995 (best fit) to -4588 (worst fit). The simulation design included different climate inputs based on climate projections from three GCMs run for two RCPs and nine shuffles of each of these projections used in combination with a representative sample of parameter sets. This allowed us to explore the uncertainty caused by weather variability in predicting climate change effects on forest growth in the context of other sources of uncertainty. With this ensemble of simulation designs, we simulated several output variables related to the growth and the functioning of the forest. For this study we used the output for basal area, standing volume, yield, DBH, height and carbon (C) in, wood, roots, leaves, and soil. Produced volume was calculated as the sum of standing volume and cumulative yield.

Variance analyses

The uncertainty assessment was based on a decomposition of the total variance of basal area and produced volume. First, a complete uncertainty assessment was carried out on final simulation output values, which included fixed effects for each of the sources of uncertainty present in the simulation design, i.e. the 2 RCP scenarios, the 3 GCMs, the 9 climate shuffles and the 10 parameter sets, and their two-way interactions. After this global analysis, we focused on analyses per parameter set (the dominant source of uncertainty) to compare the importance of the climate-related sources of uncertainty between them, and their evolution over time. For this, a separate analysis of variance was carried out for each decade, using its end value (i.e. value in years 2030, 2040, 2050, 2060, 2070 and 2080). Again, the two-way interactions between the sources of uncertainty were considered. The variance in the output explained by each of the sources of uncertainty was calculated by dividing the Sum of Squared Errors of the factors in the model (the sources of uncertainty) by the Total Sum of Squared Error of the response. The statistical analyses as well as the graphs were made in R3.4.3.

Evaluation of the differences between scenarios

Difference between the no-mitigation scenario RCP6.0 and the stringent mitigation scenario RCP2.6 was calculated for each pair of simulation runs obtained using the same GCM, shuffle pattern and parameter taking the mitigation scenario as a baseline. The absolute difference was calculated as $RCP6.0 - RCP2.0$ and the relative difference (%) as $RCP6.0/RCP2.0 \times 100$. The probability of a higher than 10% decrease in a variable in case of a no mitigation scenario compared to a mitigation scenario baseline was calculated for selected variables using the final model output as the proportion of simulation pairs for which the relative difference was lower than 90 %. The probability of a >10 % increase was calculated as the proportion of simulation pairs for which the relative difference was higher than 110 %.

Results

The average of all simulation runs exhibited expected patterns of steady increase in produced volume (obtained as sum of standing volume and cumulative yield) and saturating basal area responsive to thinning events over the growing cycle (Fig.1). Both basal area and produced volume were on average higher at the end of simulation under the no-mitigation (RCP6.0) scenario compared to the most stringent mitigation scenario RCP2.6 (ANOVA, $p < 0.05$, Table S1, S2). However, the main source of uncertainty in our exercise was the use of different parameter sets, which explained 92% and 96% of final basal area and produced volume, respectively (Table S1, S2).

For example, the mean produced volume varied between 304 and 1694 $\text{m}^3 \text{ha}^{-1}$ depending on the parameter set used and a similar pattern was found for basal area (Fig. S1). Apart from the parameter set and scenario, also the type of the GCM model had a significant main effect ($p < 0.05$) in case of the final produced volume (Table S2). Moreover, all three two-way interactions between GCM, scenario and parameter set had significant effects on both basal area and produced volume.

In the next step, we focused on the climate-related sources of uncertainty by analyzing simulations of each parameter set separately and looked at how their importance changed over the simulation period. Across parameter sets and time, the highest proportion of variance was explained by the global climate model (GCM) and by the interaction of GCM and shuffling for both basal area and produced volume (Fig. 2A). The main effect of GCM decreased over time for both variables and was more important in the case of produced volume. The variance explained by scenario was one of the lowest but tended to increase in time in the case of produced volume. Interestingly, shuffling explained on average more variability than the scenario - across all decades for basal area and in the first 5 decades for produced volume. Across decades and parameter sets, climate shuffles explained 12 and 10 % of uncertainty in the simulated basal area and produced volume, respectively. However, its interaction with GCM

and scenario explained additional 24% and 13%, respectively, with similar but slightly lower values for produced volume (21% and 11%). In total, climate shuffling and its two-way interactions with GCM and scenario were on average responsible for 49 and 42% of the uncertainty not related to parameters in basal area and produced volume, respectively.

As already suggested by the significance of two-way interactions with parameter set in the global ANOVAs, the total explained uncertainty, as well as its composition, differed substantially between parameter sets (Figure 2B, Table S1, S2). For example, depending on the parameter set, the main effect of shuffle ranged between 5 and 28 % for basal area and between 3 and 31% for produced volume (Table S1, S2). However, it was significant ($p < 0.05$) only in case of two parameter sets (no. 2 and 4) for basal area and in case of one parameter set (no. 4) for produced volume (Table S1, S2, Figure S1). Similarly, the interaction between the climate shuffle and the GCM explained 18 to 41 % of basal area and 10 to 38% of produced volume (Fig. 2B) but was significant only in the case of one parameter set for basal area (Table S1). The most frequently significant effect was GCM, which was still significant only for half of the parameter sets for both variables (Table S1, S2). Second in place, the variability explained by RCP scenario was significant in combination with three and five parameter sets for BA and produced volume, respectively.

To further unravel how the weather variability created by different GCMs and their shuffles affects the simulated response of forest growth to different mitigation scenarios, we looked at the difference between the two selected scenarios using means over all parameter sets for each shuffle (Fig. 3). Depending on the choice of climate input, the model predicted contrasting differences between the two scenarios. The predicted difference in produced volume between the RCP6.0 and RCP2.6 scenario ranged between -42 and 199 $\text{m}^3 \text{ha}^{-1}$ depending on GCM and shuffle. On average, the simulations using GFDLESM2M model output yielded close-to-zero effect of mitigation scenarios on the final basal area and produced volume while the outputs of

the other two GCMs were associated with an average positive effect of the no-mitigation scenario. Although the mean effect of pronounced climate change on produced volume and basal area was positive, five out of the 27 GCM shuffles (3 GCM x 9 shuffles) yielded a negative effect on produced volume.

Finally, we investigated the difference between the two scenarios also in other simulated variables, for which we used their final values at age 80, across all paired simulations (Fig.4). The probability distribution densities of the differences showed that although a part of the runs yielded high and both positive and negative differences between both scenarios, the highest density of the difference was close to 0 for all the investigated variables. Positive mean effects of no-mitigation scenario were observed for all variables except C in soil and DBH, and the relatively highest difference (123.8%) was found for C in leaves.

Discussion

Our study revealed some important insights regarding the potential output uncertainty of forest growth models. Firstly, the projected weather variability can have a large effect on the conclusions drawn from a model study (Fig. 3). Although the importance of the inherent variability in climate predictions is recognized and has been quantified in some studies (a.o. Hawkins and Sutton 2009, 2011), it has been widely neglected in impact studies. We have shown that the variability in the weather or its interaction with the used GCM, had a higher effect on the basal area of the forest than the RCP scenario. Overall, the weather variability introduced by shuffles and its two-way interactions with the global climate model and RCP scenario were responsible for 42–49 % of the uncertainty in the model output that was not related to parameterization of the model (Fig. 2A). We also showed how very different conclusions concerning the effect of climate change can be obtained by the random choice of a specific order of daily climate data (Fig. 3, 4). Although we rarely found significant effect of

shuffling on the predicted results using the performed ANOVA analyses, this is not surprising because the shuffles were always influenced by being nested within a scenario and GCM. It was therefore not possible to properly statistically test whether they differ since technically they were single replicates. However, we could see that shuffling was associated with considerable uncertainty. The shuffles also provided replicates that allowed us to statistically analyze the effect of different GCMs, scenarios and their interaction on modelled results.

Weather is, and will remain, highly unpredictable. As science progresses, parameter estimation, model structure and climate predictions improve and variance analyses can guide us to put more effort where we can gain most, but, as suggested by the chaos theory, the complex and chaotic weather system can never be predicted, no matter how good our understanding of climate and weather becomes (Slingo and Palmer 2011). Furthermore and as confirmed by this study, ecosystem simulation models are very sensitive to variation in weather (Olesen 2007). Beside the uncertainty brought in by environmental disturbances including extreme weather events that are difficult to implement in impact models (Seidl et al 2011), our study shows that less extreme weather variability is also an important source of uncertainty in model results. We conclude that this uncertainty is probably larger than previously thought and propose using the shuffling procedure as one way to introduce inter-annual climate variability and the associated uncertainty into impact studies.

Secondly, we found that the relative importance of the different sources of uncertainty strongly depended on the parameter set used for the simulation. ANAFORE has been previously shown to be associated with a high parameter uncertainty because it is a very complex model with a large number of parameters (Van Oijen et al. 2008). Also, the calibration used (Bortier et al. 2018) was carried out on relatively large scale data, leaving the uncertainty of parameters linked to stomatal behavior, photosynthesis, allocation and soil processes rather wide. This also means that the used prior parameter distributions for the Bayesian calibration were wide, i.o.w.

the prior uncertainty of physiological parameters was large. However, this is not a model-specific problem, but can be generalized to the lack of precise parameter estimates on leaf and stand scale (a.o. Yousefpour et al. 2012). Several authors have reported on the parameter uncertainty (a.o. Horemans et al. 2016; Reyer et al. 2016) and it is now generally included in simulation designs. In many studies however, only the best fitting parameterization is still used which of course decreases the reported uncertainty.

Thirdly, the mean of a simulation ensemble is not representative of the possible outcome of specific future emission/climate scenarios and is as useless as the outcome of a single model run. To illustrate this, for our particular study we found a mean difference of $49 \text{ m}^3 \text{ ha}^{-1}$ in produced volume between the no-mitigation scenario RCP6.0 and the strong mitigation scenario RCP2.6, suggesting a small positive effect of climate change on forest growth of the hypothesized forest grown between 2020-2100 in Peitz (Germany). However, the likelihood to obtain a 10% increase (33.7%) is only around 19% more than the likelihood of obtaining a 10% decrease (14.4%). The obtained mean differences of 0.5, 0.2 and 0 kg C m^{-2} for the C stocks in wood, roots and the leaves, respectively, is in a stochastic way translated to likelihoods between 37 and 47% to obtain an increase of more than 10%. A mean difference of -0.1 kg C m^{-2} for the C stock in the soil would be stochastically translated in a 18% chance of a greater than 10% decrease in the soil C stock. These results are within the described ranges of effects for similar forests (Gustafson et al. 2017), where both positive and negative effects on growth have been measured and modelled, whereas the effect of global change on soil C tends to be negative (as increased soil temperature increases soil organic matter turnover, Bottner et al. 2000). More generally, we propose that any impact studies should report a probability distribution of the results, and a description and quantification of the included sources of uncertainty. By taking into account and reporting on the many uncertainties, forest models can better support decision making in forest management even if the choice of the sources of uncertainty remains somewhat

subjective. Due to the inherent high uncertainties and the fact that managers do not have the accuracy in information they need from simulation studies (Pilkey and Pilkey-Jarvis, 2007), new approaches such as, for example, portfolio diversification (Millar et al., 2007; Temperli et al. 2012; Schelhaas et al. 2015) and robust decision making (McInerney et al. 2012; Yousefpour & Hanewinkel 2016) seem an appropriate solution, even if production concessions have to be made to reduce the risk of a very negative impact.

In summary, we conclude that the variability in weather should be included in simulation ensembles for forest growth and in the accompanying uncertainty assessment. Uncertainty assessment should be part of the modeler's protocol and the results thereof should always be reported with the complete density distribution of the model results, providing information by which policy makers and forest managers can base their risk assessments. Scientists should abandon the deterministic dogma and instead show their results in a probabilistic way.

Acknowledgements

This study was financially supported by the Belgian Science Policy Office (BELSPO) within the program BRAIN-be (contract BR/121/A2/MASC) and Co-funding by the Slovenian Research Agency through the research program P4-0107 is acknowledged. O.V. was supported by the H2020-MSCA-IF project no. 793485. This work has been conducted under the framework of *COST Action FP1304 PROFOUND* and of the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP), funded by the German Federal Ministry of Education and Research (reference number 01LS1201A). We thank Reinhart Ceulemans for having provided scientific support and feedback.

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Table 1: Mean difference, mean % of difference, probability of a 10 % decrease and probability of a 10 % increase of different output variables when comparing the final results at 80 years of age between the no-mitigation scenario RCP6.0 and the strong mitigation scenario RCP2.6 over all 270 simulation pairs (3 GCMs x 9 shuffles x 10 parameter sets)

Variable	Mean difference	Mean % difference	Prob > 10% decrease (%)	Prob > 10% increase (%)
basal area (m ² ha ⁻¹)	2.0	115.6	20.4	34.4
produced volume (m ³ ha ⁻¹)	48.9	112.7	14.4	33.7
standing volume (m ³ ha ⁻¹)	29.2	114.0	20.4	37.4
height (m)	0.2	101.1	1.5	4.8
diameter at breast height (cm)	0.0	98.8	21.9	12.6
wood C (kg C m ⁻²)	0.5	115.3	21.1	36.7
root C (kg C m ⁻²)	0.2	119.6	21.5	37.8
leaf C (kg C m ⁻²)	0.0	119.9	39.6	47.0
soil C (kg C m ⁻²)	-0.1	99.8	18.1	18.5

Figure captions

Figure 1: Mean±CI of the predicted produced, standing and yield volume and basal area averaged over all parameter sets, GCMs and shuffles, with black lines for RCP2.6 (most stringent mitigation scenario) and red lines for RCP6.0 (no-mitigation scenario). Each line represents an average of 270 runs.

Figure 2: Contribution of the different sources of uncertainty to predicted basal area (top) and produced volume (bottom) (a) at the end of each decade, averaged over ten parameter sets, (b) at final harvest (age 80) for each of the ten parameter sets. GCM: global climate model, RCP: RCP scenario, climate shuffles and their two-way interactions. For ANOVA results used for (b), see Tables S1 and S1.

Figure 3: The difference in basal area (A) and produced volume (B) between RCP6.0 (no-mitigation scenario) and RCP2.6 (most stringent mitigation scenario) for each of the 9 shuffles of three global climate models: GFDL-ESM2M (top), IPSL-CM5A-LR (middle) and MIROC5 (bottom). Each line represents one climate shuffle and is color-coded based on its y-axis value. Green and red color represent positive and negative effect, respectively, of the no-mitigation scenario (pronounced climate change) on the predicted variables, compared to the mitigation scenario. Blue line represents mean of all shuffles.

Figure 4: Histograms and overlaying distribution densities of the difference between RCP6.0 and RCP2.6 at age 80, for all 270 simulation pairs (3 GCMs x 9 shuffles x 10 parameter sets) for nine output variables: basal area, produced volume, standing volume, diameter at breast height (DBH) and C stocks in wood, roots, leaves and soil. Dashed line represents zero difference between the two scenarios. Full vertical blue line represents the mean (for values see Table 1).

RCP6.0 - RCP2.6 difference