Title: “Accuracy, realism and general applicability of European forest models”

Running head: “Forest Model Evaluation”

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Abstract

Forest models are instrumental for understanding and projecting the impact of climate change on forests. A considerable number of forest models have been developed in the last decades. However, few systematic and comprehensive model comparisons have been performed to date to compare model agreement with field data and evaluate structural uncertainties. Here, we evaluate 13 widely-used, state-of-the-art, stand-scale forest models against field measurements of forest structure and eddy-covariance data of carbon and water fluxes over multiple decades across an environmental gradient at nine typical European forest stands. We test the models' performance in three dimensions: *accuracy of local predictions* (agreement of simulated and observed annual data), *realism of environmental responses* (agreement of modelled and observed responses of daily gross primary productivity to temperature, radiation and vapor pressure deficit) and *general applicability* (proportion of European tree species covered). We find that multiple models are available that excel according to our three dimensions of model performance. For the accuracy of local predictions, variables related to forest structure have lower random and systematic errors than annual carbon and water flux variables. Moreover, the multi-model ensemble mean provided overall more realistic daily productivity responses to environmental drivers across all sites than any single individual model. The general applicability of the models is high, as almost all models are currently able to cover Europe's common tree species. We show that forest models complement each other in their response to environmental drivers and that there are several cases in which individual models outperform the model ensemble. Our framework provides a first step to capturing essential differences between forest models that go beyond the most commonly used accuracy of predictions. Overall, this study provides a point of reference for future model work aimed at predicting climate impacts and supporting climate mitigation and adaptation measures in forests.

Introduction

Forest models are widely used to assess the impacts of changing environmental conditions such as climate, atmospheric CO_2 concentration and nitrogen deposition on forest functioning, dynamics and structure (e.g. Reyer et al. 2013). Yet, because of our incomplete understanding of forest ecosystems and computational constraints, these models differ in the way specific processes are represented, leading to differences in their predictions (Bugmann et al. 2019; Collalti et al. 2019; Huber et al. 2021). Hence, models need to be comprehensively evaluated using different data types at different spatio-temporal scales before we can judge their structural uncertainties and suitability for answering specific questions (Maréchaux et al. 2021; Oberpriller et al. 2021).

Model simulations need to be in adequate agreement with independent observations. Moreover, models have to be sensitive to environmental drivers to ensure that system responses are realistically predicted under a wide range of environmental and climatic conditions (Collalti et al. 2016). Additionally, for spatially comprehensive assessments of climate impacts it is also required that the models have a large range of applicability covering different ecological conditions. Ideally, models meet all these requirements.

Levins (1966) categorized these requirements as trade-offs between three dimensions: model accuracy, realism and generality. Accuracy indicates the goodness-of-fit between prediction and observation, realism refers to causally correct internal model processes, and generality represents robust applicability across space and time (Kramer et al. 2002). While it is difficult to maximize accuracy, realism and generality simultaneously, model developers have to identify an optimal point on the trade-off according to the overall aim of the model.

Many climate sensitive forest models have been developed in Europe for different applications, regions and species (e.g., Fontes et al. 2010; Pretzsch et al. 2015). Yet, it is unknown how they perform relative to the same benchmark conditions, and how their structure leads to trade-offs between accuracy, realism and generality since model inter-comparisons across large numbers of complex models are missing. Earlier model evaluations have either focused on selected processes (e.g., NPP: Morales et al. 2005; mortality: Bugmann et al. 2019), relied on short time series of observed data (Kramer et al. 2002), or investigated only few models and sites (Horemans et al. 2017). Yet, the increasing amount of harmonized data recently becoming available across Europe (e.g. Reyer et al. 2020a,b) allows for a rigorous evaluation of the state-of-the-art in forest modeling across different biogeographical regions, forest types and types of data. Such an evaluation may provide a deeper understanding of model differences and structural uncertainties, and provide crucial guidance for designing ensemble studies of climate impacts on forests.

The objective of this paper is to evaluate and compare 13 widely applied forest models in managed forests across an environmental gradient in Europe. The models range in complexity from empirically-based to highly mechanistic approaches, while the evaluation data types range from ground-based inventories to tower-based eddy-covariance measurements. To achieve this objective, we: (i) compare model outputs to observations to quantify the accuracy of local predictions by deriving the statistical fit between observations and model output of important forest variables; (ii) determine the realism of environmental responses by assessing the agreement of observed and modeled relationships between stand productivity and climatic drivers; (iii) describe the general applicability by deriving the proportion of European forest stands that a model is able to cover; and (iv) integrate these three dimensions in a model performance framework. We hypothesize that trade-offs in our ensemble of forest models can be traced back to differences in accuracy, realism and generality as described by Levins (1966).

Methods

Vegetation models and simulation protocol

We used simulation outputs from 13 state-of-the-art, structurally different, forest models (3D-CMCC-FEM LUE, 3D-CMCC-FEM BGC, 3PG, 3PGN-BW, 4C, BASFOR, ForClim v.3.3, FORMIND, GOTILWA+, LandscapeDNDC, PREBAS, SALEM, SIBYLA) that participated in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP, Frieler et al. 2017). The key assumptions and formulations for simulating processes or variables between models as well as their differences are described in Tab. 1. All models are designed to predict long-term (multiple decades) forest growth and forest dynamics. Empirical models are geared towards one full stand rotation while gap models focus on describing successional dynamics in multi-species stands. Mechanistic models describe forest dynamics based on the dynamics of plant carbon and water exchange at a high temporal resolution. Ten of the models describe the ecosystem-atmosphere exchange of carbon, and nine of them the exchange of water in forest stands at a daily to annual time step. All 13 models have been applied as research tools to study climate impacts on managed forests.

The simulations followed the ISIMIP phase 2a simulation protocol (https://www.isimip.org/protocol/), which provides a consistent simulation setup based on common, harmonized data for initializing, driving and evaluating models from the PROFOUND database (Reyer et al. 2020a,b). The models were initialized with observed stand characteristics (e.g. stem diameter at breast height, tree height, stand density, stand age) and then driven with locally measured weather data (e.g. surface air temperature, precipitation, vapor pressure deficit), atmospheric CO_2 concentration and nitrogen deposition data, as well as historically observed forest management interventions. Simulated management was based on observed stem numbers and thinning regimes, i.e. thinning from above (higher diameter classes preferentially removed) or from below (lower diameter classes preferentially removed). Forest management was the only explicitly simulated disturbance. Drought effects were implicitly included by the driving weather data. The models were run for 13 to 63 years on nine forest stands across Europe that are contrasting in climate, species composition, phenology, management type and age (Tab. 2). Not all sites were simulated by all models due to incomplete parameterization for species. Site-specific parameter calibration on the observed data was not permitted.

Tab. 1: Overview of main processes implemented in all forest models as well as examples of model applications. NSC: non-structural carbon; GPP: gross primary productivity; VPD: vapor pressure deficit; DBH: diameter at breast height; NA: not included explicitly. Models are classified according to their complexity into empirical (E), hybrid (H) and process-based (P) types. This classification is based on expert judgment to provide a rough overview of model complexity; in reality these models align along a continuum from more empirical to more process-based models. References are indicated by numbers.

								structure development				
model	photosynthesis	stomatal conductance	aut. respiration	evapo-transpiration	soil water balance	phenology	carbon allocation	height	diameter	mortality	example applications	model class
SALEM	NA	NA	NA	NA	NA	NA	NA	allometric equations (1)	Diameter, density, and site index specific stand level- dependent increment model (1,2)	diameter-dependent specific self thinning (1)	1,3,4	E
SIBYLA	NA	NA	NA	NA	NA	NA	NA	empirical: based on tree age, site specification, tree vitality and competition	empirical: based on site specification, tree vitality and competition	empirical: based on tree dimensions, growth and stand density	5,6,7	E
ForClim v.3.3	NA	NA	NA	8 based on 9	Single layer bucket model (10)	temperature sensitive and species specific	NA	derived from diameter increment under consideration of light availability and climate specific maximum tree height	modified carbon budget model (11) considering environmental constraints	age-related, stress-related	v.3.3: 12; for most recent version v.4.0.1 see 13,14	H
FORMIND	Light-use efficiency (15)	NA	Maintenance respiration + dynamic growth respiration	Water-use efficiency as a function of GPP	Single layer bucket model	Degree day sum approach (16)	dynamic allocation based on phenology, temperature, light and water availability	allometric equations	Dependent on carbon allocation to stem mass and current DBH of the tree	carbon-based stress mortality	17,18,19	H

3PG	Light-use efficiency (20)	NA	Constant fraction of GPP	Penman-Monteith	Single-layer soil-water-balance	Fixed species-specific growing season	Dynamic allocation based on age, size, soil water, VPD	allometric equation from dbh, competition, ets.	Dependent on carbon allocation to stem mass and current DBH of the tree	age-dependent + stress-related + self-thinning	21,22,23	H
3PGN-BW	Light-use efficiency (20)	NA	Maintenance respiration + dynamic growth respiration	Penman-Monteith	Single-layer soil-water-balance	species-specific based on minimum monthly temperature	dynamic allocation based on environmental modifiers	allometric equations	dependent on carbon allocation to stem mass and current DBH of the tree	age-dependent + stress-related + self-thinning with stochastic component	24,25	H
BASFOR	Light-use efficiency	NA	Fixed ratio NPP/GPP	Penman	Single layer bucket model	Function of temperature, chilling days, day length	Branch and stem fractions constant, leaf and root fractions functions of water- and N-status	Function of stem dry matter	Function of stem dry matter and height	NA	26,27	H
PREBAS	Light-use efficiency (28)	NA	Maintenance respiration + growth respiration (29)	Empirical formulation based on daily photosynthesis, VPD, and Priestley-Taylor (30)	Bucket model (30)	Photosynthesis: Reversible temperature based model (31) Deciduous:, additionally a temperature sum based on (32)	dynamic allocation based on pipe-model and functional balance and crown allometry	Follows from carbon allocation	Follows from carbon allocation	competition	33,34,35,36	H
3D-CMCC-FEM LUE	Light-use efficiency (20)	37,38	Maintenance respiration + dynamic growth respiration (39,40)	Penman-Monteith	Single-layer soil-water-balance	species-specific temperature (i.e. Thermic sum), eliophany, LAI and others	dynamic allocation based on phenology, light and water availability (*sensu* 41)	allometric equations from dbh	allometric equations from stem biomass	age-dependent + self-thinning + NSC pool depletion + stochastic component	42,43,44,45	H
3D-CMCC-FEM BGC	Farquhar, von Caemmerer and Berry (46,47)										48,49	P
4C	Light-use efficiency (15,50)	NA	Constant fraction of GPP	Turc-Ivanov/Penman-Monteith/Priestley-Taylor	Dynamic multi-layered bucket model	inhibitor-promotor system (51)	dynamic allocation based on pipe-model and functional balance theory	function of foliage mass and crown architecture	dependent on carbon allocation	self-thinning + carbon starvation + age-related (52)	53	P
GOTILWA+	Farquhar (46)	Stomatal conductance after 54	Maintenance respiration + dynamic growth respiration	Penman-Monteith. Transpiration calculated from stomatal conductance, leaf area and vapor pressure deficit.	Two layer bucket model	Temperature sensitive (55)	dynamic allocation based on pipe-model and functional balance	allometric equations from dbh	allometric equations from dbh	NSC pool depletion + loss of active sapwood	56,57,58	P

Landscape-DNDC (PSIM)	Farquhar (46)	Optimization scheme after 59 (considering soil water influence)	Maintenance respiration (60) + Growth respiration (fixed fraction)	61, stomatal conductance after 59	Multi-layer model	Cumulative temperature approach (62)	sink-source approach driven by phenology (63)	based on stem carbon allocation and density-dependent height:diameter relations (64)	based on stem carbon allocation and density-dependent height:diameter relations (64)	fixed fraction + density related limits (65)	66,67,68	P

References 1: Aussenac et al. 2021; 2: Toïgo et al 2015; 3: Vallet et al 2018; 4: Toïgo et al. 2018; 5: Fabrika and Ďurský 2005; 6: Hlásny et al. 2014; 7: Merganič et al. 2020; 8: Bugmann and Cramer 1998; 9: Thornthwaite and Mather 1957; 10: Bugmann and Solomon 2000; 11: Moore 1989; 12: Mina et al. 2015; 13: Huber et al. 2020; 14: Huber et al. 2021; 15: Haxeltine and Prentice 1996a; 16: Sato et al. 2007; 17: Bohn et al. 2014; 18: Rödig et al 2017; 19: Bohn et al. 2018; 20: Monteith et al. 1977; 21: Landsberg and Warring 1997; 22: Gupta and Sharma 2019; 23: Trotsiuk et al. 2020; 24: Xenakis et al. 2008; 25: Augustynczik and Yousefpour 2021; 26: van Oijen et al. 2014; 27: Cameron et al. 2013; 28: Mäkelä et al. 2008; 29: Mäkelä 1997; 30: Peltoniemi et al. 2015; 31: Mäkelä et al., 2004; 32: Linkosalo et al. 2008; 33: Kalliokoski et al. 2018; 34: Kalliokoski et al. 2020; 35: Holmberg et al. 2019; 36: Forsius et al. 2021; 37: Jarvis 1976; 38: Jarvis and Davies 1998; 39: McCree and Setlick 1970; 40: Thornley 1970; 41: Friedlingstein et al. 1999; 42: Collalti et al. 2014; 43: Collalti et al. 2016; 44: Collalti et al. 2018; 45: Marconi et al. 2017; 46: Farquhar et al. 1980; 47: De Pury and Farquhar 1997; 48: Collalti et al. 2019; 49: Collalti et al. 2020; 50: Haxeltine and Prentice, 1996b; 51: Schaber and Badeck 2003; 52: Botkin 1993; 53: Gutsch et al. 2018; 54: Leuning et al. 1995; 55: Leinonen 1996; 56: Sabaté et al. 2002; 57: Keenan et al. 2011; 58: Nadal-Sala et al. 2019; 59: Leuning 1995; 60: Cannell and Thornley 2000; 61: Thornthwaite 1948; 62: Grote 2007; 63: Grote 1998; 64: Grote et al. 2020; 65: Grote et al. 2011; 66: Lindauer et al. 2014; 67: Schweier et al. 2017; 68: Dirnböck et al. 2020.

Evaluation data

The PROFOUND database (Reyer et al. 2020a,b) hosts observed data from nine boreal and temperate forest stands located across Europe (Tab. 2). The database provides measurements of forest structure including basal area (*BA*), arithmetic mean diameter at breast height (*DBH*) and arithmetic mean tree height (*H*). On a subset of five sites, carbon and water fluxes measured at eddy-covariance towers are available (Tab. 2) including gross primary productivity (*GPP*), ecosystem respiration (*Reco*), net ecosystem exchange (*NEE*) and actual evapotranspiration (*AET*).

Tab. 2: Features of evaluation sites in the PROFOUND database used in this study. MAP: mean annual precipitation (mm/year); MAT: mean annual temperature (°C); lat.: latitude; long.: longitude; structure: structure variable time coverage; flux: flux variable time coverage.

site	dom. species	forest type	MAP	MAT	elevation (m a.s.l)	country	lat.	long.	structure	flux
Hyytiälä	*Pinus sylvestris*	even-aged	604	4.4	185	FI	61.85	24.23	1995-2011	1996-2014
Solling beech	*Fagus sylvatica*	even-aged	1113	6.8	500	DE	51.77	9.57	1967-2014	NA
Solling spruce	*Picea abies*	even-aged	1113	6.8	508	DE	51.77	9.57	1967-2014	NA
Collelongo	*Fagus sylvatica*	even-aged	1179	7.2	1560	IT	41.85	13.59	1992-2012	1996-2014
Bily Kriz	*Picea abies*	even-aged	1434	7.4	875	CZ	49.30	18.32	1997-2015	2000-2008
Kroof	*Fagus sylvatica*, *Picea abies*, decid. species	mixed	849	8.2	502	DE	48.25	11.4	1997-2010	NA
Sorø	*Fagus sylvatica*	even-aged	774	9.0	40	DK	55.49	11.65	1997-2013	1996-2012
Peitz	*Pinus sylvestris*	even-aged	608	9.2	50	DE	51.92	14.35	1948-2011	NA
Le Bray	*Pinus pinaster*	even-aged	920	13.4	61	FR	44.72	-0.77	1986-2009	1996-2008

For the carbon flux data, there are multiple products available for the same variable due to varying underlying estimation techniques (Pastorello et al. 2020). We used the data derived with constant friction velocity (USTAR) threshold where the reference is selected based on model efficiency for processing *NEE* (NEE_CUT_REF; https://fluxnet.org/data/fluxnet2015-dataset/data-processing/, Pastorello et al. 2020) and the daytime (DT) method (Lasslop et al. 2010) for partitioning *NEE* into *GPP* and *Reco*. The first year of carbon flux measurements at each site was discarded since the majority of data points had a quality flag of “poor”. Daily *AET* was derived from measured latent heat flux (*LE*) to the atmosphere by $AET = LE/\lambda$, with $\lambda = (2.501 - 0.00237 * T_{air}) * 10^6$, where T_{air} is the mean daily temperature (Foken 2008). Annual *AET* was aggregated as the sum of daily *AET* derived from the measured daily latent heat flux.

Evaluation framework

We evaluated the models in three dimensions based on the framework by Levins (1966) and further specified by Kramer et al. (2002): accuracy of local predictions, realism of environmental responses and general applicability. We defined the *accuracy of local predictions* as the agreement between observed and predicted data of relevant forest variables at the annual time scale; the *realism of environmental responses* as the agreement of simulated to observed relationships between daily climatic drivers and gross primary productivity; and the *general applicability* as the proportion of European forests a model can represent based on parameterized tree species. In addition to the individual models, we evaluated the model ensemble as the arithmetic mean time series of all individual model predictions available for a given site and variable. We used the statistical computing language R (R Core Team 2020) for all analyses.

Uncertainty in model predictions arises from model structural uncertainty, parameter uncertainty and input data uncertainty (Lindner et al. 2014; Collalti et al. 2019). Here we focused on evaluating compound model uncertainty originating from all uncertainty sources except for input data uncertainty which is shared across all models. The coverage of sites and variables is model-specific and the temporal resolution of model predictions varies from daily to monthly to annual. The models used their individual default species-specific parameter settings for the simulations.

Accuracy of local predictions

The accuracy of local predictions was quantified for the primary variables of interest on an annual resolution: *BA, DBH increment* (*DBHinc*), *H increment* (*Hinc*), *GPP*, *Reco*, *NEE*, *AET*. *DBHinc* and *Hinc* were evaluated instead of *DBH* and *H* to eliminate the temporal autocorrelation that is associated with these variables, resulting from the incremental nature of diameter and height growth. In this way, we covered increments as well as the structure through *BA* (which is strongly dominated by temporal autocorrelation). *DBHinc* and *Hinc* were computed as the average annual change of stand scale mean *DBH* and *H*, respectively, for the period between two consecutive observations, since there were no measurements available for every year at all sites and the uncertainty in single year increment measurements is high. The same approach was applied to derive increments from the simulated data. *DBHinc* and *Hinc* integrate individual tree increments related to growth as well as changes of the stand scale mean *DBH* and *H* resulting from the removal of certain trees during management interventions and/or natural tree mortality.

Following Gauch et al. (2003), we computed multiple metrics describing different aspects of the disagreement between predictions and observations. The mean squared deviation (*MSD*) and its components squared bias (*SB*), lack of correlation (*LC*) and non-unity slope (*NU*) were computed for each model-site-variable combination. These metrics describe three sources of error: a systematic error (SB), random errors (LC) and linear patterns in the residuals (NU):

$$MSD = \frac{\sum_{n=1}^{N}(X_n - Y_n)^2}{N} = SB + NU + LC \qquad (1)$$

with X = simulated data, Y = observed data and n = {1,2, … N}, with N = number of data pairs.

$$SB = (\bar{X} - \bar{Y})^2 \quad (2)$$

$$NU = (1 - b)^2 * \left(\frac{\sum_{n=1}^{N} {x_n}^2}{N}\right) \quad (3)$$

with $b = \sum_{n=1}^{N} x_n y_n \ / \ \sum_{n=1}^{N} {x_n}^2$ which is the slope of the least-square-regression between Y and X. The deviations from the mean are described by $y_n = Y_n - \bar{Y}$ (analogous: $x_n = X_n - \bar{X}$).

$$LC = (1 - r^2) * \left(\frac{\sum_{n=1}^{N} {y_n}^2}{N}\right) \quad (4)$$

with $r^2 = (\sum_{n=1}^{N} x_n y_n)^2 \ / \ \sum_{n=1}^{N} {x_n}^2 \sum_{n=1}^{N} {y_n}^2$ which is the square of the correlation between Y and X.

The quantification of these three completely independent components of the *MSD* allowed us to derive which components drive the inaccuracies most strongly.

For cross-variable and cross-site comparability, we normalized the *MSD* (*norm. MSD;* and analogous *SB*, *LC*, and *NU*) with the observed variance of a given variable at a specific site:

$$norm.MSD = \frac{MSD}{\frac{1}{N}\sum_{n=1}^{N}(Y_n - \bar{Y})^2} \quad (5)$$

$$norm.SB = \frac{SB}{\frac{1}{N}\sum_{n=1}^{N}(Y_n - \bar{Y})^2} \quad (6)$$

$$norm.LC = \frac{LC}{\frac{1}{N}\sum_{n=1}^{N}(Y_n - \bar{Y})^2} \quad (7)$$

$$norm.NU = \frac{NU}{\frac{1}{N}\sum_{n=1}^{N}(Y_n - \bar{Y})^2} \quad (8)$$

Then we aggregated the *norm. MSD* over all sites by computing the arithmetic mean of *norm. MSD* for a given model-variable combination. To derive a unique accuracy of local predictions score (A) for each model, we first computed the coefficient of determination as $R^2 = 1 - norm. MSD$ for each variable (cf. Moffat et al. 2010). Then we calculated the arithmetic mean of the R^2 values across all structure variables and all carbon and water variables (${R^2}_{structure}$ and ${R^2}_{carbon\ and\ water}$) and re-projected the resulting values to the range from 0.1 to 1 to derive $A_{structure}$ and $A_{carbon\ and\ water}$. Overall A was then derived analogous to $A_{structure}$ and $A_{carbon\ and\ water}$ but with all variables available for a model. The predictive skill of a forest model was higher than the predictive skill of the observed mean in terms of the overall absolute error if *norm. MSD* < 1.

Realism of environmental responses

The realism of environmental responses was derived by quantifying the agreement of simulated to observed relationships between climatic drivers and productivity, i.e., *GPP,* since *GPP* is sensitive to several interacting climatic drivers (Zhang et al. 2017, Zhang et al. 2019, Zhou et al. 2021). Only those models that output daily *GPP* could be evaluated for their realism of environmental responses. We considered mean daily temperature (*temp*), daily global incoming radiation (*rad*) and daily mean vapor pressure deficit (*vpd*) as forcing variables on the daily *GPP*. For each of the five FLUXNET sites, we assessed the realism of the environmental responses for the relation of *GPP* to *temp*, *rad* and *vpd* of every model. The observations were filtered for FLUXNET quality flags 0 (measured) and 1 (good quality gap-filled). Additionally, the data was filtered for days with *temp* > 5 °C (cf. Franklin et al. 2013, Rehfeld et al. 2006) to ensure that the bulk of the data lie within the growing season, because this is the most important period in which the model needs to exhibit realistic responses of productivity to environmental drivers.

First, we visually compared the form of the observed and simulated relationships between *GPP* and the three forcing variables including their interactions by deriving general additive models (GAMs) for the 0.5 quantile. The computation was done using the R library qgam (Fasiolo et al. 2017). The quantile GAMs have the form

$$GPP = f_1(temp) + f_2(rad) + f_3(vpd) + f_4(temp, rad) + f_5(temp, vpd) + f_6(rad, vpd) + f_7(temp, rad, vpd) \tag{9}$$

using tensor product (te) smooth functions f_i.

Second, to formally compute model scores for the realism of environmental responses, the residuals between daily simulated and observed *GPP* were derived from the GAMs. We computed simple linear regression models relating the residual daily *GPP* from the GAMs to each of the three forcing variables. The GAM predictions were obtained by fixing two of the three independent variables to their arithmetic mean value. The linear regressions take the form

$$GPP_{sim,rad_{fixed},vpd_{fixed}} - GPP_{obs,rad_{fixed},vpd_{fixed}} = \beta_1 + \alpha_1 * temp \tag{10}$$

$$GPP_{sim,temp_{fixed},vpd_{fixed}} - GPP_{obs,temp_{fixed},vpd_{fixed}} = \beta_2 + \alpha_2 * rad \tag{11}$$

$$GPP_{sim,temp_{fixed},rad_{fixed}} - GPP_{obs,temp_{fixed},rad_{fixed}} = \beta_3 + \alpha_3 * vpd \tag{12}$$

Similar *GPP*-environment relationships in observed and simulated data were characterized by small residuals, or at least by a lack of patterns in the residuals across the environmental drivers. Hence, small absolute slopes in the linear regression of the residuals indicated an agreement of observed to simulated relationships. For each environmental variable we re-projected the mean absolute slope across all models and sites $\overline{|\alpha_i|}$ to the range between 0 and 1 ($\overline{|\alpha_i|}'$) to account for differences in the magnitude of the variable units (*temp*: °C; *rad*: J/cm^2; *vpd*: kPa). Then we derived the realism of environmental responses for each model as the mean of the re-projected slope ($\frac{\overline{|\alpha_1|}'+\overline{|\alpha_2|}'+\overline{|\alpha_3|}'}{3}$) of these linear regressions.

General applicability

We interpreted the general applicability of the models as the application range across tree species. As opposed to the accuracy of local predictions and the realism of environmental responses, this quantification was independent of the actual simulations and solely based upon the tree species represented in the models. We computed the share of European forests covered by dominant tree species each model is currently parameterized for. Data on tree species group coverage across Europe were derived from Brus et al. (2011). In case a model covered only subsets of a tree species group (e.g. only *Larix decidua* and not *Larix kaempferi* for genus *Larix*), we assumed the forest area of that species group to be covered fully by the model. We only expect a minor overestimation of the area covered by a model because the tree species groups with many species are the ones that are less dominant in Europe. In this way, we derived a rough approximation of the share of European forests where a given model could be applied without considering the actual predictive skill that the model would have in these forests.

Standardization and aggregation

The results for the accuracy of local predictions, the realism of environmental responses and the general applicability were projected back to a range from 0.1 to 1, which can be interpreted as relative differences across models. We would like to stress that the designation of 0.1 to a model does not indicate a failure or lack of performance but rather that the model had the lowest metric value (relative performance) across the models that were investigated here. We selected 0.1 as the lower boundary simply to avoid misinterpretation that may be intuitively associated with the number zero.

Results

Accuracy of local predictions

There was no model that was able to predict all variables at all sites with high accuracy and only few models showed a high accuracy of local predictions for all variables at one site (SALEM at Bily-Kriz, 3PG at Solling-spruce and 3D-CMCC-FEM BGC at Solling-beech). At the same time, every model predicted at least one variable at one site with an adequate accuracy of local predictions except for 3PGN-BW which showed consistently lower predictive skill than the average of observations. (Fig. 1)

Partitioning the accuracy differences between models into the three *MSD* components showed that the offset between model prediction and observed data had varying origins (Fig. 1). Random errors (*LC*) made up the largest share of the overall error except for *BA* and *AET*. Systematic errors (*SB*) of the structure variables may have been a result of offsets in model initialization from the reference data (see Figs. S4-S9 in the supplementary material). Flux variables were also prone to SB due to systematic over- or underestimation. Persistent underestimation of *GPP* was evident in GOTILWA+ and FORMIND as well as for a range of models at Hyytiälä, while 3PG persistently overestimated *GPP* and Landscape-DNDC overestimated *GPP* at Bily Kriz. Most models underestimated *AET* in Le Bray, while overestimation was evident at Bily Kriz (see Figs. S10-S17 in the supplementary material). Predicted-observed offsets from linear patterns in the residuals (*NU*) were generally low except for *BA* and *DBHinc* simulated by FORMIND, *DBHinc* simulated by ForClim v.3.3 as well as *Reco* and *AET* for 3PGN-BW.

Forest structure variables displayed a higher overall accuracy of local predictions than the carbon and water variables. On average, simulated *BA* showed the highest accuracy of local predictions. This is partly related to the temporal autocorrelation of the variable. Annual carbon variables had the lowest accuracy of local predictions, while *NEE* had the lowest accuracy of the annual carbon variables. No model had a better predictive skill at any site than the observed mean *NEE*. None of the sites' observed data could be predicted with a high accuracy of local predictions for all carbon and water variables simultaneously by any given model.

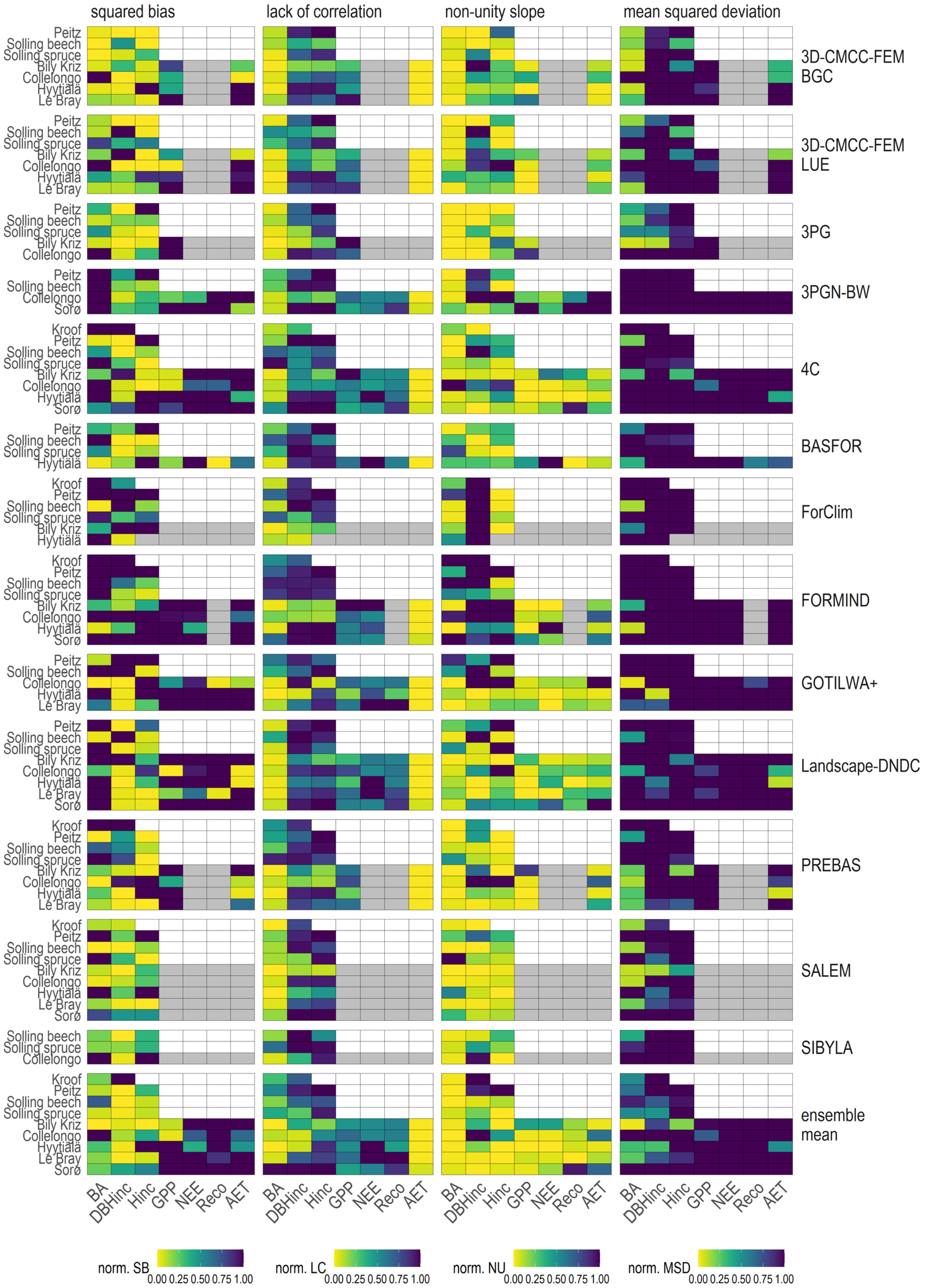
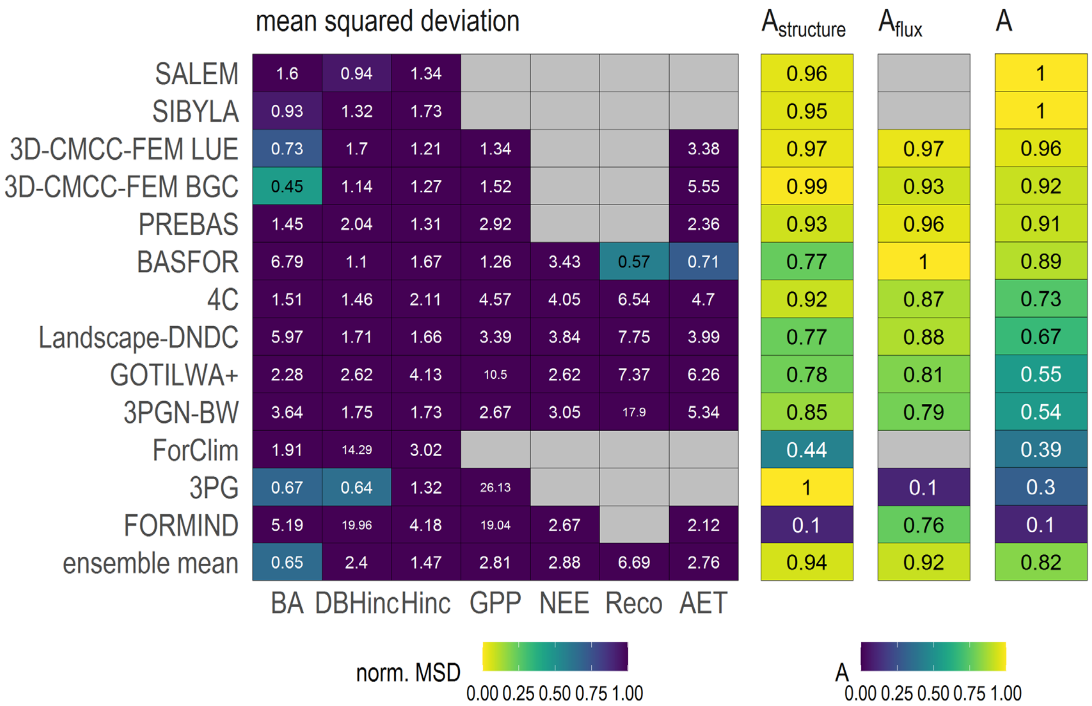

squared bias
lack of correlation
non-unity slope
mean squared deviation
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Le Bray
3D-CMCC-FEM BGC
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Le Bray
3D-CMCC-FEM LUE
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
3PG
Peitz
Solling beech
Collelongo
Sorø
3PGN-BW
Kroof
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Sorø
4C
Peitz
Solling beech
Solling spruce
Hyytiälä
BASFOR
Kroof
Peitz
Solling beech
Solling spruce
Bily Kriz
Hyytiälä
ForClim
Kroof
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Sorø
FORMIND
Peitz
Solling beech
Collelongo
Hyytiälä
Le Bray
GOTILWA+
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Le Bray
Sorø
Landscape-DNDC
Kroof
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Le Bray
PREBAS
Kroof
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Le Bray
Sorø
SALEM
Solling beech
Solling spruce
Collelongo
SIBYLA
Kroof
Peitz
Solling beech
Solling spruce
Bily Kriz
Collelongo
Hyytiälä
Le Bray
Sorø
ensemble mean
BA
DBHinc
Hinc
GPP
NEE
Reco
AET
norm. SB
norm. LC
norm. NU
norm. MSD
0.00
0.25
0.50
0.75
1.00

Fig. 1: Metrics for the accuracy of local predictions for all site-model-variable combinations. On the y-axis are the sites, the x-axis shows variables, vertical panels are different models and horizontal panels show the different metrics. Colors visualize the normalized metric values, where yellow indicates high agreement and blue indicates low agreement of observed and predicted data. Cells in the column for mean squared deviation (right) in dark blue (norm. MSD ≥ 1) indicate cases where the observed average has a higher predictive skill than the model predictions. White cells indicate cases with no evaluation data available whereas grey cells indicate cases that are not provided by the model. The model coverage of sites and variables depends on the model application range. norm. SB: normalized squared bias; norm. LC: normalized lack of correlation; norm. NU: normalized non-unity slope; norm. MSD: normalized mean squared deviation.

The models varied regarding the overall accuracy of local prediction score (*A*, Fig. 2). Only few models had a consistently better predictive skill for single variables than the observed mean (*norm. MSD* < 1): SALEM for *DBHinc*, 3D-CMCC-FEM BGC, 3D-CMCC-FEM LUE and SIBYLA for *BA*, 3PG for *BA* and *DBHinc* and BASFOR for *Reco* and *AET*. Although 3PG had a high predictive skill for structure variables, the predictions for *GPP* had the lowest predictive skill of any model. While some models performed consistently well for one or two variables over multiple sites, other models performed worse than the observed mean for all variable-site combinations. The ensemble mean ranked sixth for accuracy of local predictions of forest structure variables and fourth for carbon and water fluxes. Overall, the ensemble mean had a higher accuracy of local predictions than eight of the individual models.



	mean squared deviation							$A_{structure}$	A_{flux}	A
	BA	DBHinc	Hinc	GPP	NEE	Reco	AET			
SALEM	1.6	0.94	1.34					0.96		1
SIBYLA	0.93	1.32	1.73					0.95		1
3D-CMCC-FEM LUE	0.73	1.7	1.21	1.34			3.38	0.97	0.97	0.96
3D-CMCC-FEM BGC	0.45	1.14	1.27	1.52			5.55	0.99	0.93	0.92
PREBAS	1.45	2.04	1.31	2.92			2.36	0.93	0.96	0.91
BASFOR	6.79	1.1	1.67	1.26	3.43	0.57	0.71	0.77	1	0.89
4C	1.51	1.46	2.11	4.57	4.05	6.54	4.7	0.92	0.87	0.73
Landscape-DNDC	5.97	1.71	1.66	3.39	3.84	7.75	3.99	0.77	0.88	0.67
GOTILWA+	2.28	2.62	4.13	10.5	2.62	7.37	6.26	0.78	0.81	0.55
3PGN-BW	3.64	1.75	1.73	2.67	3.05	17.9	5.34	0.85	0.79	0.54
ForClim	1.91	14.29	3.02					0.44		0.39
3PG	0.67	0.64	1.32	26.13				1	0.1	0.3
FORMIND	5.19	19.96	4.18	19.04	2.67		2.12	0.1	0.76	0.1
ensemble mean	0.65	2.4	1.47	2.81	2.88	6.69	2.76	0.94	0.92	0.82

Fig. 2: Aggregated metrics for accuracy of local predictions for all model-variable combinations assessed (aggregated across sites). Numbers indicate the metric value and colors visualize the normalized metric values, where yellow indicates high agreement and blue indicates low agreement of observed and predicted data.

Realism of environmental responses

Observed relationships of daily *GPP* to *temp*, *rad* and *vpd* followed plausible patterns for all models while the distinct patterns differed from site to site (Fig. 3). Increasing *temp* and increasing *rad* were related to increasing daily *GPP*, except for *temp* relationship at higher *temp* values in Bily Kriz, while an increase in *vpd* was related to decreasing daily *GPP*. Most models were able to reproduce these observed patterns. Distinct site-specific patterns however were not predicted well at all sites by all models. Strong non-linear patterns were observed for the *temp* relationship in GOTILWA+ at Collelongo and for the *vpd* relationship of 4C at Sorø, which may be artifacts of the model fitting procedure or model responsiveness to other drivers such as water availability, which was not analyzed here due to the lack of observed data at the sites. For *vpd*, models overestimated daily *GPP* at high *vpd*. High daily *GPP* at high levels of *vpd* for 4C at Bily-Kriz and Sorø and many models at Le Bray and Hyytiälä indicated unrealistic productivity responses.

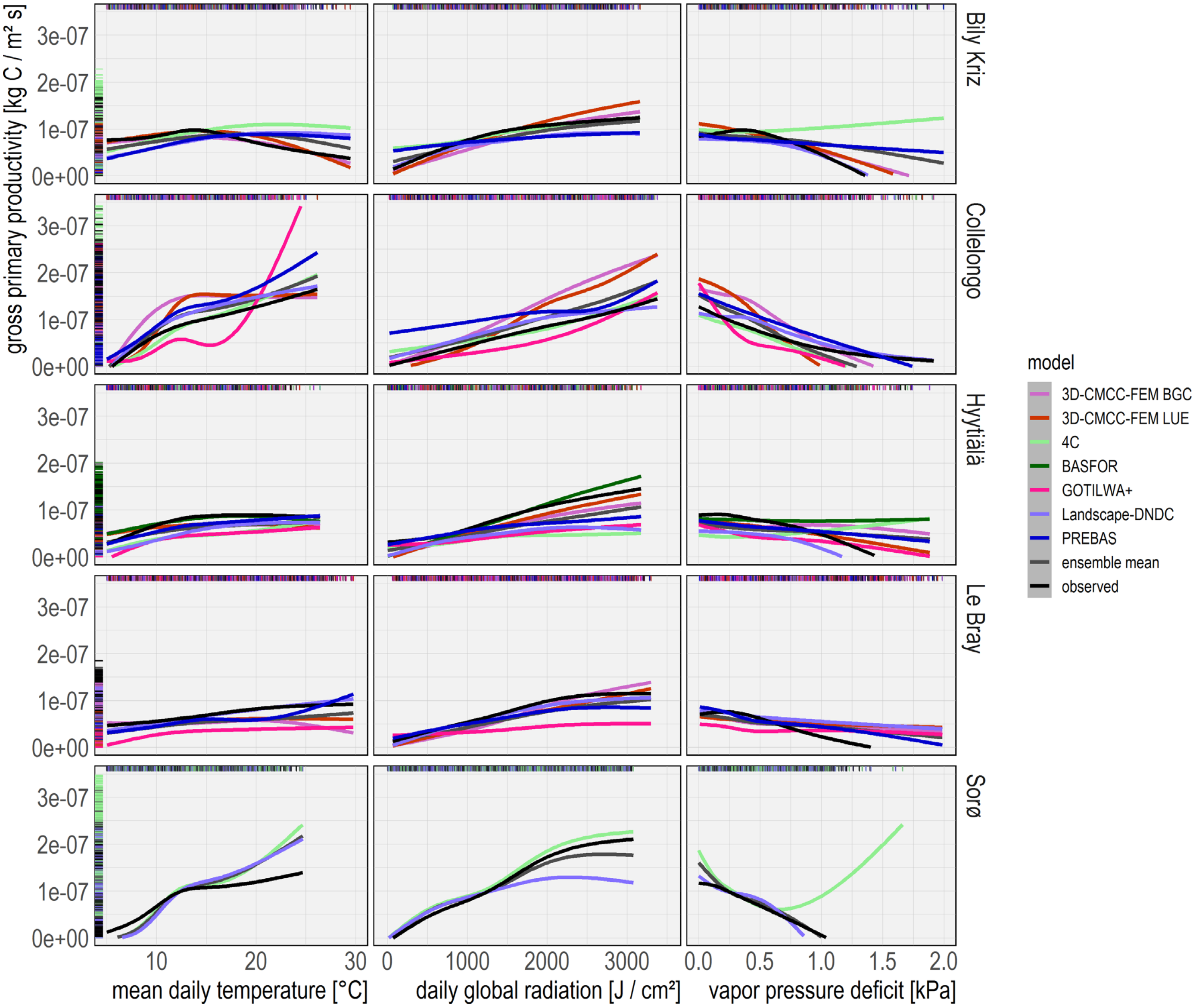


Fig. 3: Relationship between climate variables and simulated and observed gross primary productivity (GPP). Quantile general additive models are displayed (as lines) by fixing two of the three independent variables to their arithmetic mean value. Small indicators along the axes display individual simulated and observed daily GPP data and observed data on temp, rad and vpd.

The slopes of the linear regressions of the daily *GPP* residuals (sim. *GPP* - obs. *GPP*) to environmental variables indicated varying agreement of observed and simulated environmental responses across models and sites (Tab. 3; Fig. S2 in the supplementary material). The *temp* and *rad* response had the lowest average absolute slope at Le Bray and Sorø had the lowest average absolute slope for *vpd* (see Tab. S2 in the supplementary material).

On average, the ensemble mean showed the most realistic environmental responses while Landscape-DNDC and 3D-CMCC-FEM BGC also show highly realistic responses of daily *GPP* to different environmental drivers. Yet, there is no individual model that shows the most realistic responses of *GPP* to all three environmental variables at all sites. Some models feature intermediate realism of environmental responses to all environmental variables, e.g. 3D-CMCC-FEM LUE. The most realistic response to *rad* was obtained by the ensemble mean. Landscape-DNDC had the most realistic *GPP* response to *vpd*, while GOTILWA+ had the most realistic *GPP* response to *temp*. At the same time GOTILWA+ had the least realistic *GPP* response to *rad*, 4C had the least realistic *GPP* response to *temp* and BASFOR had the least realistic *GPP* response to *vpd*.

Tab. 3: Realism of environmental responses per model and environmental variable derived from multiple linear regression slopes of residuals from simulated to observed daily GPP. The overall realism of the environmental response score is the average of the variable-specific realism of environmental responses re-projected to the range 0.1 to 1. Note that for the models not listed here realism of environmental responses was not derived because of missing representation of daily GPP.

	Mean absolute slope (re-projected mean absolute slope)			Realism of environmental responses
model	temp	rad	vpd	
ensemble mean	$1.887 * 10^{-9}$ (0.601)	$0.913 * 10^{-11}$ (0.000)	$4.488 * 10^{-8}$ (0.511)	1.00
Landscape-DNDC	$2.121 * 10^{-9}$ (0.716)	$1.587 * 10^{-11}$ (0.677)	$1.686 * 10^{-8}$ (0.000)	0.70
3D-CMCC-FEM BGC	$1.376 * 10^{-9}$ (0.352)	$1.396 * 10^{-11}$ (0.485)	$3.847 * 10^{-8}$ (0.612)	0.63
GOTILWA+	$0.654 * 10^{-9}$ (0.000)	$1.909 * 10^{-11}$ (1.000)	$3.856 * 10^{-8}$ (0.615)	0.45
PREBAS	$1.602 * 10^{-9}$ (0.462)	$1.908 * 10^{-11}$ (0.998)	$2.631 * 10^{-8}$ (0.268)	0.33
BASFOR	$1.351 * 10^{-9}$ (0.340)	$1.319 * 10^{-11}$ (0.408)	$5.215 * 10^{-8}$ (1.000)	0.31
3D-CMCC-FEM LUE	$1.865 * 10^{-9}$ (0.590)	$1.412 * 10^{-11}$ (0.501)	$4.412 * 10^{-8}$ (0.772)	0.18
4C	$2.705 * 10^{-9}$ (1.000)	$1.198 * 10^{-11}$ (0.286)	$3.995 * 10^{-8}$ (0.654)	0.10

General applicability

The most common tree species and species groups in Europe are *Pinus sylvestris*, *Picea* spp., *Fagus sylvatica* and *Quercus robur* and *Quercus petraea*, which dominate around 75 % of Europe's forests (Brus et al. 2011). Almost all models covered these species with species-specific parameterizations. Only PREBAS and BASFOR were missing *Quercus robur* and *Quercus petraea*, whereas GOTILWA+ was missing *Picea* spp. and *Quercus robur* and *Quercus petraea*. Additionally, most models covered other species that are less common in Europe, hence most models had species parameterized that represented the dominant tree species on 73 - 98 % of Europe's forest cover. The two models covering the least of Europe's forest cover are BASFOR and GOTILWA+ with 66 % and 54 %. The ensemble mean had the highest general applicability because it combined the species covered by all models. (Tab. 4)

Tab. 4: Tree species groups parameterized in complex forest models as an indicator for the general applicability across European tree species groups. Tree species group cover ("cover Europe") is according to Brus et al. (2011). The general applicability per model is the coverage of European forests re-projected to a range of 0.1 to 1.

	Abies spp.	*Alnus* spp.	*Betula* spp.	*Carpinus* spp.	*Castanea* spp.	*Eucalyptus* spp.	*Fagus* spp.	*Fraxinus* spp.	*Larix* spp.	other broadleaves	other conifers	*Pinus* spp.	other *Quercus* spp.	*Picea* spp.	*Pinus pinaster*	*Pinus sylvestris*	*Populus* spp.	*Pseudotsuga menziesii*	*Quercus robur*, *Q. petrarea*	*Robinia* spp.	cover Europe [%]	General applicability
ensemble mean	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	100.0	1.00
3D-CMCC-FEM BGC 3D-CMCC-FEM LUE	X		X		X		X		X	X	X	X	X	X	X	X			X		97.34	0.97
ForClim v.3.3	X	X	X	X	X		X	X	X	X	X	X	X	X		X	X	X	X		96.93	0.95
Landscape-DNDC	X		X			X	X	X	X	X		X	X	X	X	X	X	X	X		97.29	0.91
3PG	X		X				X	X	X	X		X		X		X		X	X		90.02	0.84
3PGN-BW	X		X				X	X	X	X		X		X		X		X	X		90.02	0.84
SALEM	X						X					X	X	X	X	X		X	X		88.88	0.83
4C	X		X			X	X					X		X		X	X	X	X	X	86.97	0.79
FORMIND			X				X	X						X		X	X	X	X		80.16	0.68
SIBYLA	X						X							X		X			X		78.87	0.67
PREBAS			X			X	X							X	X	X	X			X	73.38	0.57
BASFOR							X							X		X					66.04	0.46
GOTILWA+						X	X	X				X	X		X	X				X	54.11	0.1
cover Europe [%]	3.59	1.05	4.12	0.35	0.97	0.44	10.55	0.45	0.20	3.05	0.28	3.17	4.11	22.73	2.57	32.75	0.15	0.16	9.24	0.06		

Model performance along the three dimensions of the model performance framework

Besides the analysis of model performance, accuracy of local predictions, realism of environmental responses and general applicability in isolation, we also analyzed the relations between the three dimensions. Figure 4 shows that the ensemble mean had the highest overall score across the three dimensions. 3D-CMCC-FEM BGC, Landscape-DNDC and 3D-CMCC-FEM LUE performed best across the three dimensions, followed by PREBAS, BASFOR, 4C, and GOTILWA+. The models covering only two dimensions of model performance ranked as follows: SALEM, SIBYLA, 3PGN-BW, ForClim v.3.3, 3PG and FORMIND.

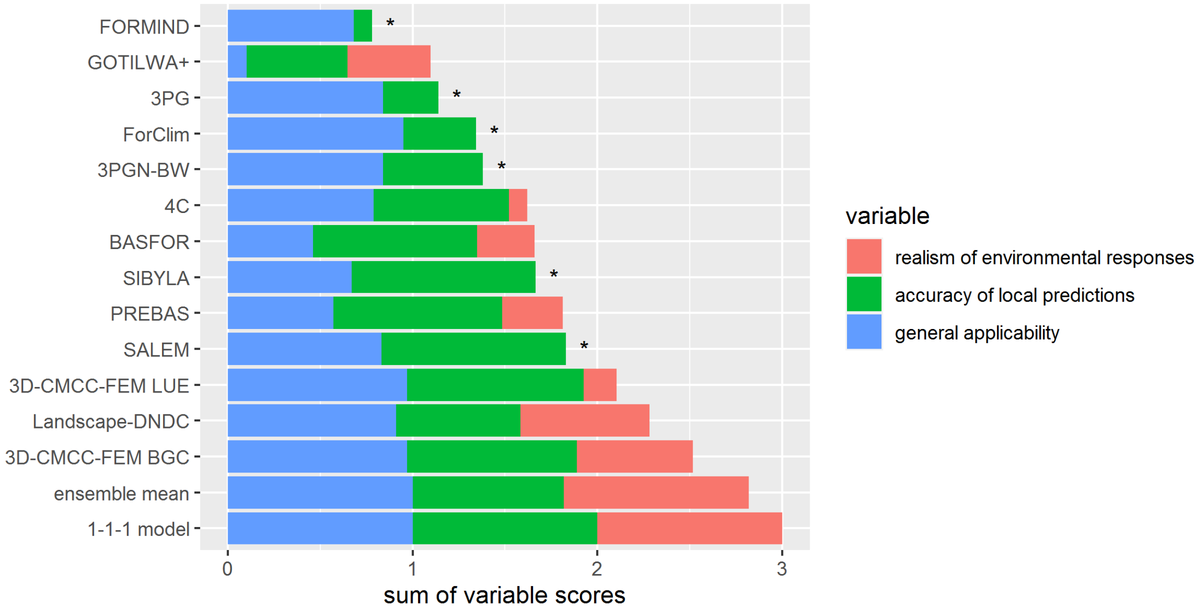


*Fig. 4: Model performance along with accuracy of local predictions, realism of environmental responses and general applicability. The highest theoretical total score along three dimensions is 1-1-1 ("1-1-1 model"). *note that for SALEM, SYBILA, 3PGN-BW, ForClim v.3.3, 3PG and FORMIND realism of environmental responses could not be calculated. For further information regarding the interpretation of individual metrics cf. the methods section.*

Discussion

This study evaluates a large number of complex forest models in an unprecedented model comparison study against a large number of observations: 72 (carbon and water variables) to 128 (forest structure variables) site-years with multiple data sources covering forest structure, carbon and water variables. We developed a model performance framework based on Levin's (1966) concept to evaluate accuracy, realism and general applicability of the participating models against this data. Overall, we find that no individual model outperforms the others across all three dimensions, and that the model ensemble performs mostly well.

Model performance

Accuracy of local predictions

3PG and 3D-CMCC-FEM BGC simulate the structure variables most accurately, while BASFOR and 3D-CMCC-FEM LUE do so for the carbon and water variables. The main difference between 3D-CMCC-FEM BGC and 3D-CMCC-FEM LUE is the representation of photosynthesis (see Tab. 1), with the BGC version featuring a more process-based approach. The BGC version performs better for the structure variables than the LUE version, while the LUE version is more accurate than the BGC version regarding carbon flux variables at the annual scale. This unexpected trade-off cannot be explained in a straight-forward manner by the differences in the model versions, but indicates that more empirical photosynthesis models (LUE version) do not necessarily produce less accurate predictions of annual flux variables than more process-based approaches (BGC version). 3PG is rather simple compared to the other models applied here (Tab. 1), but it still produces accurate predictions of *DBHinc* for the subset of sites in this study that are truly monospecific and even-aged*.* Apparently, less detailed but more robust model formulations are an advantage when simulating these types of forests. Likewise, the other models that focus on forest dynamics alone rather than also simulating biogeochemical fluxes, such as SALEM and SIBYLA, also show a high accuracy of local predictions for structure variables. ForClim v.3.3 and FORMIND show a lower accuracy of local predictions for structure variables mainly because the predictions of *DBHinc* have a large offset to observations. These offsets result from the simulated thinning regime and, in the case of ForClim v.3.3, a bias in the allocation (which has been addressed in v4.01, Huber et al. 2020). Low accuracy of *BA* among all models may be explained by simulated mortality reducing stand density below the observed stem numbers (see Fig. S9 in the supplementary material). BASFOR, which is also among the less complex models of our ensemble, produces accurate predictions of carbon and water variables while it predicts the structure variables with low accuracy. Such systematic errors regarding structure variables may also result from specifics in model initialization (see Figs. S4-S9 in the supplementary material), e.g. BASFOR initialized trees with a planting procedure while most models were initialized with observed data of adult stands. In models that operate at the forest stand-scale rather than the tree level, systematic errors may also arise from the underestimation of *BA* if it is calculated internally from a multimodal *DBH* distribution and stem number. For example, Landscape-DNDC and 3PGN-BW initialized mean *DBH* assuming a mean weighted by basal area and not an arithmetic mean, leading to systematically higher *BA*, *DBH* and *H* (but not growth) at sites with a heterogenous diameter distribution as is the case in particular in Sorø. Finally, the systematic over- as well as underestimation of flux variables shown by most models at least for some sites may be an effect of an insensitivity for specific environmental conditions defined by either model structure or the generic parameter sets used in this study.

Generally, the models predicted structure variables more accurately than annual carbon and water variables, except for BASFOR and FORMIND. Earlier findings by Kramer et al. (2002) and Morales et al. (2005) suggested that forest models have an adequate accuracy regarding daily carbon and water fluxes. Yet, on the multi-annual time scale, Horemans et al. (2017) found larger uncertainties for *NEE* than on the daily time scale. Our findings using a much larger ensemble of models confirm these earlier findings. Carry-over effects from preceding years, which are usually not well represented in models, may be a reason for the inaccurate year-to-year variation of carbon fluxes in the models (Aubinet et al. 2018).

Moreover, besides the reasons for individual model-data mismatches discussed above, the quality of the observed data may affect all models collectively. Systematic and unsystematic observation errors affect the reference data the models are compared to, e.g. uncertainty from the method used to partition *NEE* into *GPP* and *Reco* (Oikawa et al. 2017). Checking the agreement of estimates from these different methods, we found that *GPP* estimated with the DT partitioning method (Lasslop et al. 2010) is highly correlated with *GPP* estimated with the nighttime method (NT, Reichstein et al. 2005) in the evaluation data with no apparent bias (see Fig. S3 in the supplementary material). Consequently, using DT- or NT-based *GPP* estimates led to only minor changes in the results. Moreover, abiotic or biotic disturbances that affect the reference data but are not represented in model simulations may affect model accuracy (Finzi et al. 2020, Trugman et al. 2021). Furthermore, the understory contribution to the carbon balance was not assessed in any of the models but contributes to the measured carbon balance (Dirnböck et al. 2020).

Additionally, uncertainties in model forcing data may contribute to model-data mismatches. For example, the climate data used to drive the simulations was sometimes observed at or close to the forest stand, but in some cases only inferred from the nearest climate station (Reyer et al. 2020a), which may introduce additional uncertainties, e.g. due to orographic effects. Likewise, even though the stands are managed using standard silvicultural treatments (Reyer et al. 2020a), specific, local forest management actions may not be perfectly covered by the models' approximation of the management.

Overall, we find that simpler models, like SALEM, SIBYLA, 3PG, BASFOR and PREBAS did not necessarily perform worse than more complex models like 3D-CMCC-FEM BGC, 3D-CMCC-FEM LUE, 4C, Landscape-DNDC or GOTILWA+. The ensemble mean has an intermediate overall accuracy. Hence, in most cases there are more accurate individual models available for each site-variable combination. Moreover, the range of annual model predictions did not always overlap with observations. Hence, assessing the range of the model ensemble and assuming that the "true" value lies within that range is not always advisable. This was most pronounced for *Hinc* at Hyytiälä, Le-Bray, Solling-beech, Solling-spruce and Sorø, *Reco* at Collelongo and Sorø, *NEE* at Collelongo, Bily-Kriz and Sorø as well as *DBHinc*, *GPP* and *AET* at Le Bray. Hence, in some cases all models overestimate or underestimate the observed data, which points either to general issues in model structure and/or parameterization across all models, or it may relate to issues with the reference data outlined above.

Realism of environmental responses

Earlier findings by Kramer et al. (2002) showing realistically simulated relationships of daily *GPP* to daily mean temperature and global radiation can be confirmed by our large ensemble. In addition, we find that models exhibit also realistic responses of *GPP* to vapor pressure deficit (*vpd*). Properly capturing *GPP* responses to *vpd* has proven to be fundamental to reproduce annual productivity patterns (Medlyn et al., 2011), especially in stands where the most limiting environmental driver for *GPP* shifts from water availability to *vpd* along the year (e.g. Nadal-Sala et al., 2021), and given that *vpd*-driven limitation of productivity is expected to increase under global warming (e.g. Novick et al., 2016). In this regard, our lumped GAM analysis is not able to fully determine the exact driver that is limiting *GPP* at a given moment, and therefore interactive effects of constraining environmental drivers cannot be fully discarded. Hence, the impact of *vpd* on *GPP* for each individual model remains unassessed, with the realism of this key response potentially being masked by its positive correlation with temperature and radiation.

While 3D-CMCC-FEM BGC shows relatively realistic daily *GPP* response, the closely related model 3D-CMCC-FEM LUE has the second least realistic *GPP* response. The single difference between these two models is the description of photosynthesis that is more process-based for 3D-CMCC-FEM BGC which used the Farquhar, von Caemmerer and Berry biochemical photosynthesis model (Farquhar et al. 1980) and the 3D-CMCC-FEM LUE which uses the Monteith empirical approach (Monteith et al. 1977). While the BGC version shows more realistic daily environmental responses of *GPP* the LUE version is more accurate at the annual scale. Since the BGC version was constructed to provide daily estimates of productivity while the LUE version was originally constructed to provide estimates at the monthly time scale, and compensating for possible over and under estimations, this performance relation can be expected. Biases originating from missing site-specific calibration and, given the higher number of parameters in biochemical photosynthesis models, increased uncertainty in the daily outputs of the BGC version could explain the worse performance at the annual scale. The issue related to the temporal scale in modeling *GPP* has already been discussed by Collalti et al. (2016) and Lasch-Born et al. (2020).

Overall, the individual models complemented each other with regard to the realism of environmental responses of productivity. On average, the ensemble mean produced more realistic daily *GPP* responses to environmental variables than any of the individual models. This is due to overestimating and underestimating individual models that cancel out when aggregated into an ensemble mean. Nevertheless, the ensemble mean's performance relative to individual models strongly depends on whether the underlying models are balanced (over- as well as underestimation) and represent different model structures.

General applicability

Following our rather simple definition of the general applicability of models, we find that most of the models are able to simulate a relatively large share of European forests. However, having a tree species parameterized does not necessarily mean that the models can really cover all potential mixtures in which that species might grow. Still, it is encouraging to see that the models generally cover the main species that are of commercial and ecological relevance in Europe, and hence from this point of view most models are suitable to be applied in climate impact studies covering different European forests. However, the focus of forest policies on adapting forests by generating more complex and species rich forests will challenge the general applicability of the models. Finally, the ensemble covers almost all European forest tree species because the individual models complement each other especially for the less common tree species.

Trade-offs between the three dimensions of the model performance framework

Even though our framework of model performance does not theoretically prevent models from scoring high in all three dimensions, we did not expect that any model would do so, but that trade-offs between accuracy of local predictions, realism of environmental responses and general applicability were present. While our results confirm that there is no “silver bullet”, we could not find explicit trade-offs such as a systematic negative relation between general applicability and accuracy of local predictions either. Models that have a high general applicability score such as 3D-CMCC-FEM BGC also perform well in terms of accuracy of local predictions and realism of environmental responses. In general, the scores of the three dimensions of model performance seem to be more or less balanced for most models although at different overall levels. One of the exceptions is the model GOTILWA+ which has a relatively low score for accuracy of local predictions but a comparably high score for realism of environmental responses.

Such results may originate from parameter uncertainties in the initial model setup, as physiological and allometric parameters for a given species have not been calibrated, though they have been observed to be highly site-dependent (e.g. allometric and photosynthetic parameters) and varying also with forest developmental stages (Collalti et al. 2019). Also, the lack of trade-offs between accuracy of local predictions, realism of environmental responses and general applicability may be an artifact of the way we derived the realism of environmental responses. The potential trade-off in the framework provided by Levins (1966), and further elaborated by Weisberg (2006), may not be apparent in the suggested framework here, because we did not strictly follow the definitions of accuracy, realism and generality since they are inherently difficult to assess and not meant to be operationalized for actual simulation models. Operationalizing the framework for complex forest models may have distorted the relation between the three dimensions as defined by Levins (1966). Furthermore, although a balance between the three dimensions is advisable, it may not always be necessary. For example, qualitatively correct insights about forest growth and dynamics under global change may be sufficient to guide adaptation planning, e.g. insights about the growth dominance of one species over the other, indicating that realism and generality may be more important for this purpose than accuracy.

Another key aspect that might explain the differences in performance among models is that some models were initially developed for other scopes. Some models have been developed to simulate forest growth and fluxes in the short-term (i.e. the variables of interest here), but others to simulate forest growth and demography over the medium- to long-term (decadal to centennial) and, thus, focusing more on processes such as reproduction and mortality (not analyzed here). For instance, a specific strategy for model development in ForClim is that each model development step should lead to better predictions of long-term (centennial) forest dynamics and/or of potential natural vegetation (simulations over >1000 years) (Didion et al. 2009). Testing for these model capabilities would probably lead to a different model ranking than presented here. Furthermore, some models have been developed with the primary aim to capture multi-decadal dynamics in complex multi-species stands (e.g. SIBYLA, FORMIND, ForClim), but eight of the nine stands used here were rather homogenous single-species stands (see Tab. 2), which may be, in theory, easier to simulate using mechanistic biogeochemistry models.

Limitations of the model performance framework

Most model evaluation studies to date have assessed the accuracy of local predictions (e.g., Irauschek et al. 2021). Yet, in addition to the agreement of predicted and observed variables of primary interest, also realistic secondary patterns, like the responses of productivity to environmental drivers are important, especially when assessing models that are being used for climate impact studies. Likewise, given the rapid expansion of model uses and users, the general applicability is important to help the latter to assess whether the model is likely to be useful for comprehensive impact studies across a large range of tree species. Our model performance framework is a first attempt to operationalize Levins' (1966) ideas within the context of climate impact assessments with complex vegetation models.

We quantified the accuracy of local predictions by deriving the average differences between predicted and observed data for forest variables of primary interest at multiple sites on an annual time scale. The approach is a robust way for assessing the agreement of predicted-observed data for models with different numbers of variable outputs. Models that provide more output variables for assessment in the performance framework are not necessarily less accurate. Nevertheless, those models that assess variables which are generally more difficult to accurately predict will have lower levels of accuracy than those models only assessing variables that are less difficult to predict. Future applications of the framework could explore different weightings of the variables depending on the difficulty in predicting them and the availability of data to test them. Furthermore, we acknowledge that model predictions are also useful if they have less predictive skill than the observed mean because there are many instances where no data are available to derive the mean for a given variable. Here, we used the observed mean as threshold to identify especially well performing models and not to penalize poorly performing models.

Besides an accurate representation of historical data, forest models should be characterized by a realistic response of productivity to environmental drivers under varying climatic conditions. However, to assess model realism more comprehensively all processes represented in the model need to be assessed, rather than only the productivity response (see also Huber et al. 2020). Therefore, even though we test the models with carbon and water variables, further refinements of the model performance framework should include testing other variables for their realism to environmental responses such as structure and mortality variables or autotrophic and soil respiration to test model realism across a broader range of processes. Likewise, model comparisons in which the models have been forced to mimic experimental changes in environmental variables such as shifting of atmospheric CO_2 concentrations in FACE experiments (Zaehle et al. 2014, Walker et al. 2021) or rainfall manipulation experiments (Paschalis et al. 2020) could help us to learn further about the model's realism of environmental responses. Whether the model includes flexible traits (Berzaghi et al. 2019) and whether it is able to mimic natural adaptive processes (Collalti et al. 2020) could be a further element of testing the realism of environmental response.

Moreover, restricting the quantification of realism to periods when the environmental driver analyzed (e.g. temperature, radiation or vapor pressure deficit) is actually the one that is driving the process should be included in the evaluation of the *GPP* response (e.g. Nadal-Sala et al., 2021). Additionally, model parameterization is important. For instance, if a model assumes the same allometric relationship for a single species regardless of environmental conditions, we expect it to be less accurate than other models that account for site differences by using either different allometric coefficients in different stands or incorporating environmental drivers (Cysneiros et al. 2021), or if models, and their parameterizations, account for changes in tree growth and carbon allocation and acclimation in response to environmental stressors as well as during different stages of forest development (Collalti et al. 2019; Merganičová et al. 2019). These considerations also hold for other structural aspects such as leaf distribution or process parametrization, e.g. regarding photosynthesis. Evaluating process rates (e.g. *GPP*) in contrast to model states (e.g. *BA*) requires a higher realism of environmental responses to produce accurate predictions, because model states are dominated more strongly by long-term model assumptions on stand dynamics (such as mortality definitions, carbon allocation, allometric relationships, management regime). Overall, to test realism properly, one should test the response of the models to different forcing conditions, and compare the (qualitative) responses of the models to our general understanding of the processes and observed data describing these responses.

Also, it is noteworthy that even though we interpret the results along three dimensions, the quantification of the accuracy of local predictions and the realism of environmental responses are not fully independent of each other. These two dimensions are both based on the comparison of predicted to observed data, therefore there is no trade-off *sensu stricto* to be expected. Furthermore, the quantification of realism of environmental responses does not consider other non-linear patterns in the residuals of simulated to observed values which may overestimate the agreement of simulated to observed responses of *GPP* to climatic drivers. Thus, in this respect future studies could refine the relationship between the computation of accuracy of local predictions and realism to environmental responses.

Generality, as the robust model applicability across space and time, is challenging to assess since extensive data are needed to apply and evaluate models across large spatial and temporal scales. We did not derive the general applicability across time but focused on the general applicability in space. However, simply being able to simulate tree species or plant functional types does not warrant that models area able simulate for example complex forest mixtures or management systems (Grote et al. 2011, Pretzsch et al. 2015, Bravo et al. 2019). Information on whether the models are able to simulate mixed forests with a complex structure, comprising both managed and natural dynamics, could be used to widen the general applicability metric which is important since the structural complexity of forests may increase in the future as part of forest adaptation to climate change (Huber et al. 2020, Pardos et al. 2021, de Wergifosse et al. 2022).

Finally, because we investigated the model performance based on current model parameterization without further site specific parameter calibration, the resulting uncertainty is originating from both model structure and model parameterization. The model performance is reflecting the current state of the model only. However, model parameterization and calibration have the potential to increase the performance along all three dimensions of the model performance framework. In theory, if a model is general in its structure (i.e., more process-based models), it would need less data to be parameterized to different environments or species, if it is less general (i.e., more empirical models) it would need more data. Hence, the effort that is needed for calibrating a model to specific environments is model specific and different calibration efforts would lead to varying levels of improvement of the three dimensions of model performance. But not all three dimensions are dependent on model structure and parameterization to the same extent. The realism of environmental responses is mostly driven by model structure, accuracy of local predictions is affected by both model structure and parameterization while the general applicability is mostly dependent on the model parametrization effort. In summary, the current model performance can be improved not only by development of the model structure itself but also by model parameter calibration.

Conclusions and implications for model applications

We performed the, to our knowledge, largest forest model comparison with a wide range of multi-source evaluation data in an innovative model performance framework. We found that the accuracy of local predictions in the historical period is not related to the level of complexity of a model, i.e. empirical models do not necessarily provide less accurate predictions than hybrid or process-based models under current climate conditions. Furthermore, accurate predictions of carbon variables at annual scale are more difficult to obtain than accurate predictions of structure variables. The realism of environmental responses in model simulations provides an approximation how well relationships that are crucial to assessing climate impacts are covered. We showed that the model ensemble mean has the most realistic daily *GPP* responses to environmental variables. General applicability, in terms of the coverage of European tree species is high for most models but less common species that may become more important under climate change are only partly covered by models.

We conclude that, if accuracy is the objective, individual models may provide the best results at single specific locations. Which model will provide optimal results depends on the environmental conditions, structural properties, disturbances, etc. of those locations. Moreover, most individual models cover the most relevant European tree species, but to cover all and particularly the less abundant species, multiple models need to be applied. Finally, we highlight the importance to evaluate several model output variables with a wide range of data, because models struggle to achieve high accuracies for several variables at the same time. Because already multiple models exist to study climate impacts on forests we expect that our study will provide a common benchmark to test whether new modelling efforts outperform the models presented here to add value to the existing set of tools.

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