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Variance decomposition of predictions of stem biomass increment for European beech: Contribution of selected sources of uncertainty



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ABSTRACT

The contribution of selected sources of uncertainty to the total variance of model simulation results of stem biomass increment - calculated from annual stem biomass predictions - of European beech (Fagus sylvatica L.) was quantified. Sources of uncertainty were defined as the selected variables that influence the total variance of the model results. Simulations were made: (i) for ten regional climate models (RCMs) based on the IPCC scenario A1B and providing an ensemble of climate projections up to 2100; (ii) with two forest model types (FMTYPEs); (iii) for four forest management intensities (MANFORs); and (iv) for three time windows (TIMEWINDs), each spanning 15 years, starting in 2019, in 2049 and in 2079. Both models, the empirical SIBYLA model and the process-based ANAFORE model, were calibrated using experimental tree growth data from four plots in central Slovakia between 1989 and 2003. Three of these plots, representing the four MANFORs, were subject to different prior intensities of thinning while one was left untouched as a control. The FMTYPE explained most of the total variance in the simulation results (39.9%), followed by MANFOR (i.e. thinning intensity: 22.2%) and TIMEWIND (12.0%), while the effect of RCMs on model uncertainty was limited (<1%). Stem biomass increment results obtained from the two FMTYPES were different in absolute terms, but the models agreed well in their relative response to RCM, to MANFOR and to TIMEWIND. The total variance of the predictions was 10 times higher for the process-based model (ANAFORE) than for the empirical model (SIBYLA). These observations are the reason for the large contribution of FMTYPE to the total variance of the simulated stem biomass increment results.

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1. Introduction

As trees grow old, forests unavoidably face the impact of imminent climate change. Forest management measures can contribute significantly to mitigation of and adaptation to these environmental changes. Conventional statistical models implicitly based on the assumption of stationary conditions may not be applicable for forest management decisions, but novel and improved process-based models predict forest growth under changing conditions. Management plans developed using either type of model require appropri-

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ate risk assessments (Walker et al., 2003). Uncertainty analysis of forest model results is thus crucial to support management decisions. The model uncertainties partly originate from input variables, including data required for the model set-up and the calibration, as well as from climate and forest management predictions. Uncertainty is also associated with the model boundaries (i.e., the extent of the ecosystem complex covered by the model), with the model structure itself and with the model parameters (Jones, 2000; Reyer et al., 2013). Only a part of this model uncertainty, however, is reflected in the variance of the model results. Other sources of error may also contribute to model uncertainty, but may not be quantifiable: either because they are unknown or because they are not included in the model.

Forest models incorporate aspects of system complexity as well as the non-linear relations and the feedback mechanisms among

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the system drivers (Tian et al., 2012). Over the last three decades forest models have become more process-driven and they now incorporate a multitude of parameters (Landsberg, 2003; Matala et al., 2003). Process-based models (PBMs) integrate the mechanistic functioning of the ecosystem by reproducing the ecological and physiological processes that drive the system, as well as their responses to external factors (Landsberg, 2003; Kurbatova et al., 2008). PBMs are useful tools for understanding the dynamics of an ecosystem and they can provide answers to guestions on how ecosystems should be managed under changing environmental conditions (Korzukhin et al., 1996; Matala et al., 2003; van Oijen et al., 2005). However, having a multitude of parameters does not necessarily guarantee that the model predictions will be reliable (Larocque et al., 2014). The complexity of PBMs can be a strength, but also a weakness, because they rarely provide a unique answer to a practical management question (Mohren and Burkhart, 1994: Sands et al., 2000: Matala et al., 2003: van Oijen et al., 2005). Model improvements can result from a better understanding of the internal processes of the system, e.g., carbon allocation processes, nutrient availability in soils, nutrient uptake by trees, and competitive interactions (Seidl et al., 2011b). A better knowledge of the external impacts and disturbances - often human-induced - as well as their dependence on site location is also required (Landsberg, 2003; Kearney and Porter, 2009; Seidl et al., 2011a). The feedbacks and compensating mechanisms between ecological drivers create challenges in model development (Ceulemans et al., 1999; Matala et al., 2005; Penuelas et al., 2008).

In contrast, empirically-based models (EBMs) are built on statistical relationships between forest growth and environmental variables obtained from field measurements (Fabrika, 2007; Hlásny et al., 2014; Pan et al., 2014). The choice of the forest model best suited for a particular research or management question is of crucial importance. Efforts have been made to combine the advantages of PBMs (theoretical understanding, flexibility, predictive power under changing conditions) and EBMs (robustness, limited input demand, ease of interpretation) by using multi-model inference (Hlásny et al., 2014) or by developing hybrid models (Makela et al., 2000; Baldwin et al., 2001; Peng et al., 2002; Girardin et al., 2008; Taylor et al., 2009).

When climate predictions provide an input for forest models, uncertainty is transferred from the climate model to the forest growth simulation (Lindner et al., 2014; Keenan, 2015). The uncertainties in regional climate predictions are caused by three sources: (i) the climate model uncertainty, which is resulting from the model structure and the parameterization and causes different responses to the same radiative forcing, (ii) the scenario uncertainty, which arises from the uncertainty in future environmental changes, as e.g. greenhouse gas emissions, and (iii) the internal variability, which is the inherent temporal randomness of climate in the absence of any radiative forcing (Hawkins and Sutton, 2009, 2010). The relative importance of these three sources of uncertainty changes with the spatial and temporal scale. The internal variability becomes more important with decreasing spatial scale and with an increased occurrence of extreme events (Lindner et al., 2014). Model uncertainty increases with longer prediction periods. Scenario uncertainty increases even more with lead time (Hawkins and Sutton, 2009). Uncertainties from regional climate models (RCMs) can be quantified by using an ensemble approach, combining the results of multiple models to give the statistical probability of possible future climates (Lindner et al., 2014). Beside the physiological aspects, the state of a forest - i.e., its extent, species composition and canopy structure - and its biogeographical location also affect its response to disturbance and vice versa (Allen et al., 2010; Seidl et al., 2011b; Jactel et al., 2012). The effects of forest state and forest history should be correctly understood and taken into account in forest simulation studies, especially for European forests that are generally intensively managed (Spiecker, 2003; Boisvenue and Running, 2006; De Vries et al., 2006; Solberg et al., 2009). It is important to correctly estimate the costs and the benefits of different forest management measures and to account for a wide range of forest situations and potential future climate conditions.

In this contribution we (i) quantified the variance coming from different sources of uncertainty on predictions of tree growth; (ii) tested the significance of these sources of uncertainty; and (iii) assessed the contribution of different RCMs to the total uncertainty in the climate predictions. So, this study only investigated the uncertainty of the model results and it did not consider the effects of the different sources of variance on the actual predictions.

In this study we have modelled the annual stem biomass increment (ASBI) of European beech (*Fagus sylvatica* L.), a dominant tree species in European forests and the most common deciduous species in central Europe (Dittmar et al., 2003). Drought-induced growth reduction and/or a decline of the species have been reported in southern Europe (Ciais et al., 2005; Jump et al., 2006; Piovesan et al., 2008; Bontemps et al., 2010; Charru et al., 2010; Kint et al., 2012; Zang et al., 2014), but for central Europe an accelerated growth has been reported (Pretzsch et al., 2014).

2. Materials and methods

2.1. Site description and sampling design

The forest site was located in the Kremnické Vrchy Mountains of the Western Carpathians, Slovakia (48° 38′ N, 19° 04′ E). The altitude ranged from 470 m to 510 m, with a total area of 4.5 ha having a slope with a western aspect and an inclination of 13–20%. The soil substrate consisted of andesite-tuff agglomerates and the soil type was Andic Cambisol with a high skeleton content (10–60%). During the measurement period (i.e., the calibration period) of 1989–2003 the annual average temperature was 8.6 °C and the average annual precipitation was 677 mm.

At the start of the 1989–2003 calibration period, the forest was 100 years old. Before 1989, it was managed according to usual forestry practice of less intensive thinning interventions from below (mostly the removal of damaged and low-quality trees). In the 30 years preceding the calibration period, the stand was thinned three times. In the period 1963–1972, 54 m³ ha⁻¹ were harvested from the stand. In the following two periods (1973-1982 and 1983–1988) the harvested thinning was 54 and 40 m³ ha⁻¹, respectively. European beech (F. sylvatica L.) was the dominant species (65–90%) in the forest stand, but hornbeam (Carpinus betulus L.), oak (Quercus robur L.) and fir (Abies alba Mill.) were also present. In February 1989 three plots of 0.35 ha each were established. These plots were subjected to strip shelterwood cutting of different intensities. The remaining number of trees per ha was respectively 160 for the heavily thinned plot (H), 243 for the medium thinned plot (M) and 397 for the lightly thinned plot (L). A fourth plot of 0.15 ha was left uncut as a control (C) with 700 trees per hectare. The thinning primarily focused on removing the interbreed species, dying and damaged trees, and trees of very low stem quality. Branches were left on the site to decompose naturally. More detailed information about the forest site and the forest management has been reported previously (Jamnická et al., 2007; Kellerová, 2009; Barna et al., 2010; Janík et al., 2011; Barna and Bosela, 2015).

During the calibration period (1989–2003) stem diameter at breast height (DBH) was measured annually using a diameter tape with a precision of 1 mm. Individual trees and measurement positions were clearly marked to minimize measurement errors. Tree height (h) was measured three times over the calibration period

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