1   # How to predict tree death from inventory data – Lessons

2   # from a systematic assessment of European tree mortality

3   # models

4   **Lisa Hülsmann, Harald Bugmann & Peter Brang**

5   **Hülsmann, L.** (lisa.huelsmann@wsl.ch)[1,2]

6   **Bugmann, H.** (harald.bugmann@env.ethz.ch)[2]

7   **Brang, P.** (peter.brang@wsl.ch)[1]

8   [1] Research Unit Forest Resources and Management, WSL Swiss Federal Institute for Forest,

9   Snow and Landscape Research, Zürcherstrasse 111, 8903 Birmensdorf, Switzerland

10  [2] Forest Ecology, Institute of Terrestrial Ecosystems, ETH Zurich, Universitätstrasse 16, 8092

11  Zurich, Switzerland

12

13  **Corresponding Author**

14  Lisa Hülsmann

15  telephone: +41 44 739 28 62

16  fax: +41 44 739 22 15

17  email: lisa.huelsmann@wsl.ch

## Abstract

The future development of forest ecosystems depends critically on tree mortality. However, the suitability of empirical mortality algorithms for extrapolation in space or time remains untested. We systematically analyzed the performance of 46 inventory-based mortality models available from the literature using nearly 80000 independent records from 54 strict forest reserves in Germany and Switzerland covering 11 species. Mortality rates were predicted with higher accuracy if covariates for tree growth and/or competition at the individual level were included and if models were applied within the same ecological zone. In contrast, classification of dead vs. living trees was only improved by growth variables. Management intensity in the calibration stands as well as the census interval and size of the calibration datasets did not influence model performance. Consequently, future approaches should make use of tree growth and competition at the level of individual trees. Mortality algorithms for applications over a restricted spatial extent and under current climate should be calibrated based on datasets from the same region, even if they are small. To obtain models with wide applicability and enhanced climatic sensitivity, the spatial variability of mortality should be addressed explicitly by considering environmental influences using data of high temporal resolution covering large ecological gradients. Finally, such models need to be validated and documented thoroughly.

## Key-words

Dynamic vegetation models; Empirical mortality models; Forest inventory data; Independent validation; Systematic review

## Introduction

38

39  Tree death within a forest ecosystem initiates a wide range of responses (Franklin et al. 1987;

40  Gendreau-Berthiaume et al. 2016) and is a key factor shaping forest structure in terms of

41  diameter distribution, stand density and species diversity (Friend et al. 2014). Typically, tree

42  mortality is the result of several interacting factors such as competition, drought, pathogens,

43  snow, fire or frost, all of which decrease tree vitality (Waring 1987). Consequently, tree death can

44  hardly be associated with a single cause, which greatly complicates the mechanistic

45  understanding of mortality (Wang et al. 2012). Robust tree mortality algorithms (Manusch et al.

46  2012) are an important component of Dynamic Vegetation Models (DVMs), which have proven

47  to be useful for simulating forest succession, species range dynamics and the provisioning of

48  ecosystem services in response to environmental changes (Bugmann 2014; Snell et al. 2014)

49  from the local (Bugmann 2001) to the global scale (Bonan et al. 2003).

50  Mechanistic tree mortality models typically emphasize a single mortality factor, e.g. drought

51  (Anderegg et al. 2015), and thus are not qualified to predict the multiple and interacting

52  physiological processes of tree mortality beyond the scale of case studies (Adams et al. 2013). In

53  contrast, empirical mortality formulations are not process-oriented but consider the underlying

54  mechanisms implicitly (Woolley et al. 2012). They are expected to have a lower parameter

55  uncertainty and require fewer data because of fewer model parameters. Therefore, they were

56  suggested as a valid and rapid alternative to process-based models (Adams et al. 2013).

57  Empirical mortality models for European tree species have been developed based on inventory

58  and dendrochronological data. Although inventory data feature a lower temporal resolution, with

59  plots being typically re-measured every 5-15 years only, inventory-based models are more

60  frequent and cover more species and larger ecological gradients because more data are available

61  compared to tree-ring records. Here, we focus on mortality models based on inventory data.

62  The available mortality algorithms were developed following contrasting strategies concerning

63  the covariates considered, the types of forest stands used for calibration and the extent and

64  temporal resolution of the calibration data, as reviewed below.

65  First, mortality predictions are typically based on tree size and a measure of competition or

66  growth to consider resource availability and tree vitality (Waring 1987). While nearly all models

67  include a covariate of tree size - most commonly diameter at breast height (*DBH*) - competition

68  and growth are typically used alternatively. It remains open which approach warrants higher

69  model performance.

70  Second, climate, site conditions and development stage are influential in shaping forest dynamics

71  including tree mortality (Aakala et al. 2009). Thus, site-specific tree mortality models or the

72  incorporation of additional covariates have been proposed (e.g. Monserud and Sterba 1999). Yet,

73  the superiority of 'regional models', i.e. mortality functions that are calibrated and applied under

74  similar ecological conditions, has not been verified. Inventory data for the calibration of tree

75  mortality models typically stem from three types of permanent plots: National Forest Inventories

76  (NFI, e.g. Fridman and Ståhl 2001), growth and yield research plots (e.g. Crecente-Campo et al.

77  2010) and networks of strict forest reserves (e.g. Wunder et al. 2008a). In contrast to NFI and

78  growth and yield plots, no management is carried out in strict forest reserves. Since mortality

79  rates in unmanaged forests are expected to be higher and thus tree death events more frequent, the

80  use of such data has been favored for the derivation of mortality algorithms (e.g. Bravo-Oviedo et

81  al. 2006). Yet, it is not known whether model applications should be restricted to the

82  management intensity in the calibration data.

83　　Lastly, the number of records used for the calibration of mortality models differs strongly.

84　　Although the authors usually emphasize the need for large datasets for model development (e.g.

85　　Metcalf et al. 2009), the influence of sample size on model robustness has not been assessed in a

86　　systematic way (but cf. Wunder et al. 2008b). Additionally, inventories are carried out at

87　　different census intervals. However, mortality rates estimated for inhomogeneous populations

88　　decrease with increasing time between censuses since trees at high risk die on a short term, while

89　　trees with a lower mortality probability dominate estimates on the long term (Lewis et al. 2004).

90　　Yet, the impact of different census intervals has not been examined in the context of mortality

91　　modeling of individual trees.

92　　In spite of the many contrasting approaches that have been pursued in model development, their

93　　influence on the predictions and performance of mortality algorithms has not been investigated.

94　　Furthermore, the majority of the mortality models have not been validated with independent data.

95　　However, this is a prerequisite for assessing their transferability to other conditions as well as for

96　　selecting approaches for implementation in DVMs (Hawkes 2000; Keane et al. 2001). Yet, due to

97　　a lack of alternatives, empirical mortality models are increasingly applied in models of forest

98　　dynamics (e.g. Bircher et al. 2015), although often no information on their temporal or spatial

99　　applicability is available.

100　　We thus review mortality models based on European inventory data to assess their transferability

101　　and suitability for incorporation in DVMs. We rigorously validate the mortality models with

102　　extensive inventory data from unmanaged forests in Germany and Switzerland and systematically

103　　analyze model performance to address the following questions: (1) Which predictors warrant

104　　high accuracy of simulated tree mortality? (2) Are 'regional models', i.e. functions that are

105　　calibrated and applied in similar environments, required to account for the variation in mortality?

106     (3) Should model applications be restricted to the management intensity in the calibration data?

107     (4) Does the size of the calibration and validation datasets influence the accuracy of mortality

108     predictions? (5) Are predictions of individual tree mortality models sensitive to the length of

109     census intervals?

# Material and methods

## Study sites and validation data

Inventory data from 54 strict forest reserves in Switzerland and Germany that have been monitored repeatedly for up to 60 years were used to validate the mortality models (Appendix S1, Fig. S1). Trees with a diameter at breast height (*DBH*) of > 4 and > 7 cm for Switzerland and Germany, respectively, have been measured on permanent plots ranging from 0.01 to 1.8 ha in size with census intervals of 4-27 years. We excluded permanent plots with considerable disturbances (wind: Josenwald, fire: Pfynwald; both Switzerland) or that are collapsing because of severe bark beetle infestation (Bruchberg, Germany). Data of 11 tree species or genera, i.e. *Abies alba* Mill., *Alnus glutinosa* Gaertn., *Betula* spp. (*B. pendula* Roth and *B. pubescens* Ehrh.), *Carpinus betulus* L., *Fagus sylvatica* L., *Fraxinus excelsior* L., *Larix decidua* Mill., *Picea abies* (L.) Karst, *Pinus sylvestris* L., *Quercus* spp. (*Q. petraea* Liebl. and *Q. robur* L.) and *Tilia cordata* Mill. were selected (Appendix S1, Table S1). Below, we refer to the species by their Latin genus name. Annual mortality rates were 1.7 % on average but differed between species (cf. Table 3).

A set of three consecutive inventories was used to generate records of trees that were alive in the first and second inventory, and either dead or alive in the third inventory. Since for 44.2 % of the permanent plots more than three inventories were available, individual trees can appear more than once in the dataset, as all possible sets of inventory data were used (29.6 % of the records are such 'repeated measures'; for verification cf. Hülsmann et al. 2016). The derivation of the tree, stand and site characteristics (cf. Table 1) that were used in the mortality models to explain tree status (dead or alive) in the third inventory is described in detail in Appendix S2. Covariates for tree growth were derived for the interval between the first and the second inventory. All other tree and stand characteristics were calculated based on data from the second inventory.

## Mortality models

134    Literature databases and the reference lists of relevant papers were searched for publications that

135    fulfill the following criteria: They (1) consider the mortality of individual trees, i.e. not of

136    seedling populations or stand-level mortality rates, (2) predict mortality of native European tree

137    species, (3) derive models that were calibrated with inventory data and (4) focus on 'regular', i.e.

138    'background' mortality (Keane et al. 2001). Models restricted to 'irregular' mortality, e.g. after

139    wind disturbance (e.g. Schmidt et al. 2010) or at polluted sites (e.g. Juknys et al. 2006) were

140    discarded. From the resulting set of models we used only those that employed logistic regression

141    (Table 2), by far the most common approach. We did not consider models that are based on

142    survival analysis, neural networks or semiparametric approaches since these techniques either

143    require annual inventory data or are based on entirely different statistics, thus making predictions

144    less comparable. In addition, we excluded models requiring covariates that were unavailable from

145    the inventories and could not reasonably be derived from existing data, e.g. tree and stand age,

146    spatially explicit competition indices or information on soil fertility. Although mixed-effects

147    approaches are increasingly applied in tree mortality models to account for the hierarchical

148    structure of the data, only two such models could have been applied to our dataset; the others

149    require covariates that were unavailable (e.g. Boeck et al. 2014, cf. Table 2). Thus, we focused on

150    fixed-effects models.

151    Overall, 13 publications provided suitable mortality models for varying sets of species and

152    species groups, resulting in 46 model formulations that could be applied to one or more species

153    (Appendix S1, Table S3). Where a publication proposed more than one model per species, the

154    models were distinguished using an index (cf. Table 2). From these mortality models, the

155    coefficients and their units were extracted (Appendix S3). Subsequently, the parameterized

156    mortality models were applied to our reserve dataset. To this end, mortality model $j$ calibrated to

157    data of species $k$ was used to predict the mortality probability $p$ of tree $i$ of the same species

158    following

$$p_{i,j,k} = logit^{-1}\big(X_i\beta_{j,k}\big) = \frac{\exp(X_i\beta_{j,k})}{1 + \exp(X_i\beta_{j,k})} = \frac{1}{1 + \exp(-X_i\beta_{j,k})} \qquad \text{eqn 1}$$

159    with $X_i$ denoting the design matrix of the linear predictor and $\beta_{j,k}$ the respective parameter vector.

160    Eqn 1 was modified if (1) models predicted survival rather than mortality and/or (2) the logistic

161    model was formulated differently (cf. Appendix S2). In addition, the mortality probability

162    predicted for $\Delta t_j$ was rescaled to the census interval ($\Delta t$) of the respective permanent plot (cf.

163    Appendix S2).

164    Independent external validation of the mortality models was ensured by applying every model

165    only to those reserves that had not been used for its calibration; i.e. models based on data from

166    Swiss forest reserves were only applied to previously unused reserves (Wunder et al. 2008a;

167    Wunder et al. 2007). Since we solely used measured crown ratios ($CR$, cf. Appendix S2), models

168    including $CR$ were only applied to trees for which this variable had been assessed in the field.

169    Consequently, some models were applied to partial datasets of a species (Table 3).

## Model performance

171    Predicted mortality probabilities were compared with observed tree status by calculating two

172    performance criteria. To quantify prediction accuracy (correct mortality rates), we defined

173    prediction bias ($p_{bias}$) as the absolute difference of the mean predicted mortality probability

174    ('simulated mortality') and the mean mortality rate ('observed mortality') both given in % over

175    $\Delta t = 1$ year (cf. Appendix S2). The Area Under the receiver operating characteristic Curve ($AUC$)

176    quantifies classification accuracy (correct attribution of tree status dead/alive) (Fawcett 2006).

177   AUC values > 0.5 indicate an increasing ability to distinguish dead from living trees that is

178   maximal for AUC = 1 (Hosmer and Lemeshow 2000).

179   $p_{bias}$ and *AUC* were calculated for the entire dataset of each species to assess the overall

180   performance of each of the 58 possible model-species combinations (note that models calibrated

181   for species groups were applied to several species). For both performance criteria, bootstrap

182   confidence intervals (*CI*) were derived. Additionally, both performance criteria were derived at

183   the level of each reserve, thus resulting in 857 'observations' of $p_{bias}$ and *AUC* (note that not all

184   species were present in every reserve). These 'observations' were used to assess the influence of

185   model and dataset characteristics on model performance and to address the research questions (1-

186   5).

187   We hypothesized that the performance of a mortality model in external validation depends on the

188   explanatory variables included in the model (1), i.e. covariates that quantify growth (*DI* = annual

189   diameter increment, *BAI* = annual basal area increment, *relBAI* = annual relative basal area

190   increment) or competition at the individual level (*BAL* = basal area of larger trees, *relBAL* = share

191   of *BAL* of stand basal area) or at the stand level (*BA* = stand basal area, *N* = number of trees, cf.

192   Appendix S1, Table S3). In addition, we tested if model performance is higher when a model is

193   applied inside the same ecological zone (2). To this end, we assigned the models to ecological

194   zones following Kuusela (1994), i.e. Alpine, Central, Eastern, Mediterranean, Northern and Sub-

195   Atlantic, associating the German and Swiss reserves with the Central and Alpine zone,

196   respectively. Furthermore, we expected management intensity (3), i.e. with the categories

197   'managed' and 'unmanaged' to affect model performance. Note that only models calibrated with

198   data from strict forest reserves were considered as 'unmanaged'. To account for influences of

199   dataset size (4), the number of records used to fit the mortality models ($N_{cal}$) and the number of

200 records per species and reserve used for model validation ($N_{val}$) were considered as predictors of

201 model performance. Finally, we investigated the effect of different census intervals (5) using the

202 interval length in the calibration and validation data with the latter calculated as the median of all

203 censuses in each forest reserve.

204 To test these hypotheses, we used linear mixed-effects models to explain model performance

205 ($p_{bias}$ and $AUC$) using the model and data characteristics as fixed effects (cf. Table 4). Since tree

206 species are expected to differ considerably concerning the predictability of tree death, we

207 included an additional fixed effect for 'species' and examined differences using multiple pairwise

208 comparisons. To account for the hierarchical nature of the data and unexplained model

209 differences, we included a random intercept for 'reserve' as well as for 'model'. $AUC$ values

210 were arcsine-transformed and $|p_{bias}|$ values square-root transformed to improve normality of the

211 performance variables (Breiner et al. 2015; Mosteller and Tukey 1977). Since the level of

212 mortality may influence the accuracy of model predictions, we additionally tested observed

213 mortality rate as an explanatory variable in the models. However, the influences of the other

214 covariates on *pbias* or $AUC$ remained the same so that this covariate was dropped, particularly for

215 not mixing explanatory variables and the performance to be modeled, i.e. $p_{bias}$.

216 All computations were performed within R (R Core Team 2015, R Foundation for Statistical

217 Computing, Vienna, Austria). $AUC$ was calculated using the function *auc*() from the package

218 *SDMTools* (R package version 1.1-221, 2014). Since *auc*() prevents values below 0.5, which is

219 not appropriate for $AUC$ calculations for predefined models, the code was modified respectively.

220 Linear mixed-effects models were calculated and evaluated with the packages *lme4* (Bates et al.

221 2015) and *pbkrtest* (Halekoh and Højsgaard 2014). $R^2$ of the models was determined based on the

222 function *sem.model.fits*() from the package *piecewiseSEM*. Multiple pairwise comparisons were

223    calculated using the package *lsmeans* (Lenth 2016). Bootstrap confidence intervals were derived

224    using the function *boot.ci*() from the package *boot*.

## Results

### Model characteristics

The mortality models differed strongly in terms of model formulation, covariates considered and datasets used. Out of the 46 model formulations, 16 predicted the probability of tree death while the remaining simulated survival, and predictions of tree status referred to intervals of 1 to 13 years (Appendix S1, Table S3). Twenty-four mortality models included a covariate for tree growth. Competition was considered at the stand and tree level in six and eighteen models, respectively. Nearly half of the models were derived for the Alpine and ten for the Northern zone. For the Eastern, Central and Mediterranean zones, only few models were available. Twenty-six mortality models were calibrated using data from unmanaged forests while 20 were based on managed stands. The smallest calibration dataset included 216 observations, the largest 34 403 (median = 1922). The calibration datasets included between seven and 2382 dead trees (median = 143). Census intervals in the calibration data ranged between 5 and 13 years.

### Mortality patterns

Observed mortality as a function of *DBH* was reverse J-shaped for nearly all species, i.e. mortality rates continuously decreased with increasing tree size (Fig. 1). In contrast, mortality risk of *Picea* was almost constant over the entire *DBH* range. Mortality rates of *Betula* revealed a maximum at a *DBH* of ca. 15 cm. For none of the species, the mortality pattern was clearly U-shaped. Only *Quercus* exhibited a slight increase of mortality for the largest trees. In contrast to the dominating J-shaped pattern, the magnitude of mortality differed considerably. Annual mortality rates for *Abies*, *Larix* and *Tilia* were rather low, while mortality was more pronounced for *Betula* and *Quercus*. Specifically, species differed in the mortality risk of small and/or large trees and in the *DBH* above which mortality rates remained constantly low.

248    Consistent with observed mortality patterns, predictions of almost all mortality models resulted in

249    reverse J-shaped mortality rates as a function of *DBH* (Fig. 1). However, the predictions were

250    characterized by strong variability in the magnitude of mortality. While for most species the

251    models equally over- and underestimated mortality, simulated mortality rates of *Betula*, *Pinus*

252    and *Quercus* were predominantly too low. The models that deviated from the J-shaped pattern

253    either predicted a continuous increase of mortality with increasing *DBH* (*Picea*, Wunder et al.

254    2008a 1, cf. Appendix S1, Fig. S12), hump-shaped mortality (*Pinus*, Alenius et al. 2003 1), U-

255    shaped mortality (e.g. *Betula*, Fridman and Ståhl 2001) or no trend of mortality with *DBH* (e.g.

256    *Picea*, Fridman and Ståhl 2001). In most of these cases, the models did not fit well the observed

257    mortality pattern.


258    **Prediction accuracy**

259    On average, prediction accuracy was high, as indicated by the mean $p_{bias}$ of 0.03 % at the reserve

260    level. However, $p_{bias}$ at the level of the full dataset of each species (Table 3; standard deviation =

261    1.3 %) and of single reserves (Appendix S1, Fig. S2; standard deviation = 1.7 %) varied

262    considerably. While some models overestimated the observed annual mortality rate by > 3 %

263    (e.g. *Fraxinus*, Holzwarth et al. 2013), others underestimated it by > 3 % (e.g. *Betula*, Eid and

264    Tuhus 2001). At the level of single reserves, $p_{bias}$ varied even more, i.e. between -5.5 and 8.6 %.

265    Nevertheless, $p_{bias}$ between -1.6 and 2.1 % was achieved in 80 % of the applications.


266    Species identity significantly influenced the accuracy of mortality predictions as revealed by the

267    linear mixed-effect model for the square-root of $|p_{bias}|$ (Table 4). While $|p_{bias}|$ was rather low for

268    *Alnus*, *Fagus* and *Larix*, models for *Betula* simulated mortality less accurately (Appendix S1, Fig.

269    S3). Nevertheless, the results of multiple pairwise comparison between the species showed that

270    $|p_{bias}|$ is quite similar for all species except for *Betula* (Appendix S1, Fig. S4). As indicated by

271    mostly negative $p_{bias}$ values (Appendix S1, Fig. S2), low prediction accuracy of *Betula* but also of

272    *Pinus* and *Quercus* was caused by a pronounced underestimation of mortality.

273    $|p_{bias}|$ was reduced significantly when covariates for growth and/or competition at the tree level

274    were used to predict tree mortality (Table 4 and Appendix S1, Fig. S5). Moreover, mortality rates

275    were predicted more accurately when the models were applied within the same ecological zone

276    and using validation data with long census intervals (Appendix S1, Fig. S6+7). However, the

277    improvement of prediction accuracy was largest for covariates of growth (cf. Appendix S1, Fig.

278    S3). Stand-level competition, management intensity, the census interval in the calibration data as

279    well as $N_{cal}$ and $N_{val}$ did not significantly affect $|p_{bias}|$.

## Classification accuracy

281    Following the criteria of Hosmer and Lemeshow (2000), *AUC* values obtained at the level of full

282    datasets (Table 3) indicated a range of classification accuracy between no discriminative power,

283    e.g. for *Betula* (Fridman and Ståhl 2001), *Picea* (Wunder et al. in prep.) and *Pinus* (Alenius et al.

284    2003 1), and excellent classification, e.g. for *Larix* (Monserud and Sterba 1999) and *Quercus*

285    (Wunder et al. 2008a 2). Assuming $AUC > 0.7$ as acceptable, 43 of the 58 model applications

286    were successful in killing the right trees. At the reserve level, the classification accuracy was still

287    acceptable for 63.4 % of the reserves ($AUC > 0.7$).

288    Classification accuracy was not significantly influenced by model and data characteristics except

289    for 'species', 'growth' and $N_{val}$ when analyzing *AUC* at the reserve level (Table 4 and Appendix

290    S1, Fig. S8). Living and dead trees were discriminated best for *Larix* and still well for *Alnus* and

291    *Tilia*, while the models for *Abies* and *Picea* performed clearly worse (Appendix S1, Fig. S9).

292    *AUC* differed more clearly between species than $|p_{bias}|$, but the multiple pairwise comparison

293    revealed no clearly distinguishable groups. Models that included covariates of tree growth had

294   significantly higher classification accuracy (Appendix S1, Fig. S10). Additionally, *AUC*

295   increased with the size of the validation dataset ($N_{val}$, Appendix S1, Fig. S11). In contrast to

296   prediction accuracy, classification accuracy was not significantly affected by covariates for

297   competition at the tree level, the application within the same ecological zone, nor by the census

298   interval in the validation data.

# Discussion

## Documentation of mortality models

We evaluated 46 individual-tree mortality models that had been developed based on European inventory data. We found large differences concerning calibration data, methodology and the covariates considered. Bearing in mind that these characteristics influence the predicted mortality and thus the suitability of a model for being applied in a new context, a comprehensive documentation of the data and its processing, the model development and the covariate selection is pivotal, but was not consistently provided.

For example, this applies to the specification of the *DBH* range covered in the calibration data, which may severely limit the suitable application domain. Using a model in extrapolation mode (Adams et al. 2013) increases the risk of erroneous mortality predictions, particularly for small trees (Bircher et al. 2015). Documentation was also poor for disturbance-related mortality. Some authors explicitly defined the mortality type that they intended to simulate and the criteria applied for this purpose (e.g. exclusion of certain plots or trees, cf. Bravo-Oviedo et al. 2006; Wunder et al. 2007). However, often it was not documented whether a model was aimed at 'regular' or both 'regular' and 'irregular' mortality. More details are also needed concerning the covariates considered and their selection, which is not only an issue of statistical significance but often includes a pre-selection based on expert knowledge.

Although we assume that several mortality models were not published with the primary aim of allowing for their reconstruction, a comprehensive documentation of all steps that are part of model development would be very important. Much progress is still possible in mortality modeling and in the future, forest data that become increasingly available could and should be used for developing more robust models (Wunder et al. 2008a), which would benefit strongly

322    from good documentation and reporting guidelines, as suggested, e.g. for tree allometric

323    equations (Cifuentes Jara et al. 2014).

### Implications of $p_{bias}$ and $AUC$: How good is good enough?

325    Prior to discussing the performance of the mortality algorithms and the implications of particular

326    $p_{bias}$ and $AUC$ values, we wish to emphasize that models that considerably over- or

327    underestimated mortality or had a low discriminative ability when applied to the reserve data

328    should not be considered as generally poor. Rather, our validation approach revealed that these

329    models were less appropriate to predict mortality in unmanaged forests of Central Europe, e.g.

330    because of a considerably different environment in the calibration data and because the authors

331    may not have aimed to build models with high generality. Although the reserve data that we used

332    for validating the mortality algorithms consist of an extensive assemblage of trees and site

333    conditions and the size of the data exceeds the extent of the datasets used for calibrating the

334    models for most tree species (cf. Appendix S1, Tables S1+2), the reserve data, which we consider

335    here as a reference, represent only one realization of possible mortality patterns. This uncertainty

336    should be taken into account when evaluating model performance.

337    When implemented in DVMs, empirically based mortality algorithms that result in a consistent

338    overestimation of mortality rates will cause an accelerated turnover of tree populations or a

339    breakdown of the stand if mortality rates exceed the recruitment potential. In contrast, severely

340    underestimated mortality can cause exceedingly high tree density and basal area. However, it is

341    rather difficult to specify the level of $p_{bias}$ above which seriously flawed stand dynamics are

342    predicted, and the sensitivity of DVMs to $p_{bias}$ has not been systematically assessed to date.

343    Additionally, the consequences of $p_{bias}$ differ depending on the $DBH$ range affected. Over short

344    periods, considerable $p_{bias}$ for large trees affects both $N$ and $BA$, while incorrect mortality rates for

345     trees with *DBH* < 10 cm may dominantly influence *N*. For long-term simulations (> 100 years),

346     the impact of considerable $p_{bias}$ becomes more complex due to feedbacks between the number

347     and size of stems, light availability and the rates of growth and regeneration.

348     Bearing these difficulties in mind, the criterion to select models according to $p_{bias}$ should not be

349     overly strict. Assuming that mortality models with $|p_{bias}|$ < 1.5 % are promising enough to be

350     considered for incorporation in DVMs, the benefit of more than 80 % of the models investigated

351     here should be further evaluated in DVMs. Thus, only a few models need to be discarded from

352     the set of possible mortality formulations. For the selection of new algorithms predicting

353     'background' mortality in DVMs, the systematic presentation of the expected mortality patterns

354     for each algorithm (Appendix S1, Fig. S12) and of $p_{bias}$ resulting from external validation provide

355     valuable assistance.

356     Low *AUC* should be considered as less critical than considerable $p_{bias}$ since model formulations

357     that are poor in classification, i.e. *AUC* < 0.7 (Hosmer and Lemeshow 2000), may still result in

358     correct mortality rates when implemented in DVMs, although they assign mortality to the wrong

359     trees. However, problems may arise when applying a model with poor classification accuracy if

360     low *AUC* values indicate that the pattern of mortality as a function of, e.g. tree size deviates from

361     observations (*Pinus*: Alenius et al. 2003; e.g. *Betula*: Fridman and Ståhl 2001). Incorporated in

362     DVMs, this would result in incorrect predictions of the diameter distribution, with cascading

363     effects on recruitment and growth. Additionally, *AUC* maybe be consistently low for a specific

364     dataset or species if none of the considered covariates has enough explanatory power to

365     discriminate between dead and living trees. In our systematic model assessment, three out of four

366     formulations achieved a classification accuracy that was at least acceptable. Hence, the majority

367     of the algorithms investigated here capture the most relevant covariates for distinguishing living

368    from dead trees. In addition, these covariates revealed sufficient predictive ability for a large

369    fraction of the reserves.

## Species-specific differences in mortality

371    The tree species analyzed here revealed distinct patterns and magnitudes of observed as well as

372    predicted mortality. This justifies the development of species-specific models, which has been

373    suggested to account for contrasting life history strategies, lifespan, competitiveness and varying

374    reactions to abiotic factors (Franklin et al. 1987; Harcombe 1987). We cannot advocate the

375    grouping of species into 'Plant Functional Types' (PFTs) for mortality modeling, unless simple

376    distinctions such as shade tolerance classes have been proven to correctly classify the species-

377    specific mortality behavior.

378    In addition, model performance was characterized by considerable species-specific differences in

379    prediction and classification accuracy. Underestimation of mortality rates for *Betula*, *Pinus* and

380    *Quercus* may be explained by their low shade tolerance (Ellenberg and Leuschner 1996), which

381    could have caused a higher mortality probability in unmanaged stands due to more competition

382    for light. For *Pinus*, however, the validation dataset was rather small compared to the calibration

383    datasets (cf. Appendix S1, Tables S1+2), which may have induced low prediction accuracy

384    because the reserve data may not be representative for *Pinus* mortality. In contrast, simulated

385    mortality rates were fairly accurate for *Alnus* and *Larix*, presumably because most of the models

386    for these species were derived for the Alpine zone and could be applied to Swiss reserve data

387    only, as these species are largely missing in the German data.

388    For *Abies* and *Picea*, considerably lower classification accuracy was achieved, which may be due

389    to the weak or missing trend of mortality over *DBH* for these species, hence reducing the

390    predictive power of *DBH*, i.e. the most common predictor of tree death, and thus of the entire

391    model. In addition, *AUC* may be low because agents causing 'irregular' mortality are relevant,

392    including wind disturbance, snow damage and, in the case of *Picea*, also insect attacks. When

393    being implemented in DVMs, the degree of uncertainty in terms of prediction and classification

394    accuracy associated with a particular species should be taken into account.

395    **Drivers of model performance**

396    We propose that the following model and data characteristics promote high accuracy of mortality

397    algorithms and discuss restrictions regarding our validation approach.

398    First, the advantage of tree-specific covariates, i.e. one-sided competition and tree growth, for

399    accurately predicting mortality was clearly demonstrated by the linear mixed-effects models.

400    Tree growth has often been suggested as a good mortality predictor because it dynamically

401    reflects competition and tree vitality (Dobbertin 2005). Its importance is supported by the high

402    performance of tree-ring based mortality models (Cailleret et al. 2016) and the fact that growth

403    mostly remained in the models during variable selection. Our results suggest that although *BAL*

404    and *relBAL* allow for a similarly good prediction of mortality rates, tree growth has significantly

405    more power to differentiate between living and dead trees, i.e. to achieve high *AUC* values. This

406    is because growth integrates the internal and external factors that influence tree vitality much

407    better than, e.g. *BAL*, which is a measure of a tree's exposure to competition by larger trees on

408    the entire plot but does not consider neighborhood effects. In contrast to covariates at the level of

409    individual trees, covariates that quantify competition at the stand level, i.e. *BA*, did not enhance

410    model accuracy. This clearly shows that competition calculated at the plot level has little

411    explanatory power for the mortality probability of single trees, especially on large plots, whereas

412    it allows for the prediction of population-level mortality rates (Rohner et al. 2012).

413    Although we were able to show the superiority of tree growth and competition at the tree level, it

414    must be kept in mind that the incorporation of mortality algorithms in DVMs includes the

415    prediction of tree death based on simulated covariates. For example, simulated tree growth does

416    not necessarily reflect the same magnitude and interannual variability as measured growth (cf.

417    Rasche et al. 2012). In addition, growth modules in DVMs do typically neither simulate biotic

418    and mechanical damage nor reduce tree growth in response to such factors, which are of great

419    importance for forest dynamics - albeit less than competition and environmental stress (Dobbertin

420    2005). Therefore, growth rates simulated by a DVM are expected to have a lower skill than

421    observed growth to accurately predict mortality using empirical mortality algorithms. In addition,

422    tree-level competition, e.g. *BAL*, strongly relies on an adequate representation of the diameter

423    distribution. Feedbacks between such variables and tree mortality in DVMs require further

424    investigation (Bircher et al. 2015; Larocque et al. 2011; Radtke et al. 2012; Wernsdörfer et al.

425    2008).

426    Second, our results confirm the regional variation of mortality relationships proposed in other

427    studies (e.g. Monserud and Sterba 1999) since the application of models within the same

428    ecological zone resulted in more accurate mortality rates. Consequently, mortality models derived

429    from data with restricted ecological and/or environmental coverage should be considered as case

430    studies with limited transferability. Yet, we were unable to evaluate whether additional

431    environmental covariates may improve model performance (e.g. Hartmann et al. 2007), as only

432    few such covariates had been used in the mortality algorithms, e.g. elevation, growing degree-

433    days, site index or soil moisture (but cf. Hülsmann et al. 2016). In addition, the ecological zones

434    considered here are rather coarse and thus do not allow to identify an efficient geographical

435    stratification for the calibration of mortality models.

436    Third, we tested whether the management intensity of the calibration data influenced model

437    performance, particularly prediction accuracy (Bravo-Oviedo et al. 2006). However, there was no

438    indication that models from managed stands were less able to predict mortality probabilities for

439    the reserve data than those from unmanaged forests. This suggests that mortality patterns in forest

440    reserves are similar to those in managed forests and that the reserves will require more time

441    without management to develop truly natural dynamics. In addition, processes that may act to

442    amplify the mortality of large trees such as stem rot or wind breakage can be found in old-growth

443    forests only (cf. U-shaped mortality; Hülsmann et al. 2016). For the application in DVMs

444    however, a U-shaped form of mortality over tree size may be desirable since it confines tree age

445    more strongly than a reverse J-shaped relationship and thus avoids the high persistence of large

446    trees (Bircher 2015). Nevertheless, the effect of management on mortality may have been

447    attenuated by the large gradient of management intensities in the calibration data that we

448    considered as 'managed'.

449    Fourth, estimates of mortality rates may decrease with increasing census interval if the population

450    is heterogeneous (Sheil and May 1996). However, only the census interval of the validation data

451    affected the prediction accuracy of the mortality models. This is because the variation in

452    mortality rates and correspondingly also the deviation between observed and predicted mortality

453    decreases for longer intervals (Lewis et al. 2004). We conclude that different census intervals are

454    negligible in the calibration of mortality models for individual trees since accounting for species,

455    tree size and growth already captures large parts of the inhomogeneity in mortality risk that can

456    be found at the population level.

457    Finally, mortality is a 'noisy' process, and therefore it is usually thought that signal detection is

458    facilitated by extensive datasets and thus a robust empirical basis (Lutz 2015; Metcalf et al.

459    2009). To our surprise, the size of the calibration dataset did not significantly influence model

460    performance, and even models calibrated using datasets with very few total/dead observations

461    resulted in reliable mortality patterns and acceptable prediction and classification accuracy.

462    Nevertheless, we found higher classification accuracy when models were applied to larger

463    datasets, most likely due to an improved link between the predictors and mortality, i.e., trees at

464    risk may not die in an interval of five years but quite likely die within 20 years (Dursky 1997).

465    We conclude that the success of a mortality model relies more on the degree of similarity of

466    ecological processes between the forests used for calibration and validation, rather than on the

467    amount of data used in model development, provided that the few death events support reliable

468    mortality patterns and rates and no 'irregular' mortality occurred. Nevertheless, the risk that this

469    condition is not fulfilled increases if models are calibrated using very small datasets.

470    In order to apply the mortality models to different datasets, we were forced to make several

471    assumptions. Each mortality model was applied to all trees in the validation dataset, regardless of

472    the *DBH* range covered by the calibration data. Thus we partly extrapolated the relationship of

473    *DBH* and mortality probability. However, the exact degree of extrapolation remains unclear since

474    the *DBH* range was not sufficiently documented for many calibration datasets. Where model

475    covariates were not available for all records in the reserve data, e.g. tree height or site index, we

476    used allometric or eco-topographic relationships to derive the required information. This surely

477    influenced the accuracy and explanatory power of the covariates. In addition, we had to make

478    somewhat arbitrary assumptions about the value to be used in the validation exercise for a few

479    variables because they were not available in the calibration dataset (e.g. *CON* defined as distance

480    to the Mediterranean Sea; Trasobares et al. 2004). We further wish to point out that similar

481    assumptions must be made if mortality algorithms are implemented in DVMs (e.g. *DBH* range;

482    cf. Bircher et al. 2015).

483    We would like to point out that species may differ with respect to model transferability and the

484    suitability of mortality predictors. However, we were unable to test interaction terms between

485    species and the characteristics examined since the different modeling approaches were not tested

486    for every species thus resulting in rank deficiency. The same applies to species groups because it

487    was not possible to clearly classify the species based on statistical significance. Non-parametric

488    methods may provide further insights into the drivers of model performance but were not applied

489    here since appropriate methods to account for the hierarchical data structure are missing.

490    However, random effects explained a considerable proportion of the observed variation and

491    should not be ignored (cf. Table 4). This is because tree mortality and thus model performance

492    are highly variable, and it is not feasible to explicitly address this variability. Finally, the size of

493    individual plots in the calibration data can influence the accuracy of mortality estimates but could

494    not be tested since this information was not available for all mortality models. In spite of these

495    assumptions, we argue that our validation of the mortality models still allows for highly valuable

496    insights into model behavior and performance.

## Conclusions

498    In this study, the characteristics, parameterization and expected predictions of relevant European

499    tree mortality models were presented systematically for the first time. For modelers of forest

500    dynamics, this offers a unique possibility to begin an evaluation of currently available mortality

501    algorithms and to better understand their behavior based on simulated mortality patterns (cf.

502    Appendix S1, Fig. S12).

503    Validating mortality algorithms using independent datasets constitutes a rigorous examination of

504    model transferability, which is a prerequisite for their implementation in DVMs. Our results

505    indicate that many mortality models can be applied successfully outside their calibration domain.

506   However, others failed to emulate the mortality pattern or achieved low prediction or

507   classification accuracy. Consistently higher prediction accuracy was obtained by models that (1)

508   included covariates for growth or competition at the level of individual trees and (2) were applied

509   in a similar ecological context. Furthermore, our results emphasize the pivotal importance of tree

510   growth to achieve a good discrimination between dead and living trees.

511   In conclusion, we suggest two strategies for further developing mortality models: (1) For

512   incorporation in DVMs that are applied over a restricted spatial extent and under current climate,

513   mortality algorithms should be calibrated based on datasets from the same region. Our results

514   reveal that even if these datasets are small, they can still provide valid mortality estimates for the

515   calibration domain. (2) In order to obtain mortality models with wider applicability and improved

516   climatic sensitivity, the high spatial variability of mortality should be addressed explicitly. The

517   systematic screening of available mortality models for European tree species uncovered that

518   further efforts are needed in order to improve the climatic sensitivity of the mortality algorithms,

519   e.g. using environmental variables or tree growth, which may implicitly integrate climatic

520   influences into mortality models (Hülsmann et al. 2016). Since data of high temporal resolution

521   covering large ecological gradients are required to explore the influence of environmental

522   variables on mortality (Hülsmann et al. 2016; Lutz 2015), forest inventory data and

523   dendrochronological data should be combined, e.g. by applying the Bayesian framework

524   suggested by Clark et al. (2007). Future efforts should also address an improved representation of

525   disturbance-related mortality, both non-catastrophic, small-scale mortality and larger events of

526   forest dieback, which are likely to gain in importance under future climates (Seidl et al. 2011).

527   Finally, future mortality models should be thoroughly validated to determine their transferability,

528   and model development should be carefully documented, ideally based on standardized

529   guidelines.

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# Tables

**Table 1.** Tree, stand and site characteristics that were used as covariates in the mortality models. For each characteristic, the mean per tree species is given. Covariates that are considered to explain model performance are highlighted in grey, i.e. growth, competition at the level of single trees and competition at the stand level. Abbreviations: $DBH$ = diameter at breast height, $DI$ = annual diameter increment, $BAI$ = annual basal area increment, $relBAI$ = annual relative basal area increment, $h$ = tree height, $CR$ = crown ratio, $BAL$ = basal area of larger trees, $relBAL$ = share of $BAL$ of stand basal area ($BA$), $mDBH$ = arithmetic mean $DBH$, $qmDBH$ = quadratic mean $DBH$, $CVd$ = coefficient of variance of $DBH$, $hdom$ = dominant height, $BA$ = stand basal area, $N$ = number of trees, $PBA$ = percentage of basal area of the subject species, $LAT$ = latitude, $ALT$ = altitude, $GDD$ = growing degree-days, $SI50$ = site index expressed as the dominant height at the age of 50 years. For further information on the derivation of the covariates refer to Appendix S2. For minimum and maximum values of the characteristics refer to Appendix S1, Table S2.

| | | Abies | Alnus | Betula | Carpinus | Fagus | Fraxinus | Larix | Picea | Pinus | Quercus | Tilia |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tree | $DBH$ (cm) | 13.9 | 22.4 | 21.4 | 15.9 | 25.5 | 17.5 | 27.5 | 29.9 | 25.4 | 28.0 | 16.9 |
| | $DI$ (mm) | 1.02 | 1.90 | 1.84 | 0.89 | 1.87 | 2.31 | 0.96 | 1.85 | 1.86 | 1.75 | 1.20 |
| | $BAI$ (cm$^2$) | 3.47 | 7.34 | 6.94 | 2.93 | 9.85 | 7.71 | 4.95 | 10.75 | 7.78 | 8.67 | 4.12 |
| | $relBAI$ | 0.017 | 0.018 | 0.021 | 0.011 | 0.015 | 0.030 | 0.007 | 0.015 | 0.020 | 0.014 | 0.016 |
| | $h$ (m) | 9.9 | 19.4 | 18.1 | 14.4 | 20.6 | 17.9 | 17.8 | 17.9 | 15.0 | 19.4 | 14.1 |
| | $CR$ | 0.35 | 0.29 | 0.34 | 0.41 | 0.43 | 0.26 | 0.39 | 0.49 | 0.31 | 0.35 | 0.40 |
| | $BAL$ (m$^2$ha$^{-1}$) | 44.1 | 23.3 | 20.9 | 34.1 | 29.8 | 24.9 | 27.2 | 34.1 | 18.0 | 24.7 | 31.9 |
| | $relBAL$ | 0.91 | 0.63 | 0.71 | 0.90 | 0.74 | 0.75 | 0.65 | 0.75 | 0.56 | 0.64 | 0.80 |
| Stand | $mDBH$ (cm) | 18.7 | 17.1 | 17.5 | 21.5 | 24.8 | 15.7 | 22.3 | 26.8 | 15.6 | 19.6 | 17.8 |
| | $qmDBH$ (cm) | 24.0 | 19.7 | 20.5 | 25.4 | 28.1 | 18.6 | 25.3 | 31.6 | 18.4 | 23.1 | 20.7 |
| | $CVd$ | 0.82 | 0.56 | 0.62 | 0.64 | 0.57 | 0.61 | 0.55 | 0.64 | 0.61 | 0.63 | 0.60 |
| | $hdom$ (m) | 29.6 | 24.3 | 22.1 | 24.6 | 27.7 | 23.8 | 19.8 | 26.3 | 17.5 | 23.7 | 21.2 |
| | $BA$ (m$^2$ha$^{-1}$) | 48.5 | 37.6 | 29.7 | 37.7 | 40.1 | 33.3 | 42.1 | 45.8 | 33.3 | 38.2 | 39.9 |
| | $N$ (ha$^{-1}$) | 1147 | 1449 | 1064 | 971 | 851 | 1431 | 963 | 740 | 1401 | 1101 | 1408 |
| | $PBA$ | | | 0.21 | | | | | 0.73 | 0.65 | | |
| Site | $LAT$ (°) | 47.2 | 47.1 | 48.5 | 49.2 | 48.5 | 47.5 | 46.6 | 47.1 | 47.6 | 47.9 | 47.3 |
| | $ALT$ (m) | 830 | 471 | 439 | 350 | 527 | 531 | 1962 | 1336 | 551 | 478 | 601 |
| | $GDD$ | 1597 | 1983 | 1936 | 1901 | 1802 | 1868 | 600 | 1093 | 1932 | 1909 | 1843 |
| | $SI50$ (m) | | | | | | | | 14.7 | 17.0 | | |

**Table 2.** List of the publications that fulfill the selection criteria: They (1) consider the mortality of individual trees, i.e. not of seedling populations or stand-level mortality rates, (2) predict mortality of native European tree species, (3) derive models that were calibrated with inventory data and (4) focus on 'regular' mortality. For models that were not applicable to the reserve data the exclusion criteria are given. Where more than one model was proposed within one publication, the models were distinguished using a numerical index.

| Publication | Exclusion criteria |
| --- | --- |
| Adame et al. (2010) | calibrated for Quercus pyrenaica not present in Central Europe |
| Ahner and Schmidt (2011) | survival analysis |
| Alenius et al. (2003) 1 * | |
| Alenius et al. (2003) 2 * | mixed-effects approach |
| Boeck et al. (2014) | spatially explicit competition indices unavailable in reserve dataset, mixed-effects approach |
| Bravo-Oviedo et al. (2006) | |
| Castagneri et al. (2010) | spatially explicit competition indices and tree age unavailable in reserve dataset |
| Condés and Del Río (2015) | mixed-effects approach |
| Crecente-Campo et al. (2010) | |
| Diéguez-Aranda et al. (2005) | stand age unavailable in reserve dataset |
| Dobbertin and Brang (2001) | covariates (e.g. defoliation and crown form) unavailable in reserve dataset |
| Dursky (1997) | |
| Eid and Tuhus (2001) | |
| Fridman and Ståhl (2001) | |
| Hasenauer (1994) | spatially explicit competition indices unavailable in reserve dataset |
| Hasenauer et al. (2001) | neural networks |
| Hasenauer and Merkl (1997) | spatially explicit competition indices unavailable in reserve dataset |
| Holzwarth et al. (2013) | |
| Hynynen et al. (2002) | soil fertility classes unavailable in reserve dataset |
| Juknys et al. (2006) | stand age unavailable in reserve dataset |
| Jutras et al. (2003) 1 | soil fertility classes unavailable in reserve dataset |
| Jutras et al. (2003) 2 | soil fertility classes unavailable in reserve dataset, mixed-effects approach |
| Laarmann et al. (2009) | separates into different causes of death |
| Monserud and Sterba (1999) | |
| Neuner et al. (2015) | survival analysis |
| Nothdurft (2013) | survival analysis |
| Palahí et al. (2003) 1 † | stand age unavailable in reserve dataset |
| Palahí et al. (2003) 2 † | |
| Sims et al. (2009) | spatially explicit competition indices unavailable in reserve dataset, mixed-effects approach |
| Trasobares et al. (2004) | |
| Vieilledent et al. (2010) | semiparametric approach |
| Wunder et al. (2007) 1 ‡ | |
| Wunder et al. (2007) 2 ‡ | |
| Wunder et al. (2008a) 1 § | |
| Wunder et al. (2008a) 2 § | |
| Wunder et al. (in prep.) | |

\* Model 1 included only fixed-effects, model 2 included also random-effects.
† Model 1 is based on average growth, model 2 is based on growth during the past five years.
‡ Model 1 was calibrated with data from the Swiss reserve Tariche Bois Banal, model 2 with data from Tariche Haute Côte.
§ Model 1 was calibrated with data from Białowieża in Poland, model 2 with data from Swiss forest reserves.

**Table 3.** Performance of each model-species combination in terms of $p_{bias}$ and *AUC*. For each model application, the respective proportion of the data used and the annual mortality probability are indicated.

| Publication | Species | Proportion of data used | Observed annual mortality rate (%) | $p_{bias}$ (%) | $p_{bias}$ (%) CI | AUC | AUC CI |
|---|---|---|---|---|---|---|---|
| Alenius et al. (2003) 1 | *Pinus* | 1.00 | 1.6 | 1.8 | 1.6 ... 2.0 | 0.56 | 0.53 ... 0.59 |
| Bravo-Oviedo et al. (2006) | *Pinus* | 1.00 | 1.6 | -1.0 | -1.1 ... -0.8 | 0.59 | 0.57 ... 0.62 |
| Crecente-Campo et al. (2010) | *Pinus* | 1.00 | 1.6 | -0.8 | -0.9 ... -0.7 | 0.72 | 0.70 ... 0.74 |
| Dursky (1997) | *Fagus* | 1.00 | 1.3 | 2.8 | 2.7 ... 2.8 | 0.78 | 0.78 ... 0.79 |
| Dursky (1997) | *Picea* | 0.99 | 1.4 | 0.7 | 0.7 ... 0.8 | 0.57 | 0.56 ... 0.58 |
| Eid and Tuhus (2001) | *Betula* | 1.00 | 4.1 | -3.2 | -3.5 ... -2.9 | 0.58 | 0.56 ... 0.60 |
| Eid and Tuhus (2001) | *Picea* | 0.99 | 1.4 | -0.9 | -0.9 ... -0.8 | 0.60 | 0.59 ... 0.61 |
| Eid and Tuhus (2001) | *Pinus* | 1.00 | 1.6 | -1.2 | -1.3 ... -1.0 | 0.62 | 0.59 ... 0.65 |
| Eid and Tuhus (2001) | *Quercus* | 1.00 | 2.0 | -0.6 | -0.7 ... -0.5 | 0.77 | 0.76 ... 0.79 |
| Fridman and Ståhl (2001) | *Alnus* | 1.00 | 1.4 | 0.4 | 0.3 ... 0.5 | 0.74 | 0.72 ... 0.77 |
| Fridman and Ståhl (2001) | *Betula* | 1.00 | 4.1 | -2.4 | -2.7 ... -2.1 | 0.50 | 0.47 ... 0.52 |
| Fridman and Ståhl (2001) | *Fagus* | 1.00 | 1.3 | -0.2 | -0.3 ... -0.2 | 0.70 | 0.69 ... 0.71 |
| Fridman and Ståhl (2001) | *Picea* | 1.00 | 1.4 | 0.1 | 0.0 ... 0.1 | 0.61 | 0.60 ... 0.62 |
| Fridman and Ståhl (2001) | *Pinus* | 1.00 | 1.6 | -1.0 | -1.2 ... -0.9 | 0.72 | 0.70 ... 0.75 |
| Fridman and Ståhl (2001) | *Quercus* | 1.00 | 2.0 | -1.3 | -1.4 ... -1.2 | 0.78 | 0.77 ... 0.80 |
| Holzwarth et al. (2013) | *Carpinus* | 1.00 | 2.0 | 0.8 | 0.7 ... 0.9 | 0.78 | 0.76 ... 0.79 |
| Holzwarth et al. (2013) | *Fagus* | 1.00 | 1.3 | 0.7 | 0.6 ... 0.7 | 0.76 | 0.75 ... 0.76 |
| Holzwarth et al. (2013) | *Fraxinus* | 1.00 | 2.1 | 3.4 | 3.2 ... 3.5 | 0.71 | 0.70 ... 0.73 |
| Monserud and Sterba (1999) | *Abies* | 0.13 | 1.0 | 1.4 | 1.2 ... 1.6 | 0.64 | 0.58 ... 0.69 |
| Monserud and Sterba (1999) | *Alnus* | 0.12 | 1.7 | 0.1 | -0.4 ... 0.5 | 0.73 | 0.66 ... 0.81 |
| Monserud and Sterba (1999) | *Betula* | 0.20 | 3.6 | -2.1 | -2.7 ... -1.5 | 0.76 | 0.71 ... 0.80 |
| Monserud and Sterba (1999) | *Carpinus* | 0.08 | 2.0 | 0.6 | 0.1 ... 0.9 | 0.78 | 0.72 ... 0.83 |
| Monserud and Sterba (1999) | *Fagus* | 0.11 | 1.2 | -0.3 | -0.4 ... -0.2 | 0.76 | 0.73 ... 0.79 |
| Monserud and Sterba (1999) | *Fraxinus* | 0.22 | 2.6 | -0.3 | -0.5 ... -0.1 | 0.81 | 0.79 ... 0.83 |
| Monserud and Sterba (1999) | *Larix* | 0.11 | 0.4 | 0.3 | 0.0 ... 0.5 | 0.89 | 0.77 ... 0.98 |
| Monserud and Sterba (1999) | *Picea* | 0.12 | 1.1 | 0.2 | 0.0 ... 0.3 | 0.60 | 0.56 ... 0.64 |
| Monserud and Sterba (1999) | *Pinus* | 0.15 | 1.5 | -0.8 | -1.2 ... -0.5 | 0.68 | 0.61 ... 0.75 |
| Monserud and Sterba (1999) | *Quercus* | 1.00 | 2.0 | -1.5 | -1.7 ... -1.4 | 0.75 | 0.74 ... 0.77 |
| Palahí et al. (2003) 2 | *Pinus* | 1.00 | 1.6 | -1.2 | -1.3 ... -1.1 | 0.80 | 0.77 ... 0.82 |
| Trasobares et al. (2004) | *Pinus* | 1.00 | 1.6 | -0.7 | -0.8 ... -0.5 | 0.70 | 0.68 ... 0.72 |
| Wunder et al. (2007) 1 | *Abies* | 0.86 | 1.4 | -0.9 | -1.0 ... -0.8 | 0.71 | 0.69 ... 0.72 |
| Wunder et al. (2007) 1 | *Fagus* | 0.92 | 1.3 | 0.1 | 0.1 ... 0.2 | 0.80 | 0.79 ... 0.81 |
| Wunder et al. (2007) 2 | *Abies* | 0.46 | 1.2 | 0.1 | 0.0 ... 0.2 | 0.72 | 0.69 ... 0.74 |
| Wunder et al. (2007) 2 | *Fagus* | 0.92 | 1.4 | -0.3 | -0.3 ... -0.2 | 0.80 | 0.79 ... 0.81 |
| Wunder et al. (2008) 1+2 | *Betula* | 0.90 | 4.1 | -0.2 | -0.5 ... 0.1 | 0.74 | 0.72 ... 0.77 |
| Wunder et al. (2008) 1 | *Alnus* | 1.00 | 1.4 | 0.9 | 0.8 ... 1.0 | 0.77 | 0.74 ... 0.79 |
| Wunder et al. (2008) 1 | *Carpinus* | 1.00 | 2.0 | -0.8 | -0.9 ... -0.7 | 0.70 | 0.69 ... 0.72 |
| Wunder et al. (2008) 1 | *Fraxinus* | 1.00 | 2.1 | -0.5 | -0.6 ... -0.4 | 0.80 | 0.78 ... 0.81 |
| Wunder et al. (2008) 1 | *Picea* | 1.00 | 1.4 | 2.6 | 2.5 ... 2.6 | 0.59 | 0.57 ... 0.60 |
| Wunder et al. (2008) 1 | *Quercus* | 1.00 | 2.0 | 2.8 | 2.7 ... 2.8 | 0.83 | 0.82 ... 0.84 |
| Wunder et al. (2008) 1 | *Tilia* | 1.00 | 1.5 | 1.5 | 1.4 ... 1.7 | 0.78 | 0.76 ... 0.80 |
| Wunder et al. (2008) 2 | *Alnus* | 0.68 | 1.3 | -0.4 | -0.5 ... -0.2 | 0.76 | 0.73 ... 0.79 |
| Wunder et al. (2008) 2 | *Carpinus* | 0.89 | 2.0 | 0.0 | -0.1 ... 0.1 | 0.71 | 0.70 ... 0.73 |
| Wunder et al. (2008) 2 | *Fagus* | 0.79 | 1.3 | 0.5 | 0.4 ... 0.5 | 0.76 | 0.76 ... 0.77 |
| Wunder et al. (2008) 2 | *Fraxinus* | 0.89 | 2.0 | 0.9 | 0.8 ... 1.0 | 0.82 | 0.81 ... 0.83 |
| Wunder et al. (2008) 2 | *Quercus* | 0.69 | 2.2 | -1.2 | -1.3 ... -1.1 | 0.84 | 0.83 ... 0.86 |
| Wunder et al. (2008) 2 | *Tilia* | 0.69 | 1.8 | -0.2 | -0.4 ... -0.1 | 0.79 | 0.76 ... 0.81 |
| Wunder et al. (in prep.) | *Abies* | 1.00 | 1.3 | -0.6 | -0.7 ... -0.5 | 0.68 | 0.66 ... 0.69 |
| Wunder et al. (in prep.) | *Alnus* | 1.00 | 1.4 | -0.3 | -0.5 ... -0.2 | 0.76 | 0.73 ... 0.78 |
| Wunder et al. (in prep.) | *Betula* | 1.00 | 4.1 | -2.8 | -3.1 ... -2.5 | 0.72 | 0.70 ... 0.74 |
| Wunder et al. (in prep.) | *Carpinus* | 1.00 | 2.0 | -1.2 | -1.3 ... -1.0 | 0.78 | 0.77 ... 0.80 |
| Wunder et al. (in prep.) | *Fagus* | 1.00 | 1.3 | -0.8 | -0.8 ... -0.8 | 0.80 | 0.79 ... 0.80 |
| Wunder et al. (in prep.) | *Fraxinus* | 1.00 | 2.1 | -1.2 | -1.3 ... -1.1 | 0.79 | 0.78 ... 0.80 |
| Wunder et al. (in prep.) | *Larix* | 1.00 | 0.4 | 0.1 | 0.0 ... 0.1 | 0.82 | 0.77 ... 0.87 |
| Wunder et al. (in prep.) | *Picea* | 1.00 | 1.4 | -0.8 | -0.8 ... -0.7 | 0.56 | 0.55 ... 0.57 |
| Wunder et al. (in prep.) | *Pinus* | 1.00 | 1.6 | -0.5 | -0.7 ... -0.4 | 0.78 | 0.76 ... 0.81 |
| Wunder et al. (in prep.) | *Quercus* | 1.00 | 2.0 | -0.8 | -0.9 ... -0.8 | 0.81 | 0.80 ... 0.82 |
| Wunder et al. (in prep.) | *Tilia* | 1.00 | 1.5 | -0.1 | -0.2 ... 0.0 | 0.78 | 0.75 ... 0.80 |

**Table 4.** Estimates of the influence of model and data characteristics on $p_{bias}$ and $AUC$ with respective standard errors, P-values and significance levels (*** P $\leq$ 0.001, ** P $\leq$ 0.01, * P $\leq$ 0.05) estimated with linear mixed-effects models (t-tests use the Satterthwaite approximation). Model performance, evaluated by the square-root of $|p_{bias}|$ and arcsine-transformed $AUC$, was considered to be a function of species, use of covariates for growth (*DI*, *BAI*, *relBAI*) and competition at the tree (*BAL*, *relBAL*) and stand level (*BA*, *N*), application within the same ecological zone, management intensity, length of the census interval in calibration and validation and size of the calibration ($N_{cal}$) and validation datasets ($N_{val}$). Note that a 'good' model features low $|p_{bias}|$ and high $AUC$. Both performance measures show significant species differences. $|p_{bias}|$ was significantly reduced by covariates for growth and competition at the level of individual trees and when models are applied in the same ecological zone. Significantly larger $AUC$ was achieved when growth was included. 'Reserve' and 'model' were used as random effects. Marginal and conditional $R^2$ of the models were 0.14 and 0.44 for $p_{bias}$ and 0.19 and 0.52 for $AUC$.

| $p_{bias}$ | Estimate | Standard error | P-value | | $AUC$ | Estimate | Standard error | P-value | |
|---|---|---|---|---|---|---|---|---|---|
| (Intercept) | 0.145 | 0.055 | 0.018 | * | (Intercept) | 0.763 | 0.108 | <0.001 | *** |
| Species | | | <0.001 | *** | Species | | | <0.001 | *** |
|    *Alnus* | -0.020 | 0.015 | | |    *Alnus* | 0.263 | 0.038 | | |
|    *Betula* | 0.038 | 0.013 | | |    *Betula* | 0.156 | 0.032 | | |
|    *Carpinus* | -0.010 | 0.012 | | |    *Carpinus* | 0.182 | 0.030 | | |
|    *Fagus* | -0.015 | 0.011 | | |    *Fagus* | 0.165 | 0.027 | | |
|    *Fraxinus* | -0.007 | 0.012 | | |    *Fraxinus* | 0.210 | 0.029 | | |
|    *Larix* | -0.028 | 0.027 | | |    *Larix* | 0.520 | 0.069 | | |
|    *Picea* | -0.000 | 0.012 | | |    *Picea* | 0.088 | 0.030 | | |
|    *Pinus* | 0.001 | 0.013 | | |    *Pinus* | 0.141 | 0.032 | | |
|    *Quercus* | 0.004 | 0.011 | | |    *Quercus* | 0.241 | 0.029 | | |
|    *Tilia* | -0.001 | 0.014 | | |    *Tilia* | 0.267 | 0.034 | | |
| Growth | -0.027 | 0.012 | 0.021 | * | Growth | 0.057 | 0.018 | 0.005 | ** |
| Competition stand | 0.039 | 0.027 | 0.181 | | Competition stand | -0.023 | 0.022 | 0.343 | |
| Competition tree | -0.019 | 0.009 | 0.037 | * | Competition tree | 0.002 | 0.021 | 0.930 | |
| Same ecological zone | -0.014 | 0.004 | 0.002 | ** | Same ecological zone | 0.017 | 0.010 | 0.085 | |
| Managed | -0.014 | 0.020 | 0.491 | | Managed | 0.017 | 0.024 | 0.474 | |
| Census interval calibration (sqrt) | 0.008 | 0.016 | 0.647 | | Census interval calibration (sqrt) | 0.008 | 0.014 | 0.589 | |
| Census interval validation (sqrt) | -0.011 | 0.005 | 0.033 | * | Census interval validation (sqrt) | -0.004 | 0.026 | 0.872 | |
| $N_{cal}$ (sqrt) | -0.000 | 0.000 | 0.828 | | $N_{cal}$ (sqrt) | 0.000 | 0.000 | 0.631 | |
| $N_{val}$ (sqrt) | 0.000 | 0.000 | 0.696 | | $N_{val}$ (sqrt) | 0.001 | 0.000 | 0.031 | * |

# Figure captions

**Fig. 1.** Observed and predicted annual mortality rates as a function of *DBH* per tree species. Each grey line represents the predictions of one mortality model. For the sake of simplicity and to focus on overall patterns, we did not differentiate mortality models but show all model predictions in grey. Note that some models had to be validated with reduced datasets (cf. Table 3) and thus the black and grey lines do not always allow for a direct comparison of observed and predicted mortality rates. For a more precise evaluation of specific models, cf. Table 3 and Appendix S1, Fig. S12.

# Appendices

**Appendix S1.** Fig. S1-S12, Tables S1-S3

**Appendix S2.** Extended material and methods

**Appendix S3.** Table of coefficients for the validated mortality models (cf. additional .csv-file)
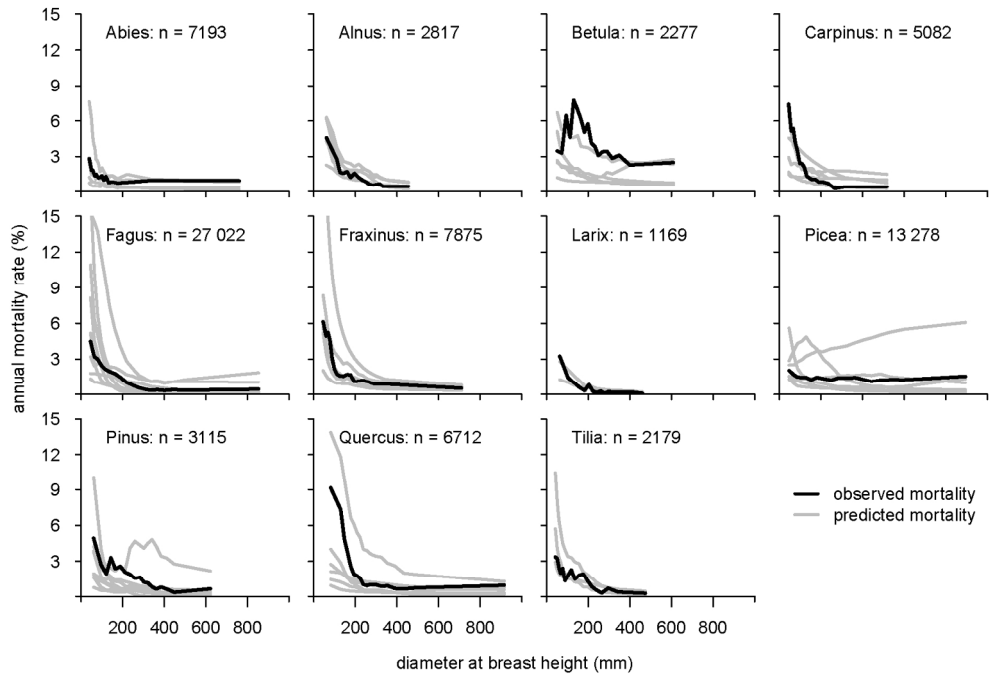
Fig. 1. Observed and predicted annual mortality rates as a function of DBH per tree species. Each grey line represents the predictions of one mortality model. For the sake of simplicity and to focus on overall patterns, we did not differentiate mortality models but show all model predictions in grey. Note that some models had to be validated with reduced datasets (cf. Table 3) and thus the black and grey lines do not always allow for a direct comparison of observed and predicted mortality rates. For a more precise evaluation of specific models, cf. Table 3 and Appendix S1, Fig. S12.

162x111mm (300 x 300 DPI)

*Supporting information to the paper*

Hülsmann, L. et al. How to predict tree death from inventory data – lessons from a systematic assessment of European tree mortality models. *Canadian Journal of Forest Research.*

**Supplement S1.** Fig. S1-S12, Tables S1-S3

Fig. S1. Map of European tree mortality models and strict forest reserves in Germany and Switzerland.

Fig. S2. Boxplot of $p_{bias}$ at the reserve level for each tree species.

Fig. S3. Fixed effects of the influence of model and data characteristics on the square-root of $|p_{bias}|$.

Fig. S4. Multiple pairwise comparison of least-squares means and confidence intervals for different species from the linear mixed-effect model of the square-root of $|p_{bias}|$.

Fig. S5. Boxplot of $|p_{bias}|$ at the reserve level achieved by models with and without a covariate of growth for each tree species.

Fig. S6. Boxplot of $|p_{bias}|$ at the reserve level achieved by models that were applied inside or outside the ecological zone in which the models were calibrated for each tree species.

Fig. S7. $|p_{bias}|$ at the reserve level as a function of the census interval in the validation dataset.

Fig. S8. Fixed effects of the influence of model and data characteristics on arcsine-transformed *AUC*.

Fig. S9. Multiple pairwise comparison of least-squares means and confidence intervals for different species from the linear mixed-effect model of arcsine-transformed *AUC*.

Fig. S10. Boxplot of *AUC* at the reserve level achieved by models with and without a covariate of growth for each tree species.

Fig. S11. *AUC* at the reserve level as a function of the number of records in the validation dataset ($N_{val}$).

Fig. S12a+b. Observed and predicted annual mortality rates as a function of *DBH* separately for each model-species combination.

Table S1. Number of records per tree species and genus.

Table S2. Minimum and maximum values of the tree, stand and site characteristics that were used as covariates in the mortality models.

Table S3. Mortality models, related species and the model characteristics used to explain achieved model performance.

**Supplement S2.** Extended material and methods

Tree characteristics

Stand characteristics

Site characteristics

Model application

Prediction bias

**Supplement S3.** Table of coefficients for the validated mortality models (cf. additional .csv file).
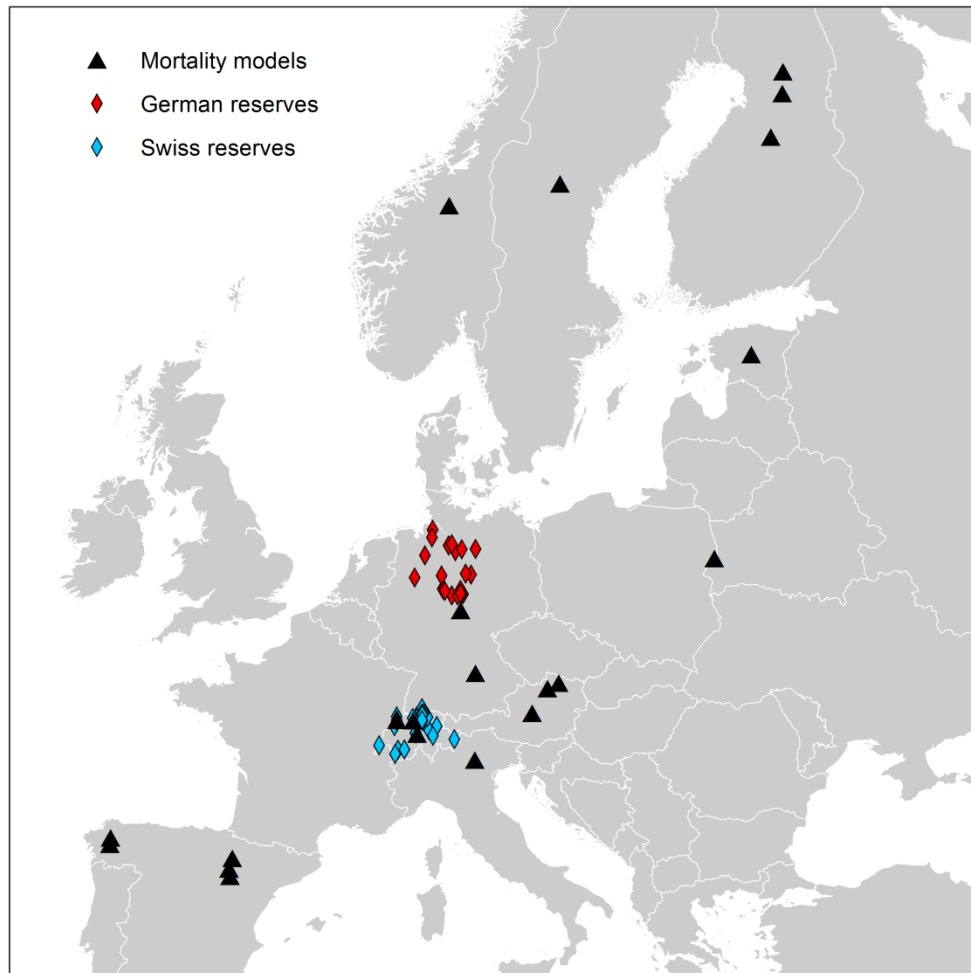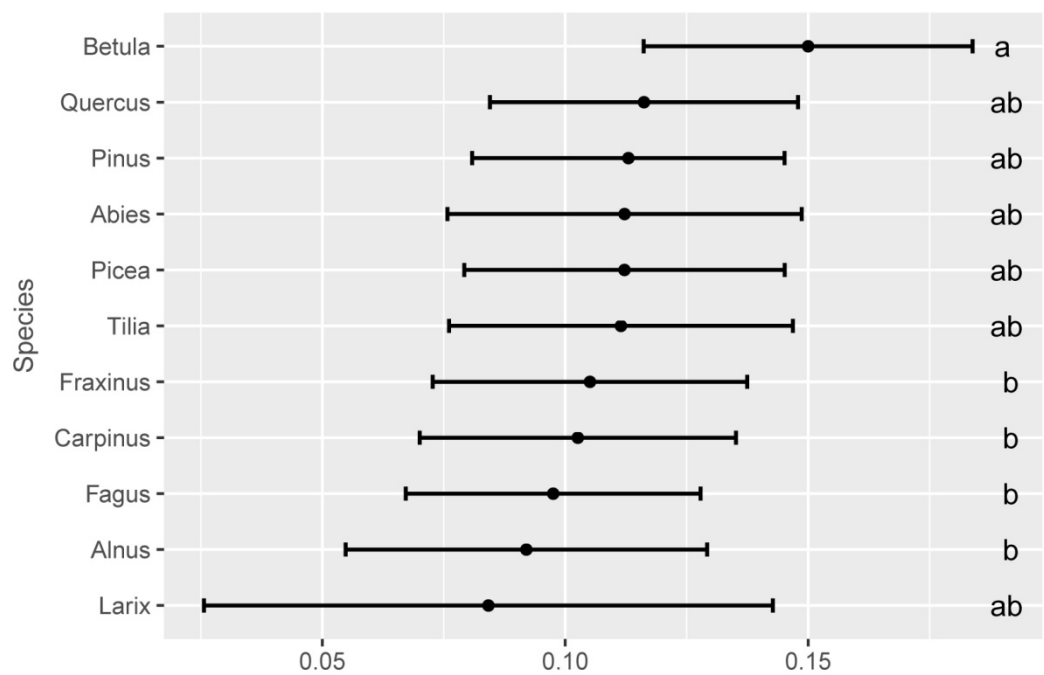
**References**

**Supplement S1.** Fig. S1-S6, Tables S1-S3



**Fig. S1.** Map of European tree mortality models and strict forest reserves in Germany and Switzerland. The location of the calibration dataset was estimated based on the information available from the publications. Number of reserves per respective validation dataset: Germany $n = 22$ and Switzerland $n = 32$.
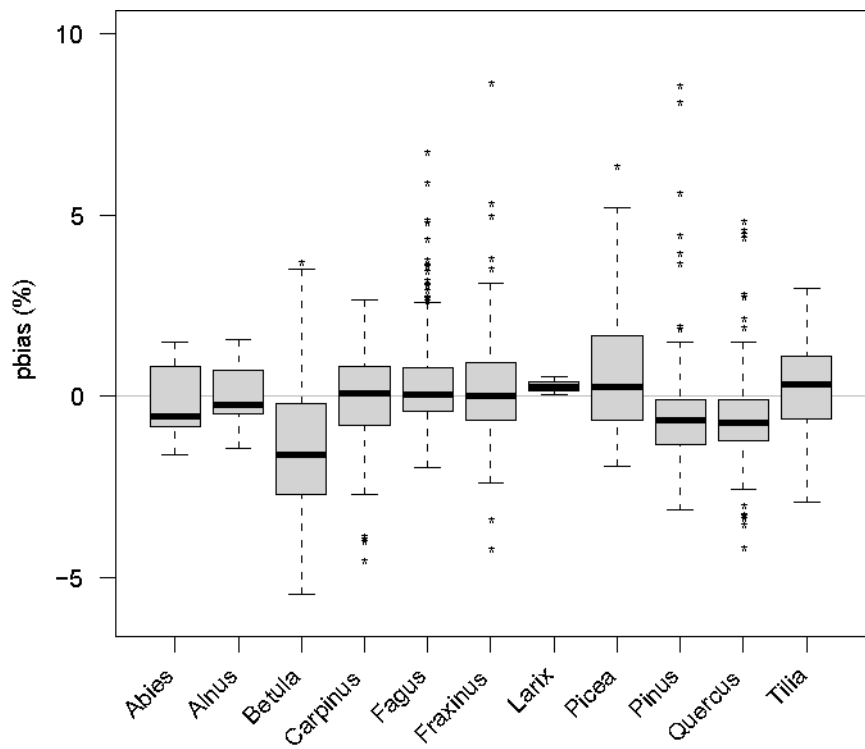
**Fig. S2.** Boxplot of $p_{bias}$ at the reserve level for each tree species. Prevailing positive or negative $p_{bias}$ values indicate that for the respective species the models used for prediction tend to over- or underestimate tree mortality, respectively.
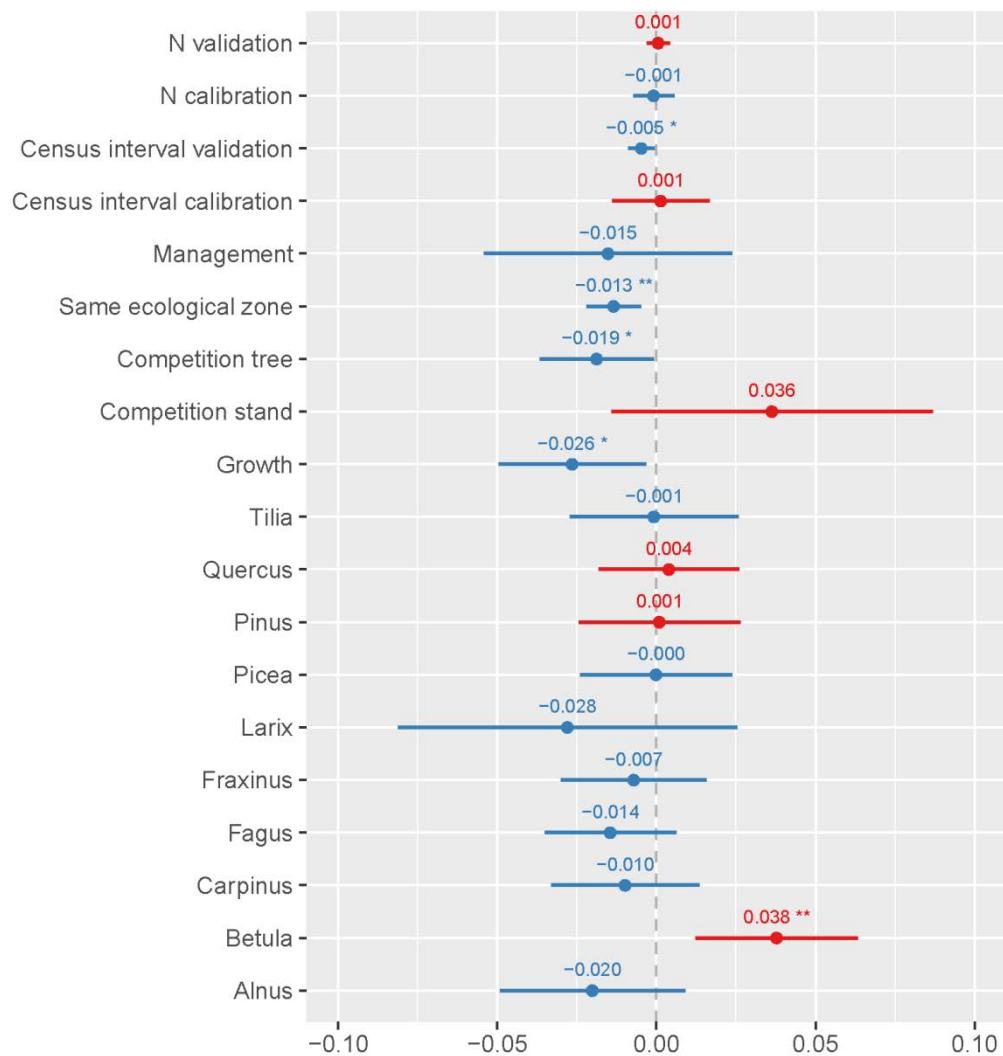
**Fig. S3.** Fixed effects of the influence of model and data characteristics on the square-root of $|p_{bias}|$. Note that a 'good' model features low $|p_{bias}|$. Positive and negative influences on performance are shown in blue and red, respectively. Note that the first level of all factors is the reference level, while the other levels are characterized by the shift relative to this reference level. The reference species is *Abies*.

**Fig. S4.** Multiple pairwise comparison of least-squares means and confidence intervals for different species from the linear mixed-effect model of the square-root of $|p_{bias}|$. Different letters (a-e) indicate significant differences between species (p<0.05).
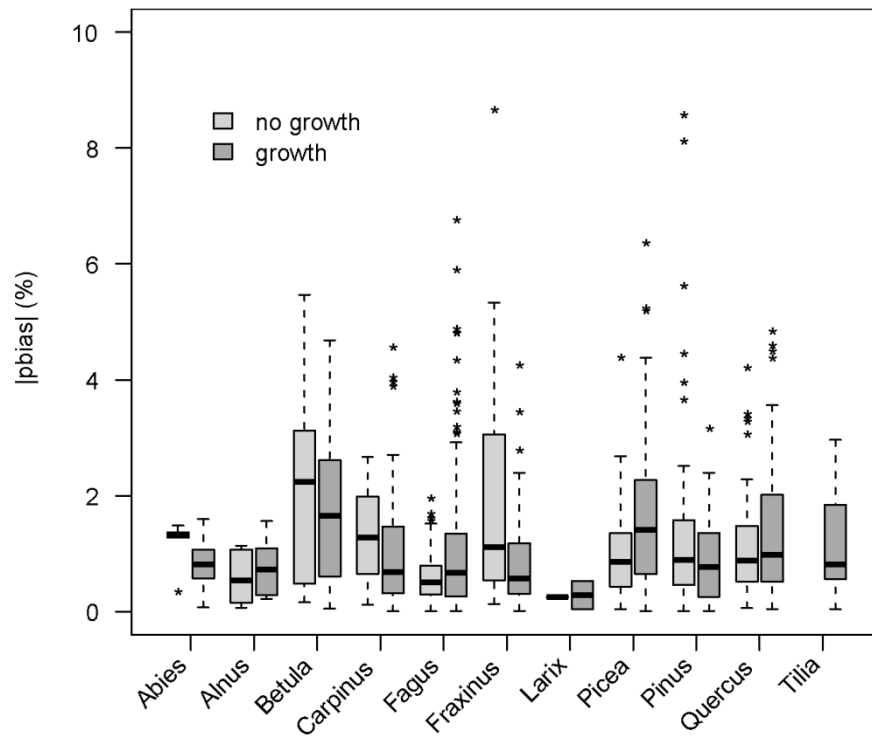
**Fig. S5.** Boxplot of $|p_{bias}|$ at the reserve level achieved by models with and without a covariate of growth for each tree species. Note that the design regarding the factors 'species' and 'growth' is not balanced.
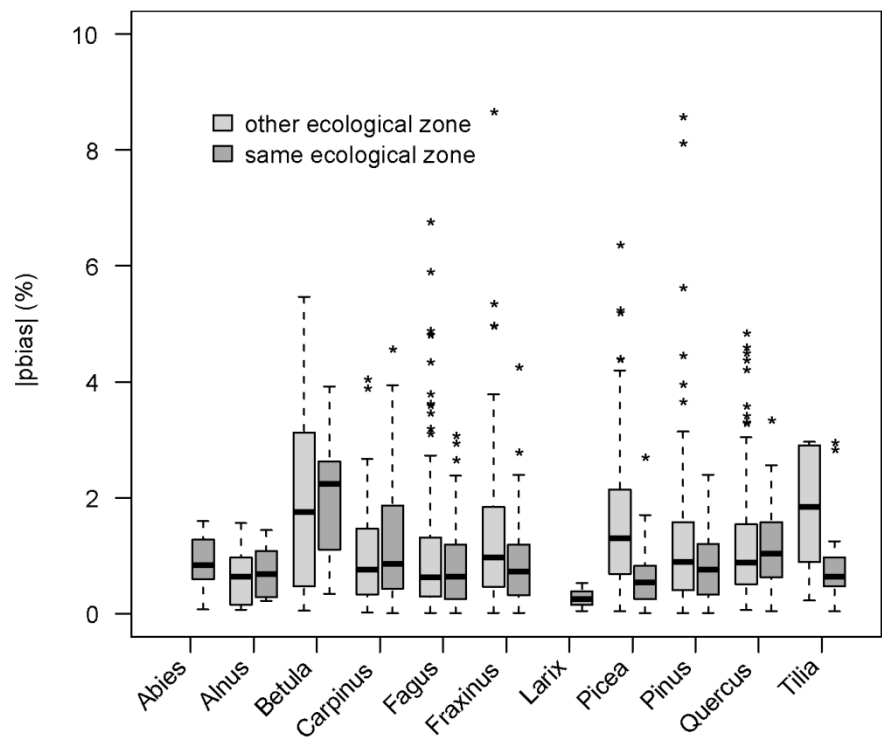
**Fig. S6.** Boxplot of $|p_{bias}|$ at the reserve level achieved by models that were applied inside or outside the ecological zone in which the models were calibrated for each tree species. Note that the design regarding the factors 'species' and 'ecological zone' is not balanced.
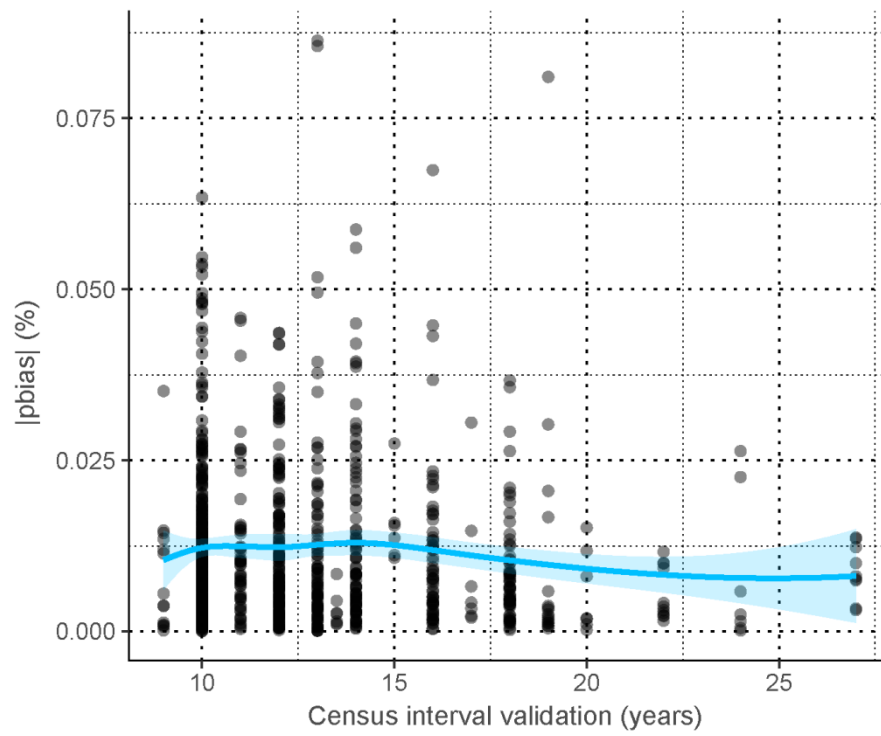
**Fig. S7.** $|p_{bias}|$ at the reserve level as a function of the census interval in the validation dataset including a loess smoothing (blue).
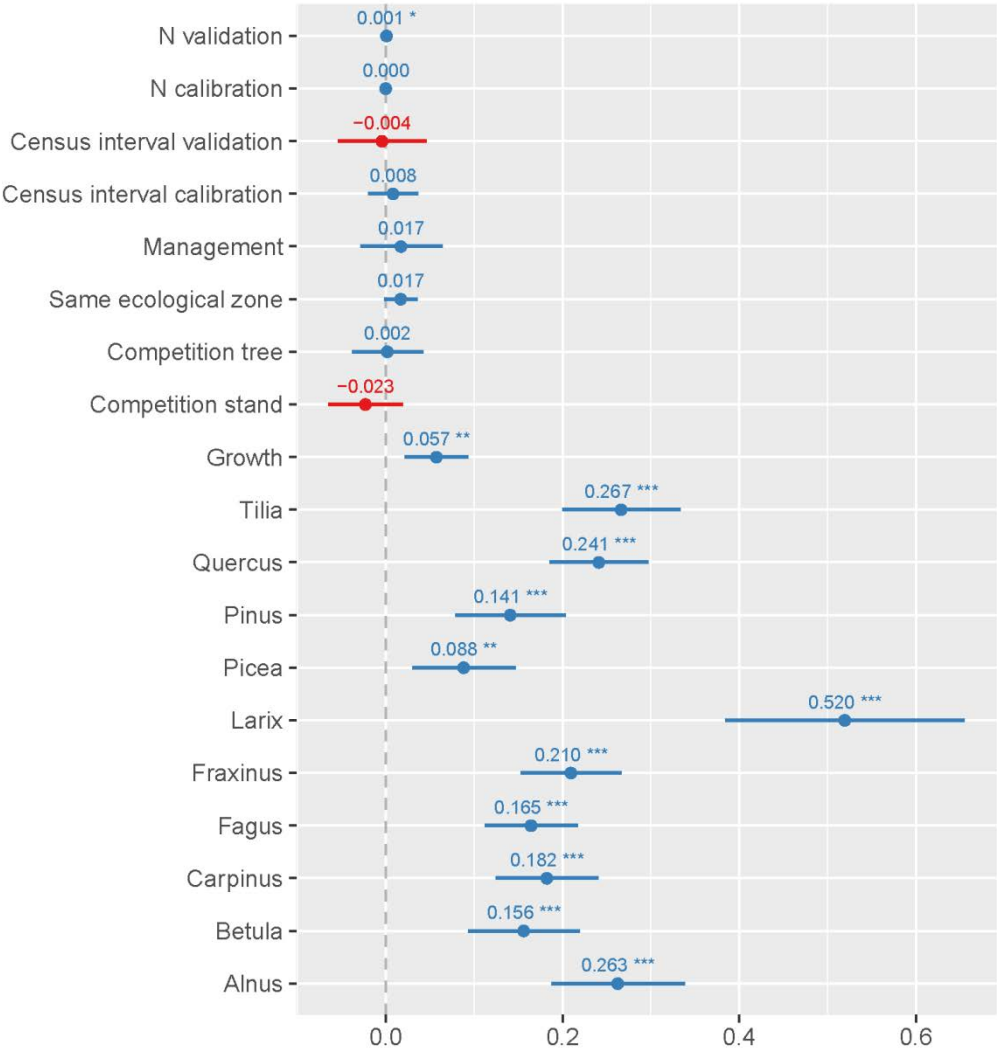
**Fig. S8.** Fixed effects of the influence of model and data characteristics on arcsine-transformed *AUC*. Note that a 'good' model features high *AUC*. Positive and negative influences on performance are shown in blue and red, respectively. Note that the first level of all factors is the reference level while the other levels are characterized by the shift relative to this reference level. The reference species is *Abies*.
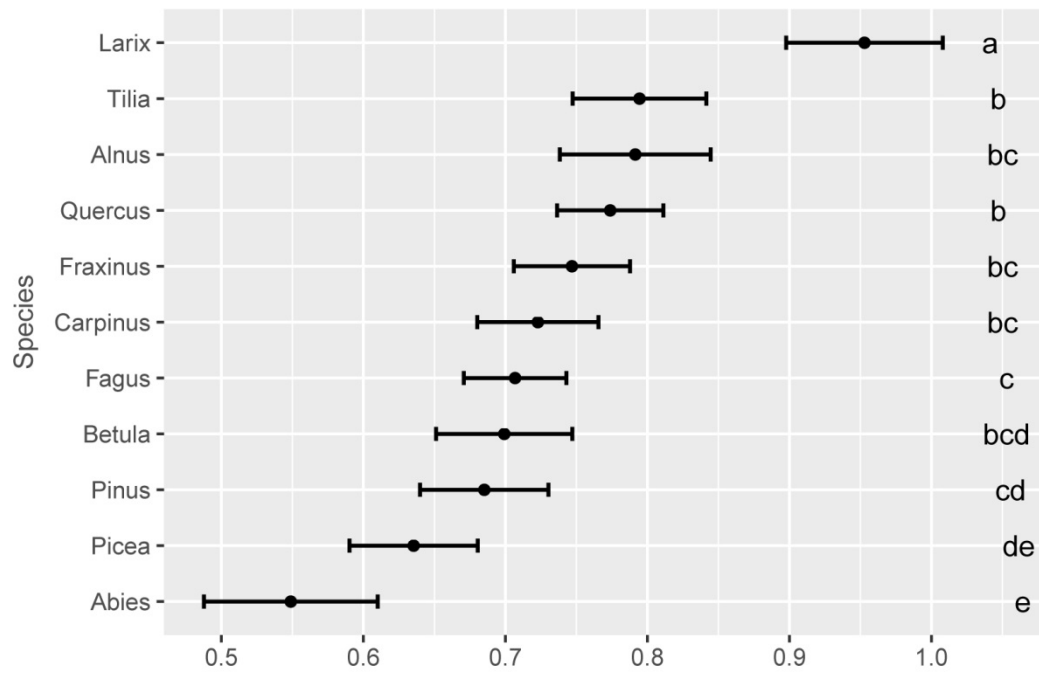
**Fig. S9.** Multiple pairwise comparison of least-squares means and confidence intervals for different species from the linear mixed-effect model of arcsine-transformed *AUC*. Different letters (a-e) indicate significant differences between species ($p < 0.05$).
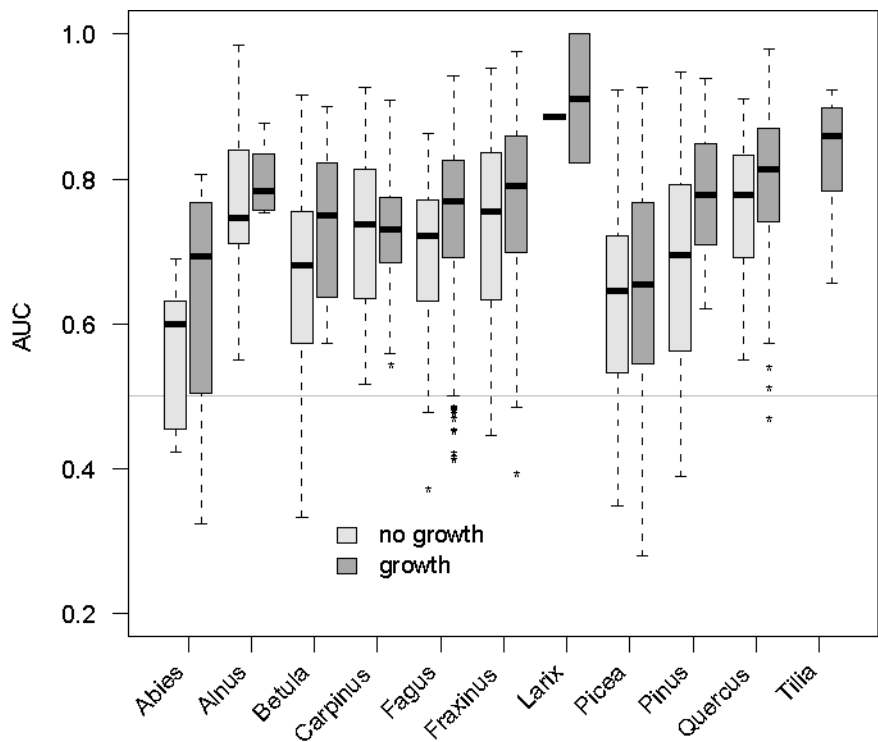
**Fig. S10.** Boxplot of *AUC* at the reserve level achieved by models with and without a covariate of growth for each tree species. Values larger than 0.5 (grey line) indicate an increasing ability to classify dead and living trees (Hosmer and Lemeshow 2000). Note that the design regarding the factors 'species' and 'growth' is not balanced.
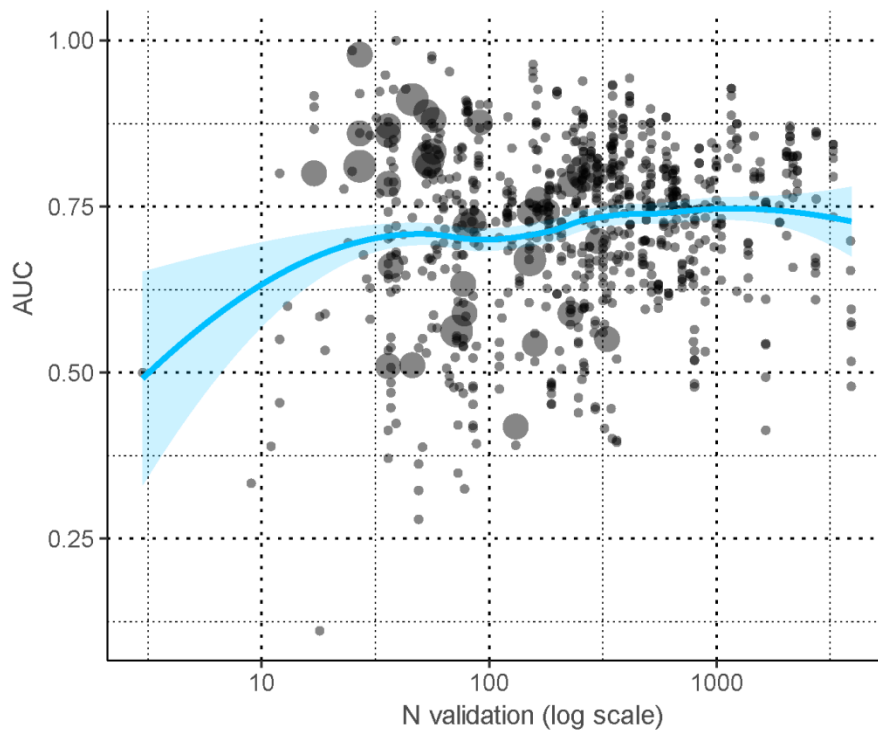
**Fig. S11.** *AUC* at the reserve level as a function of the number of records in the validation dataset ($N_{val}$) including a loess smoothing (blue). Note that the size of the points indicates the count of values at the respective location.
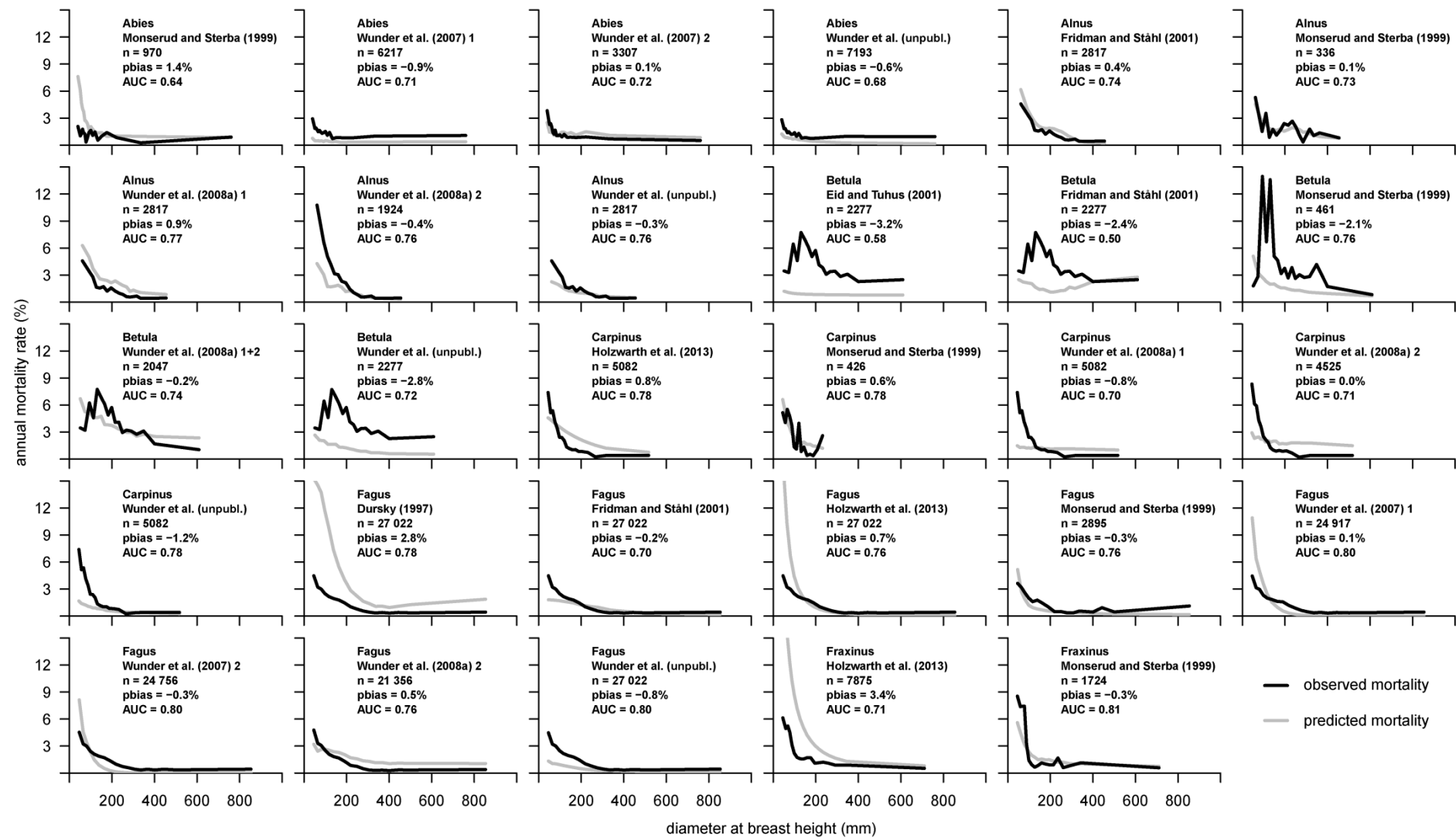
**Fig. S12a.** Observed and predicted annual mortality rates as a function of *DBH* separately for each model-species combination.
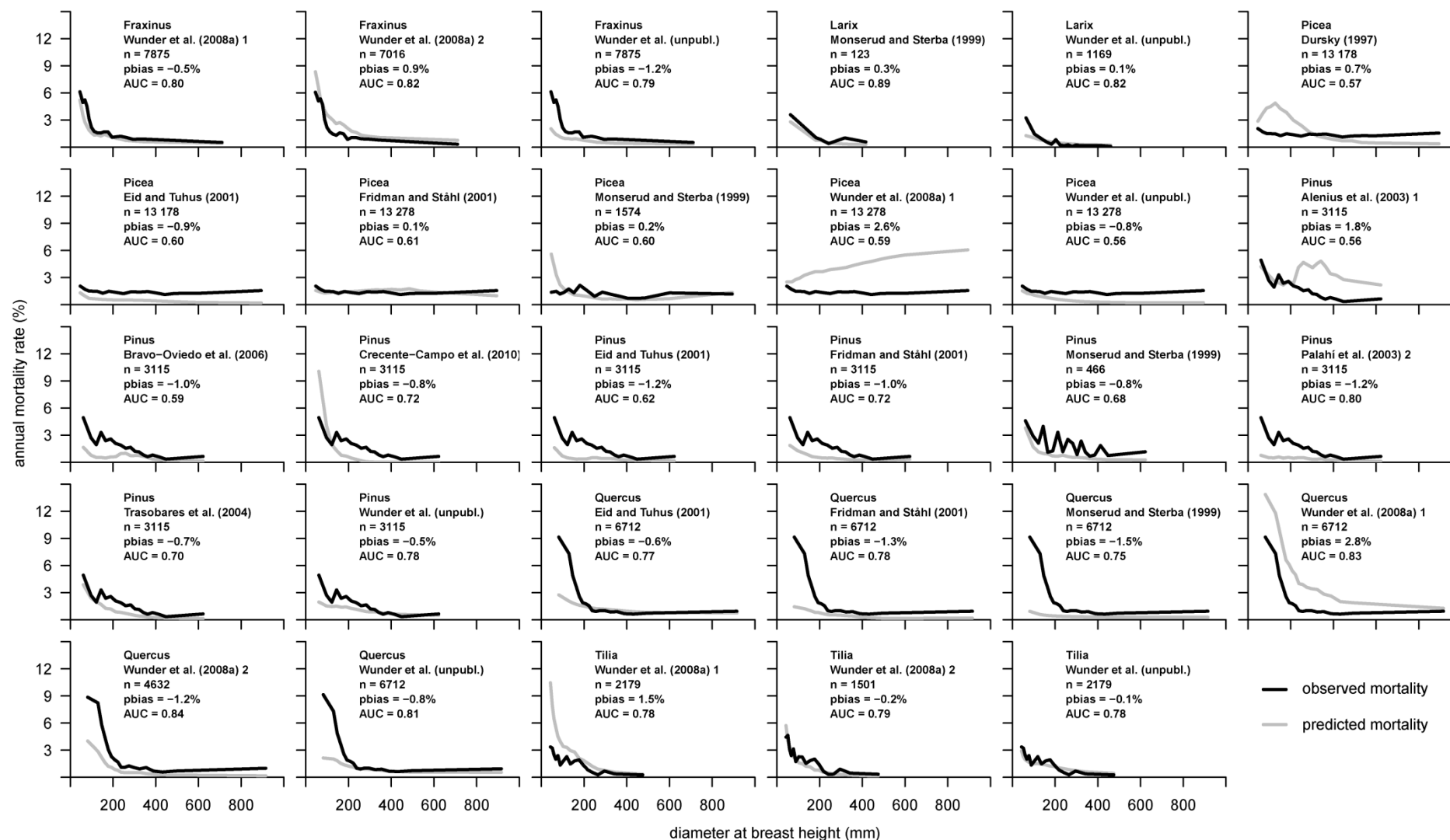
**Fig. S12b.** Observed and predicted annual mortality rates as a function of *DBH* separately for each model-species combination.

**Table S1.** Number of records per tree species and genus. Numbers are given for the total dataset, per country and for those that resulted in tree death. In addition, the number of permanent plots is given.

| Genus | Species | total | Germany | Switzerland | dead | Permanent plots |
|---|---|---|---|---|---|---|
| *Abies* | *Abies alba* | 7193 | 0 | 7193 | 1142 | 38 |
| *Alnus* | *Alnus glutinosa* | 2817 | 0 | 2817 | 380 | 11 |
| *Betula* | spec. | 2277 | 590 | 1687 | 852 | 26 |
| | *Betula pendula* | 1987 | 300 | 1687 | 764 | 23 |
| | *Betula pubescens* | 290 | 290 | 0 | 88 | 4 |
| *Carpinus* | *Carpinus betulus* | 5082 | 1637 | 3445 | 1137 | 41 |
| *Fagus* | *Fagus sylvatica* | 27 022 | 6869 | 20 153 | 4128 | 126 |
| *Fraxinus* | *Fraxinus excelsior* | 7875 | 159 | 7716 | 1757 | 80 |
| *Larix* | *Larix decidua* | 1169 | 0 | 1169 | 88 | 11 |
| *Picea* | *Picea abies* | 13 278 | 458 | 12 820 | 2242 | 82 |
| *Pinus* | *Pinus sylvestris* | 3115 | 317 | 2798 | 553 | 44 |
| *Quercus* | spec. | 6712 | 805 | 5907 | 1466 | 53 |
| | *Quercus petraea* | 32 | 32 | 0 | 25 | 1 |
| | *Quercus robur* | 6680 | 773 | 5907 | 1441 | 53 |
| *Tilia* | *Tilia cordata* | 2179 | 0 | 2179 | 396 | 42 |
| All | | 78 719 | 10 835 | 67 884 | 14 141 | 197 |

**Table S2.** Minimum and maximum values of the tree, stand and site characteristics that were used as covariates in the mortality models. For abbreviations and further explanations refer to Table 1.

| | | Abies | Alnus | Betula | Carpinus | Fagus | Fraxinus | Larix | Picea | Pinus | Quercus | Tilia |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tree | DBH (cm) | 3.2 - 110.5 | 3.9 - 53.0 | 3.9 - 78.5 | 3.7 - 68.9 | 3.5 - 117.2 | 3.6 - 104.5 | 3.8 - 78.9 | 3.2 - 114.7 | 3.8 - 77.5 | 4.3 - 129.5 | 3.7 - 57.5 |
| | DI (mm) | 0.0 - 10.4 | 0.0 - 13.2 | 0.0 - 13.7 | 0.0 - 17.1 | 0.0 - 43.0 | 0.0 - 28.4 | 0.0 - 10.5 | 0.0 - 29.6 | 0.0 - 14.7 | 0.0 - 15.6 | 0.0 - 11.3 |
| | BAI (cm$^2$) | 0.0 - 116.1 | 0.0 - 64.3 | 0.0 - 101.3 | 0.0 - 152.2 | 0.00 - 249.91 | 0.00 - 336.91 | 0.00 - 70.66 | 0.00 - 215.26 | 0.00 - 151.69 | 0.00 - 113.30 | 0.00 - 67.54 |
| | relBAI | 0.00 - 0.19 | 0.00 - 0.19 | 0.00 - 0.17 | 0.00 - 0.23 | 0.00 - 0.23 | 0.00 - 0.28 | 0.00 - 0.09 | 0.00 - 0.18 | 0.00 - 0.21 | 0.00 - 0.16 | 0.00 - 0.17 |
| | h (m) | 1.5 - 39.0 | 3.2 - 31.0 | 1.8 - 39.6 | 1.5 - 30.5 | 0.2 - 42.0 | 2.5 - 41.0 | 2.0 - 35.4 | 1.3 - 41.8 | 2.1 - 34.0 | 1.6 - 35.0 | 2.9 - 33.0 |
| | CR | 0.07 - 0.92 | 0.10 - 0.64 | 0.05 - 0.91 | 0.05 - 0.86 | 0.00 - 0.94 | 0.00 - 0.94 | 0.13 - 0.94 | 0.08 - 0.98 | 0.02 - 0.93 | 0.07 - 0.99 | 0.15 - 0.72 |
| | BAL (m$^2$ha$^{-1}$) | 0.0 - 87.5 | 0.0 - 113.7 | 0.0 - 61.9 | 4.6 - 68.1 | 0.0 - 68.1 | 0.0 - 61.8 | 0.0 - 56.9 | 0.0 - 86.3 | 0.0 - 65.3 | 0.0 - 66.6 | 1.3 - 50.9 |
| | relBAL | 0.0 - 1.0 | 0.0 - 1.0 | 0.0 - 1.0 | 0.1 - 1.0 | 0.0 - 1.0 | 0.0 - 1.0 | 0.0 - 1.0 | 0.0 - 1.0 | 0.0 - 1.0 | 0.0 - 1.0 | 0.0 - 1.0 |
| Stand | mDBH (cm) | 10.0 - 38.9 | 10.6 - 31.4 | 7.1 - 37.3 | 10.6 - 39.4 | 10.0 - 53.0 | 8.7 - 37.4 | 12.8 - 31.5 | 10.0 - 45.2 | 7.1 - 28.8 | 12.3 - 39.4 | 8.7 - 34.5 |
| | qmDBH (cm) | 14.6 - 47.6 | 11.7 - 38.8 | 7.6 - 41.8 | 11.5 - 42.8 | 11.5 - 54.9 | 10.1 - 43.7 | 14.6 - 35.7 | 11.5 - 47.6 | 7.6 - 31.6 | 14.0 - 42.8 | 11.1 - 36.9 |
| | CVd | 0.33 - 1.21 | 0.21 - 1.14 | 0.38 - 0.99 | 0.34 - 0.99 | 0.16 - 1.21 | 0.33 - 1.14 | 0.38 - 0.73 | 0.27 - 1.21 | 0.31 - 0.87 | 0.39 - 0.99 | 0.38 - 0.99 |
| | hdom (m) | 12.5 - 37.0 | 18.3 - 28.5 | 7.2 - 31.7 | 18.5 - 30.8 | 13.4 - 37.0 | 9.9 - 33.7 | 12.5 - 29.9 | 11.2 - 37.0 | 7.3 - 31.1 | 12.3 - 35.0 | 10.9 - 33.7 |
| | BA (m$^2$ha$^{-1}$) | 28.6 - 87.5 | 27.0 - 119.0 | 4.9 - 68.1 | 24.1 - 68.1 | 13.8 - 68.1 | 13.6 - 61.9 | 24.3 - 57.7 | 13.9 - 87.5 | 8.2 - 68.1 | 25.2 - 68.1 | 24.1 - 55.0 |
| | N (ha$^{-1}$) | 367 - 2780 | 282 - 4000 | 258 - 2333 | 204 - 2333 | 78 - 2780 | 253 - 3281 | 482 - 1902 | 201 - 2780 | 312 - 2500 | 244 - 2595 | 367 - 3281 |
| | PBA | | | 0.00 - 0.86 | | | | | 0.00 - 1.00 | 0.01 - 1.00 | | |
| Site | LAT (°) | 46.3 - 47.5 | 46.4 - 47.5 | 46.3 - 53.2 | 46.4 - 53.7 | 46.4 - 53.7 | 46.1 - 52.9 | 46.3 - 46.7 | 46.3 - 52.9 | 46.1 - 53.2 | 46.4 - 53.7 | 46.1 - 47.8 |
| | ELV (m) | 459 - 1560 | 334 - 564 | 24 - 599 | 4 - 632 | 4 - 1227 | 54 - 889 | 1441 - 2094 | 54 - 2034 | 83 - 1954 | 4 - 760 | 367 - 839 |
| | GDD | 903 - 2099 | 1822 - 2297 | 1654 - 2243 | 1443 - 2162 | 1169 - 2162 | 1552 - 2302 | 422 - 1019 | 465 - 2162 | 590 - 2243 | 1613 - 2162 | 1552 - 2162 |
| | SI50 (m) | | | | | | | | 4.0 - 25.0 | 2.0 - 29.0 | | |

**Table S3.** Mortality models, related species and the model characteristics used to explain achieved model performance. For each model, the calibration species or species group and the validation species are given. The information 'predicted status', 'type' of logistic regression and $\Delta t$ are required to apply the mortality models (cf. Supplement S2). The characteristics 'growth', 'competition stand', 'competition tree', 'ecological zone', 'management intensity', 'census interval' and $N_{cal}$ were used in the linear mixed-effects models to explain differences in $p_{bias}$ and $AUC$.

| Publication | Calibration species | Validation species | Predicted status | Type | $\Delta t$ | Growth | Competition stand | Competition tree | Ecological zone | Management intensity | Census interval calibration | $N_{cal}$ ($N_{dead}$) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Alenius et al. (2003) | *Pinus sylvestris* | *Pinus sylvestris* | mortality | II | 5 | no | yes | yes | Northern | managed | 5 | 17 293 (372) |
| Bravo-Oviedo et al. (2006) | *Pinus sylvestris* | *Pinus sylvestris* | survival | II | 5 | no | no | yes | Mediterranean | unmanaged | 5 | 14 197 (360) |
| Crecente-Campo et al. (2010) | *Pinus sylvestris* | *Pinus sylvestris* | survival | I | 1 | no | no | yes | Mediterranean | managed | 7 | 5447 (475) |
| Dursky (1997) | *Fagus sylvatica* | *Fagus sylvatica* | survival | II | 7 | yes | no | no | Central | unmanaged | 7.5 | 526 (263) |
| Dursky (1997) | *Picea abies* | *Picea abies* | survival | II | 5 | yes | no | no | Central | unmanaged | 5.5 | 4764 (2382) |
| Eid and Tuhus (2001) | *Betula spec.* | *Betula spec.* | survival | II | 1 | no | no | no | Northern | managed | 12 | 15 650 (706) |
| Eid and Tuhus (2001) | Broadleaf Other | *Quercus spec.* | survival | II | 1 | no | no | yes | Northern | managed | 12 | 5405 (565) |
| Eid and Tuhus (2001) | *Picea abies* | *Picea abies* | survival | II | 1 | no | no | yes | Northern | managed | 12 | 17 250 (461) |
| Eid and Tuhus (2001) | *Pinus sylvestris* | *Pinus sylvestris* | survival | II | 1 | no | no | yes | Northern | managed | 12 | 7802 (179) |
| Fridman and Ståhl (2001) | *Betula spec.* | *Betula spec.* | mortality | II | 5 | no | yes | yes | Northern | managed | 5 | 12 196 (935) |
| Fridman and Ståhl (2001) | Broadleaf Other | *Alnus glutinosa* | mortality | II | 5 | no | yes | yes | Northern | managed | 5 | 4226 (464) |
| Fridman and Ståhl (2001) | Broadleaf Southern | *Fagus sylvatica, Quercus spec.* | mortality | II | 5 | no | yes | yes | Northern | managed | 5 | 1183 (54) |
| Fridman and Ståhl (2001) | *Picea abies* | *Picea abies* | mortality | II | 5 | no | yes | yes | Northern | managed | 5 | 34 403 (1565) |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | *Pinus sylvestris* | mortality | II | 5 | no | yes | yes | Northern | managed | 5 | 19 812 (1202) |
| Holzwarth et al. (2013) | *Carpinus betulus* | *Carpinus betulus* | mortality | II | 1 | no | no | no | Central | unmanaged | 8 | 391 (30) |
| Holzwarth et al. (2013) | *Fagus sylvatica* | *Fagus sylvatica* | mortality | II | 1 | yes | no | no | Central | unmanaged | 8 | 13 297 (1535) |
| Holzwarth et al. (2013) | *Fraxinus excelsior* | *Fraxinus excelsior* | mortality | II | 1 | no | no | no | Central | unmanaged | 8 | 564 (39) |
| Monserud and Sterba (1999) | *Abies alba* | *Abies alba* | mortality | I | 5 | no | no | no | Alpine | managed | 5 | 1878 (115) |
| Monserud and Sterba (1999) | Broadleaf Other | *Alnus glutinosa, Betula spec., Carpinus betulus, Fraxinus excelsior* | mortality | I | 5 | no | no | yes | Alpine | managed | 5 | 2617 (209) |
| Monserud and Sterba (1999) | *Fagus sylvatica* | *Fagus sylvatica* | mortality | I | 5 | no | no | yes | Alpine | managed | 5 | 4484 (193) |
| Monserud and Sterba (1999) | *Larix decidua* | *Larix decidua* | mortality | I | 5 | no | no | yes | Alpine | managed | 5 | 3015 (87) |
| Monserud and Sterba (1999) | *Picea abies* | *Picea abies* | mortality | I | 5 | no | no | yes | Alpine | managed | 5 | 26 699 (1175) |
| Monserud and Sterba (1999) | *Pinus sylvestris* | *Pinus sylvestris* | mortality | I | 5 | no | no | yes | Alpine | managed | 5 | 4138 (178) |
| Monserud and Sterba (1999) | *Quercus spec.* | *Quercus spec.* | mortality | I | 5 | no | no | no | Alpine | managed | 5 | 784 (25) |
| Palahí et al. (2003) 2 | *Pinus sylvestris* | *Pinus sylvestris* | survival | II | 5 | yes | no | yes | Mediterranean | managed | 5 | 11 110 (267) |
| Trasobares et al. (2004) | *Pinus sylvestris* | *Pinus sylvestris* | survival | II | 10 | no | no | yes | Mediterranean | managed | 10 | 7823 (313) |
| Wunder et al. (2007) 1 | *Abies alba* | *Abies alba* | survival | II | 13 | yes | no | no | Alpine | unmanaged | 13 | 251 (14) |

| Publication | Calibration species | Validation species | Predicted status | Type | $\Delta t$ | Growth | Competition stand | Competition tree | Ecological zone | Management intensity | Census interval calibration | $N_{cal}$ ($N_{dead}$) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wunder et al. (2007) 1 | *Fagus sylvatica* | *Fagus sylvatica* | survival | II | 13 | yes | no | no | Alpine | unmanaged | 13 | 634 (30) |
| Wunder et al. (2007) 2 | *Abies alba* | *Abies alba* | survival | II | 12 | yes | no | no | Alpine | unmanaged | 12.5 | 527 (50) |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | *Fagus sylvatica* | survival | II | 12 | yes | no | no | Alpine | unmanaged | 12.5 | 654 (7) |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | *Betula spec.* | survival | II | 10 | yes | no | no | Eastern | unmanaged | 10 | 463 (145) |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | *Alnus glutinosa* | survival | II | 10 | yes | no | no | Eastern | unmanaged | 10 | 227 (26) |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | *Carpinus betulus* | survival | II | 10 | yes | no | no | Eastern | unmanaged | 10 | 802 (74) |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | *Fraxinus excelsior* | survival | II | 10 | yes | no | no | Eastern | unmanaged | 10 | 320 (23) |
| Wunder et al. (2008a) 1 | *Picea abies* | *Picea abies* | survival | II | 10 | yes | no | no | Eastern | unmanaged | 10 | 2253 (672) |
| Wunder et al. (2008a) 1 | *Quercus robur* | *Quercus spec.* | survival | II | 10 | yes | no | no | Eastern | unmanaged | 10 | 322 (52) |
| Wunder et al. (2008a) 1 | *Tilia cordata* | *Tilia cordata* | survival | II | 10 | yes | no | no | Eastern | unmanaged | 10 | 1024 (123) |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | *Alnus glutinosa* | survival | II | 10 | yes | no | no | Alpine | unmanaged | 10 | 278 (24) |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | *Carpinus betulus* | survival | II | 10 | yes | no | no | Alpine | unmanaged | 10 | 219 (52) |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | *Fagus sylvatica* | survival | II | 10 | yes | no | no | Alpine | unmanaged | 10 | 1999 (243) |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | *Fraxinus excelsior* | survival | II | 10 | yes | no | no | Alpine | unmanaged | 10 | 404 (83) |
| Wunder et al. (2008a) 2 | *Quercus robur* | *Quercus spec.* | survival | II | 10 | yes | no | no | Alpine | unmanaged | 10 | 1149 (141) |
| Wunder et al. (2008a) 2 | *Tilia cordata* | *Tilia cordata* | survival | II | 10 | yes | no | no | Alpine | unmanaged | 10 | 321 (24) |
| Wunder et al. (unpubl.) | high shade tolerance | *Abies alba, Carpinus betulus, Fagus sylvatica* | survival | II | 11 | yes | no | no | Alpine | unmanaged | 11 | 902 (33) |
| Wunder et al. (unpubl.) | intermediate shade tolerance | *Alnus glutinosa, Fraxinus excelsior, Picea abies, Tilia cordata* | survival | II | 11 | yes | no | no | Alpine | unmanaged | 11 | 1965 (93) |
| Wunder et al. (unpubl.) | low shade tolerance | *Betula spec., Larix decidua, Pinus sylvestris, Quercus spec.* | survival | II | 11 | yes | no | no | Alpine | unmanaged | 11 | 1448 (102) |

**Supplement S2.** Extended material and methods

In the following, we describe the tree, stand and site characteristics that were used to explain the tree status (dead or alive) in the third inventory (cf. Table 2). Herein, tree growth was derived for the interval between the first and the second inventory. All other tree and stand characteristics were calculated based on data from the second inventory.

**Tree characteristics**

Besides *DBH* as a measure for tree size, the annual increment of the diameter (*DI*) and of the basal area (*BAI*) were calculated to account for tree growth. In addition, a diameter-independent growth variable of *BAI* was derived, i.e. annual relative basal area increment (*relBAI*, cf. Wunder et al. 2008a). Tree height (*h*) has been measured only for 17.7 % of the records. For the remaining, *h* was derived based on species- and site-specific allometric height curves (where possible, separately for each inventory year) as a function of *DBH* following Michailoff (1943). Crown ratio (*CR*) defined as the proportion of the crown length to *h* was not deduced from *DBH* and/or *h* since it reflects not only the dimensions of a tree but also its vitality state. Thus, *CR* was only available for 12.9 % of all records. As a measure of one-sided competition (Cannell et al. 1984), the basal area of larger trees than the subject tree (*BAL*) and its relative counterpart *relBAL* being the share of *BAL* of the stand basal area (*BA*) were calculated. Spatially explicit competition indices could not be calculated because tree coordinates were only available for a subset of the reserves.

**Stand characteristics**

For *DBH*, two averages were calculated per permanent plot: the arithmetic (*mDBH*) and the quadratic mean (*qmDBH*, cf. Curtis and Marshall 2000). As a measure of variance of the diameter distribution, the coefficient of variance was calculated using *CVd* = *sdDBH* / *mDBH* with *sdDBH* being the standard deviation of *DBH* (Bravo-Oviedo et al. 2006). Dominant height (*hdom*) was determined as the mean height of the hundred largest trees per hectare. Furthermore, basal area (*BA*) and the number of trees per hectare (*N*) were calculated. Species composition (*PBA*) was calculated as the percentage of the basal area of the subject species (i.e. *Betula*, *Picea* and *Pinus*) of the total stand *BA*.

**Site characteristics**

The geographical location of the permanents plots was described by their latitude (*LAT*) and elevation (*ELV*). The latter was taken from digital elevation models (DEM25m) provided by the State Agency for Spatial Information and Land Surveying of Lower Saxony (Landesamt für Geoinformation und Landesvermessung Niedersachsen LGLN) and the Swiss Federal Office of Topography (Swisstopo) for German and Swiss reserves, respectively. Since linear distance to the Mediterranean Sea as a measure of continentality (*CON*, cf. Trasobares et al. 2004) is not meaningful for our data as it would result in severe extrapolation, we used the maximum value of *CON* = 186.6 km in the calibration dataset for all reserves. Mean growing degree-days (*GDD*) for the period between the first and second inventory were calculated based on interpolated annual temperature data following Baskerville and Emin (1969) using R code available online (http://geog.uoregon.edu/envchange/software/ GDD_calculator.txt). For the German reserves, temperature data from climate stations of the German Weather Service were interpolated following the WaSiM-ETH protocol (http://www.wasim.ch/downloads/doku/wasim/

interpolation_meteodata_2009_en.pdf). For the Swiss reserves, temperature data were derived following Rasche et al. (2012) based on the DAYMET model (Thornton et al. 1997; available from Landscape Dynamics, WSL). The variable *moist* indicating moist or wet conditions (Fridman and Ståhl 2001), which was only required for *Pinus* (cf. Supplement S3), was set to 0 for all relevant stands since the German reserve 'Ehrhorner Dünen' is dominated by dry conditions and none of the relevant Swiss permanent plots belongs to a moist or wet plant sociological association (Ellenberg and Klötzli 1972). The site index (*SI*) for *Picea* and *Pinus* in Switzerland was derived from the topographical position, the exposition (both based on DEM25m) and large ecological regions following Keller (1978). Resulting dominant height at the age of 50 years was scaled to the age of 40 and 100 using yield tables by Badoux (1983) and the Landesforstanstalt Eberswalde (2000) for *Picea* and *Pinus*, respectively. For Germany, no such eco-topographic information on the growing conditions is available but *SI* was derived using estimates of tree age and Lorey's mean height of the respective species in the inventory data by applying suitable yield tables (Landesforstanstalt Eberswalde 2000 for *Pinus*; Schober 1995 for *Picea*). For all covariates associated with clear cut or other forest interventions (cf. Supplement S3), no management in the reserves was assumed.

**Model application**

Mortality model *j* calibrated to data of species *k* was used to predict the mortality probability *p* of tree *i* of the same species following

$$p_{i,j,k} = logit^{-1}(X_i\beta_{j,k}) = \frac{\exp(X_i\beta_{j,k})}{1 + \exp(X_i\beta_{j,k})} = \frac{1}{1 + \exp(-X_i\beta_{j,k})}$$

with $X_i$ denoting the design matrix of the linear predictor and $\beta_{j,k}$ the respective parameter vector. Herein, *k* can also be a group of species when the model was calibrated, e.g. to a set of broadleaf species (Table S3). Since some models predict survival rather than mortality and in addition, the formulation of the logistic model was not always the same, and the equation above was modified respectively:

| Model structure | prediction of mortality | prediction of survival |
|---|---|---|
| Type I | $\frac{1}{1 + \exp(X_i\beta_{j,k})}$ | $\frac{1}{1 + exp(-X_i\beta_{j,k})}$ |
| Type II | $\frac{1}{1 + \exp(-X_i\beta_{j,k})}$ | $\frac{1}{1 + exp(X_i\beta_{j,k})}$ |

However, the proposed mortality models predict the status of the tree for unequal intervals $\Delta t_j$ (cf. Table S3). Therefore, the mortality probability valid for $\Delta t_j$ was rescaled to the census interval ($\Delta t$) of the respective permanent plot using

$$p_{i,j,k,\Delta t} = 1 - \left(1 - p_{i,j,k,\Delta t_j}\right)^{\frac{\Delta t}{\Delta t_j}}$$

**Prediction bias**

To quantify the degree of prediction accuracy (correct mortality rates), we defined prediction bias ($p_{bias}$) as the absolute difference of the mean predicted mortality probability ('simulated mortality') $\overline{p}_{\Delta t}$ and the mean mortality rate ('observed mortality') $\overline{y}_{\Delta t}$ over $\Delta t = 1$ year. To this end, the 'simulated mortality' $\overline{p}_{\Delta t} = \sum p_{i,\Delta t}/n$ and the 'observed mortality' $\overline{y}_{\Delta t} = \sum y_i/n$ were averaged for observations and predictions with the same cencus interval $\Delta t$. To render the values comparable, mean simulated and observed mortality rates were re-scaled to 1 year. Taking the example of the 'simulated mortality', this can be formulated as

$$\overline{p}_{\Delta t=1} = 1 - \left(1 - \overline{p}_{\Delta t}\right)^{\frac{1}{\Delta t}}$$

**Supplement S3.** Table of coefficients for the validated mortality models. For an explanation of the covariates refer to Table 1 and Supplement S2. Coefficients apply not only to individual tree, stand or site characteristics but also to their transformations or to interactions of two or more covariates (e.g. *relBAL\*H00\**sqrt*N*/100). Where necessary, annual growth was scaled to the interval that was used for model development using either linear or exponential scaling for absolute (*DI*, *BAI*) and relative growth increments (*relBAI*), respectively.

| Publication | Calibration species | Covariate | Coefficient | Unit | Remarks |
|---|---|---|---|---|---|
| Alenius et al. (2003) 1 | *Pinus sylvestris* | INTERCEPT | -5.719 | - | |
| Alenius et al. (2003) 1 | *Pinus sylvestris* | relBAL | 2.091 | - | |
| Alenius et al. (2003) 1 | *Pinus sylvestris* | 1-PBA | 2.133 | - | *1-PBA* refers to the proportion of birch in mixed pine-birch |
| Alenius et al. (2003) 1 | *Pinus sylvestris* | qmDBH | -0.128 | cm | forests, other than stated in the publication, the coefficient |
| Alenius et al. (2003) 1 | *Pinus sylvestris* | BA | 0.111 | m^2/ha | appears to be valid for the percentage between 0 and 1 not in % |
| Alenius et al. (2003) 1 | *Pinus sylvestris* | 1/DBH | 30.884 | mm | |
| Bravo-Oviedo et al. (2006) | *Pinus sylvestris* | INTERCEPT | 6.8548 | - | |
| Bravo-Oviedo et al. (2006) | *Pinus sylvestris* | BAL*CVd | -0.121 | m^2/ha | |
| Bravo-Oviedo et al. (2006) | *Pinus sylvestris* | SI | -0.037 | m | *SI* refers to the dominant height at the age of 100 years |
| Bravo-Oviedo et al. (2006) | *Pinus sylvestris* | 1/DBH | -9.792 | cm | |
| Crecente-Campo et al. (2010) | *Pinus sylvestris* | INTERCEPT | -2.903 | - | |
| Crecente-Campo et al. (2010) | *Pinus sylvestris* | relBAL*hdom*sqrtN/100 | 0.4687 | m/ha | |
| Crecente-Campo et al. (2010) | *Pinus sylvestris* | relBAL | -3.214 | - | |
| Crecente-Campo et al. (2010) | *Pinus sylvestris* | qmDBH | 0.3007 | cm | |
| Crecente-Campo et al. (2010) | *Pinus sylvestris* | DBH | -0.4087 | cm | |
| Dursky (1997) | *Fagus sylvatica* | INTERCEPT | 6.6686 | - | |
| Dursky (1997) | *Fagus sylvatica* | h/DBH | -7.6495 | m/cm | |
| Dursky (1997) | *Fagus sylvatica* | DBH | -0.261 | cm | *BAI* was defined as the basal area increment over 5 years |
| Dursky (1997) | *Fagus sylvatica* | h | 0.2695 | m | |
| Dursky (1997) | *Fagus sylvatica* | BAI/DBH | 3.0796 | cm^2/a/cm | |
| Dursky (1997) | *Picea abies* | INTERCEPT | 5.3908 | - | |
| Dursky (1997) | *Picea abies* | h/DBH | -5.3998 | m/cm | *SI* refers to the dominant height at the age of 50 years |
| Dursky (1997) | *Picea abies* | SI | -0.0406 | m | |
| Dursky (1997) | *Picea abies* | DBH | -0.0089 | cm | *BAI* was defined as the basal area increment over 5 years |
| Dursky (1997) | *Picea abies* | BAI/DBH | 1.4802 | cm^2/a/cm | |
| Eid and Tuhus (2001) | *Betula spec.* | INTERCEPT | 4.8923 | - | |
| Eid and Tuhus (2001) | *Betula spec.* | 1/DBH | -2.528 | cm | |
| Eid and Tuhus (2001) | Broadleaf Other | INTERCEPT | 5.1575 | - | |
| Eid and Tuhus (2001) | Broadleaf Other | BAL | -0.0199 | m^2/ha | |
| Eid and Tuhus (2001) | Broadleaf Other | 1/DBH | -7.3544 | cm | |
| Eid and Tuhus (2001) | *Picea abies* | INTERCEPT | 8.0599 | - | |
| Eid and Tuhus (2001) | *Picea abies* | BAL | -0.0281 | m^2/ha | |
| Eid and Tuhus (2001) | *Picea abies* | PBA | -0.0132 | % | *SI* refers to the dominant height at the age of 40 years |
| Eid and Tuhus (2001) | *Picea abies* | SI | -0.0264 | m | |
| Eid and Tuhus (2001) | *Picea abies* | 1/DBH | -6.702 | cm | |
| Eid and Tuhus (2001) | *Pinus sylvestris* | INTERCEPT | 8.4904 | - | |
| Eid and Tuhus (2001) | *Pinus sylvestris* | BAL | -0.0462 | m^2/ha | |
| Eid and Tuhus (2001) | *Pinus sylvestris* | SI | -0.0761 | m | *SI* refers to the dominant height at the age of 40 years |
| Eid and Tuhus (2001) | *Pinus sylvestris* | 1/DBH | -14.266 | cm | |

| Publication | Calibration species | Covariate | Coefficient | Unit | Remarks |
|---|---|---|---|---|---|
| Fridman and Ståhl (2001) | *Betula spec.* | INTERCEPT | -2.83 | - | |
| Fridman and Ståhl (2001) | *Betula spec.* | BAL | 0.0362 | m^2/ha | |
| Fridman and Ståhl (2001) | *Betula spec.* | mDBH | 15.7 | m | |
| Fridman and Ståhl (2001) | *Betula spec.* | BA | -0.0665 | m^2/ha | |
| Fridman and Ståhl (2001) | *Betula spec.* | ELV | 0.0011 | m | |
| Fridman and Ståhl (2001) | *Betula spec.* | DBH | -16.5 | m | |
| Fridman and Ståhl (2001) | *Betula spec.* | DBH^2 | 27.7 | m | |
| Fridman and Ståhl (2001) | Broadleaf Other | INTERCEPT | -5.4 | - | |
| Fridman and Ståhl (2001) | Broadleaf Other | BAL | 0.0693 | m^2/ha | |
| Fridman and Ståhl (2001) | Broadleaf Other | BA | -0.0688 | m^2/ha | the categorical variable '≤20m clearcut' was set to 0 for all |
| Fridman and Ståhl (2001) | Broadleaf Other | ELV | 0.00212 | m | observations since no management in the reserves was assumed |
| Fridman and Ståhl (2001) | Broadleaf Other | LAT | 0.0498 | degree | |
| Fridman and Ståhl (2001) | Broadleaf Other | <20m clearcut | -0.345 | - | |
| Fridman and Ståhl (2001) | Broadleaf Other | 1/DBH | 0.0634 | m | |
| Fridman and Ståhl (2001) | Broadleaf Southern | INTERCEPT | -3.67 | - | |
| Fridman and Ståhl (2001) | Broadleaf Southern | BAL | 0.168 | m^2/ha | |
| Fridman and Ståhl (2001) | Broadleaf Southern | BA | -0.14 | m^2/ha | |
| Fridman and Ståhl (2001) | Broadleaf Southern | DBH | 3.34 | m | |
| Fridman and Ståhl (2001) | *Picea abies* | INTERCEPT | -4.58 | - | |
| Fridman and Ståhl (2001) | *Picea abies* | BAL | 0.0282 | m^2/ha | |
| Fridman and Ståhl (2001) | *Picea abies* | PIDOM | -0.594 | - | the categorical variable *PIDOM* quantifies the domination of |
| Fridman and Ståhl (2001) | *Picea abies* | mDBH | 11.2 | m | *Pinus* with 1 indicating *PBA* of *Pinus* ≥ 0.7. |
| Fridman and Ståhl (2001) | *Picea abies* | BA | -0.0545 | m^2/ha | |
| Fridman and Ståhl (2001) | *Picea abies* | <20m clearcut | 0.577 | - | the categorical variable '≤20m clearcut' was set to 0 for all |
| Fridman and Ståhl (2001) | *Picea abies* | management | 0.323 | - | observations since no management in the reserves was assumed |
| Fridman and Ståhl (2001) | *Picea abies* | 1/DBH | 0.042 | m | |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | INTERCEPT | -1.98 | - | |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | BAL | 0.028 | m^2/ha | the categorical variable *PIDOM* quantifies the domination of |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | PIDOM | -0.456 | - | *Pinus* with 1 indicating *PBA* of *Pinus* ≥ 0.7. |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | mDBH | 25.6 | m | |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | mDBH^2 | -26.6 | m | the mean of the squared DBH (*mDBH^2*) is approximately equal |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | log(BA) | -0.739 | m^2/ha | to *(qmDBH)^2* |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | moist | 0.327 | - | |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | DBH | -17.4 | m | the categorical variable *moist* quantifies soil water conditions |
| Fridman and Ståhl (2001) | *Pinus sylvestris* | DBH^2 | 21.5 | m | with 1 indicating moist or wet |
| Holzwarth et al. (2013) | *Carpinus betulus* | INTERCEPT | -2.8 | - | in communication with the authors, both coefficients were |
| Holzwarth et al. (2013) | *Carpinus betulus* | DBH | -0.051 | cm | corrected and thus are different from the original paper |
| Holzwarth et al. (2013) | *Fagus sylvatica* | INTERCEPT | 1.8 | - | |
| Holzwarth et al. (2013) | *Fagus sylvatica* | log(DBH) | -2.1 | cm | |
| Holzwarth et al. (2013) | *Fagus sylvatica* | DI | -1.4 | cm/a | two models for 'early' and 'late' mortality were fitted that add |
| Holzwarth et al. (2013) | *Fagus sylvatica* | INTERCEPT | -8.9 | - | up to the total mortality |
| Holzwarth et al. (2013) | *Fagus sylvatica* | DBH | 0.052 | cm | |
| Holzwarth et al. (2013) | *Fagus sylvatica* | log(DBH) | 0 | cm | for log-transformed *DBH*, an additive constant of 8 cm was used |
| Holzwarth et al. (2013) | *Fagus sylvatica* | DI | 0 | cm/a | |
| Holzwarth et al. (2013) | *Fraxinus excelsior* | INTERCEPT | 1.3 | - | |
| Holzwarth et al. (2013) | *Fraxinus excelsior* | log(DBH) | -1.6 | cm | |

| Publication | Calibration species | Covariate | Coefficient | Unit | Remarks |
|---|---|---|---|---|---|
| Monserud and Sterba (1999) | *Abies alba* | INTERCEPT | 2.0985 | - | |
| Monserud and Sterba (1999) | *Abies alba* | 1/DBH | -10.9085 | cm | |
| Monserud and Sterba (1999) | *Abies alba* | CR | 3.9311 | - | |
| Monserud and Sterba (1999) | Broadleaf Other | INTERCEPT | 2.9223 | - | |
| Monserud and Sterba (1999) | Broadleaf Other | BAL | -0.0228 | m^2/ha | |
| Monserud and Sterba (1999) | Broadleaf Other | 1/DBH | -8.4877 | cm | |
| Monserud and Sterba (1999) | Broadleaf Other | CR | 2.0609 | - | |
| Monserud and Sterba (1999) | *Fagus sylvatica* | INTERCEPT | 3.5734 | - | |
| Monserud and Sterba (1999) | *Fagus sylvatica* | BAL | -0.0161 | m^2/ha | |
| Monserud and Sterba (1999) | *Fagus sylvatica* | 1/DBH | -13.9542 | cm | |
| Monserud and Sterba (1999) | *Fagus sylvatica* | CR | 3.1339 | - | |
| Monserud and Sterba (1999) | *Larix decidua* | INTERCEPT | 4.407 | - | |
| Monserud and Sterba (1999) | *Larix decidua* | BAL | -0.0326 | m^2/ha | |
| Monserud and Sterba (1999) | *Larix decidua* | 1/DBH | -12.9395 | cm | |
| Monserud and Sterba (1999) | *Larix decidua* | CR | 2.2039 | - | |
| Monserud and Sterba (1999) | *Picea abies* | INTERCEPT | 2.1283 | - | |
| Monserud and Sterba (1999) | *Picea abies* | BAL | -0.0186 | m^2/ha | |
| Monserud and Sterba (1999) | *Picea abies* | 1/DBH | -10.0745 | cm | |
| Monserud and Sterba (1999) | *Picea abies* | DBH | 0.0425 | cm | |
| Monserud and Sterba (1999) | *Picea abies* | DBH^2 | -0.00081 | cm | |
| Monserud and Sterba (1999) | *Picea abies* | CR | 3.8251 | - | |
| Monserud and Sterba (1999) | *Pinus sylvestris* | INTERCEPT | 4.1076 | - | |
| Monserud and Sterba (1999) | *Pinus sylvestris* | BAL | -0.0234 | m^2/ha | |
| Monserud and Sterba (1999) | *Pinus sylvestris* | 1/DBH | -18.9714 | cm | |
| Monserud and Sterba (1999) | *Pinus sylvestris* | CR | 2.3267 | - | |
| Monserud and Sterba (1999) | *Quercus spec.* | INTERCEPT | 4.4508 | - | |
| Monserud and Sterba (1999) | *Quercus spec.* | 1/DBH | -12.0041 | cm | |
| Palahí et al. (2003) 2 | *Pinus sylvestris* | INTERCEPT | 2.938 | - | |
| Palahí et al. (2003) 2 | *Pinus sylvestris* | BAL | -0.02 | m^2/ha | *DI* was defined as the diameter increment over 5 years |
| Palahí et al. (2003) 2 | *Pinus sylvestris* | DI | 2.719 | cm/a | |
| Trasobares et al. (2004) | *Pinus sylvestris* | INTERCEPT | 2.728 | - | |
| Trasobares et al. (2004) | *Pinus sylvestris* | BAL/log(DBH) | -0.148 | m^2/ha/cm | for log-transformed *DBH*, an additive constant of 1 cm was used |
| Trasobares et al. (2004) | *Pinus sylvestris* | ELV | 0.067 | 100m | |
| Trasobares et al. (2004) | *Pinus sylvestris* | CON | -0.006 | km | the covariate *CON* that quantifies continentality was set to the |
| Trasobares et al. (2004) | *Pinus sylvestris* | h | 0.107 | m | maximum value within the calibration dataset = 186.6 km |
| Wunder et al. (2007) 1 | *Abies alba* | INTERCEPT | 1.161 | - | |
| Wunder et al. (2007) 1 | *Abies alba* | relBAI | 29.17 | 1/a | for coefficients and details on the construction of the restricted |
| Wunder et al. (2007) 1 | *Abies alba* | relBAI1 | -518.37 | 1/a | cubic splines of *relBAI* refer also to Wunder (2007) |
| Wunder et al. (2007) 1 | *Abies alba* | relBAI2 | 1038.53 | 1/a | |
| Wunder et al. (2007) 1 | *Abies alba* | relBAI3 | -505.01 | 1/a | *relBAI1-4* refer to the coefficients, *KrelBAI1-4* mark the |
| Wunder et al. (2007) 1 | *Abies alba* | relBAI4 | -15.15 | 1/a | locations of the knots of the restricted cubic splines |
| Wunder et al. (2007) 1 | *Abies alba* | KrelBAI1 | 0.02 | 1/a | |
| Wunder et al. (2007) 1 | *Abies alba* | KrelBAI2 | 0.104 | 1/a | *relBAI* was defined as the relative basal area increment over 11 |
| Wunder et al. (2007) 1 | *Abies alba* | KrelBAI3 | 0.181 | 1/a | years |
| Wunder et al. (2007) 1 | *Abies alba* | KrelBAI4 | 0.395 | 1/a | |

| Publication | Calibration species | Covariate | Coefficient | Unit | Remarks |
|---|---|---|---|---|---|
| Wunder et al. (2007) 1 | *Fagus sylvatica* | INTERCEPT | -17.63 | - | |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | log(DBH) | 3.57 | mm | |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | relBAI | 29.17 | 1/a | for coefficients and details on the construction of the restricted cubic splines of *relBAI* refer also to Wunder (2007) |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | relBAI1 | -518.37 | 1/a | |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | relBAI2 | 1038.53 | 1/a | |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | relBAI3 | -505.01 | 1/a | *relBAI1-4* refer to the coefficients, *KrelBAI1-4* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | relBAI4 | -15.15 | 1/a | |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | KrelBAI1 | 0.02 | 1/a | *relBAI* was defined as the relative basal area increment over 11 years |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | KrelBAI2 | 0.104 | 1/a | |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | KrelBAI3 | 0.181 | 1/a | |
| Wunder et al. (2007) 1 | *Fagus sylvatica* | KrelBAI4 | 0.395 | 1/a | |
| Wunder et al. (2007) 2 | *Abies alba* | INTERCEPT | -0.4 | - | |
| Wunder et al. (2007) 2 | *Abies alba* | relBAI | 29.17 | 1/a | for coefficients and details on the construction of the restricted cubic splines of *relBAI* refer also to Wunder (2007) |
| Wunder et al. (2007) 2 | *Abies alba* | relBAI1 | -518.37 | 1/a | |
| Wunder et al. (2007) 2 | *Abies alba* | relBAI2 | 1038.53 | 1/a | |
| Wunder et al. (2007) 2 | *Abies alba* | relBAI3 | -505.01 | 1/a | *relBAI1-4* refer to the coefficients, *KrelBAI1-4* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2007) 2 | *Abies alba* | relBAI4 | -15.15 | 1/a | |
| Wunder et al. (2007) 2 | *Abies alba* | KrelBAI1 | 0.02 | 1/a | *relBAI* was defined as the relative basal area increment over 12.5 years |
| Wunder et al. (2007) 2 | *Abies alba* | KrelBAI2 | 0.104 | 1/a | |
| Wunder et al. (2007) 2 | *Abies alba* | KrelBAI3 | 0.181 | 1/a | |
| Wunder et al. (2007) 2 | *Abies alba* | KrelBAI4 | 0.395 | 1/a | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | INTERCEPT | -16.86 | - | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | log(DBH) | 3.57 | mm | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | relBAI | 29.17 | 1/a | for coefficients and details on the construction of the restricted cubic splines of *relBAI* refer also to Wunder (2007) |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | relBAI1 | -518.37 | 1/a | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | relBAI2 | 1038.53 | 1/a | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | relBAI3 | -505.01 | 1/a | *relBAI1-4* refer to the coefficients, *KrelBAI1-4* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | relBAI4 | -15.15 | 1/a | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | KrelBAI1 | 0.02 | 1/a | *relBAI* was defined as the relative basal area increment over 12.5 years |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | KrelBAI2 | 0.104 | 1/a | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | KrelBAI3 | 0.181 | 1/a | |
| Wunder et al. (2007) 2 | *Fagus sylvatica* | KrelBAI4 | 0.395 | 1/a | |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | INTERCEPT | 0.958 | - | |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | log(DBH) | 1.105 | cm | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | log(relBAI) | 1.217 | 1/a | |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | log(relBAI)1 | -0.092 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | log(relBAI)2 | 0.22 | 1/a | |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | log(relBAI)3 | -0.128 | 1/a | |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | KrelBAI1 | -4.8459 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | KrelBAI2 | -3.8672 | 1/a | |
| Wunder et al. (2008a) 1 | *Alnus glutinosa* | KrelBAI3 | -3.16568 | 1/a | |

| Publication | Calibration species | Covariate | Coefficient | Unit | Remarks |
|---|---|---|---|---|---|
| Wunder et al. (2008a) 1 | *Carpinus betulus* | INTERCEPT | 5.281 | - | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | log(relBAI) | 0.643 | 1/a | |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | log(relBAI)1 | -0.056 | 1/a | |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | log(relBAI)2 | 0.123 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | log(relBAI)3 | -0.067 | 1/a | |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | KrelBAI1 | -5.5368 | 1/a | |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | KrelBAI2 | -4.37017 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 1 | *Carpinus betulus* | KrelBAI3 | -3.39317 | 1/a | |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | INTERCEPT | -3.3 | - | |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | log(DBH) | 1.171 | cm | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | log(relBAI) | 0.333 | 1/a | |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | log(relBAI)1 | 0.71 | 1/a | |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | log(relBAI)2 | -1.305 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | log(relBAI)3 | 1.911 | 1/a | |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | KrelBAI1 | -4.65255 | 1/a | |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | KrelBAI2 | -3.91917 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 1 | *Fraxinus excelsior* | KrelBAI3 | -3.04359 | 1/a | |
| Wunder et al. (2008a) 1 | *Picea abies* | INTERCEPT | 4.647 | - | |
| Wunder et al. (2008a) 1 | *Picea abies* | log(DBH) | -0.384 | cm | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 1 | *Picea abies* | log(relBAI) | 0.44 | 1/a | |
| Wunder et al. (2008a) 1 | *Picea abies* | log(relBAI)1 | 0.071 | 1/a | |
| Wunder et al. (2008a) 1 | *Picea abies* | log(relBAI)2 | -0.196 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 1 | *Picea abies* | log(relBAI)3 | 0.125 | 1/a | |
| Wunder et al. (2008a) 1 | *Picea abies* | KrelBAI1 | -5.08731 | 1/a | |
| Wunder et al. (2008a) 1 | *Picea abies* | KrelBAI2 | -3.93875 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 1 | *Picea abies* | KrelBAI3 | -3.29096 | 1/a | |
| Wunder et al. (2008a) 1 | *Quercus robur* | INTERCEPT | -2.785 | - | |
| Wunder et al. (2008a) 1 | *Quercus robur* | log(DBH) | 2.075 | cm | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 1 | *Quercus robur* | log(relBAI) | 1.801 | 1/a | |
| Wunder et al. (2008a) 1 | *Quercus robur* | log(relBAI)1 | -0.157 | 1/a | |
| Wunder et al. (2008a) 1 | *Quercus robur* | log(relBAI)2 | 0.382 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 1 | *Quercus robur* | log(relBAI)3 | -0.225 | 1/a | |
| Wunder et al. (2008a) 1 | *Quercus robur* | KrelBAI1 | -5.38701 | 1/a | |
| Wunder et al. (2008a) 1 | *Quercus robur* | KrelBAI2 | -4.41242 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 1 | *Quercus robur* | KrelBAI3 | -3.73213 | 1/a | |
| Wunder et al. (2008a) 1 | *Tilia cordata* | INTERCEPT | -1.787 | - | |
| Wunder et al. (2008a) 1 | *Tilia cordata* | log(DBH) | 1.591 | cm | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 1 | *Tilia cordata* | log(relBAI) | 1.022 | 1/a | |
| Wunder et al. (2008a) 1 | *Tilia cordata* | log(relBAI)1 | -0.095 | 1/a | |
| Wunder et al. (2008a) 1 | *Tilia cordata* | log(relBAI)2 | 0.289 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 1 | *Tilia cordata* | log(relBAI)3 | -0.194 | 1/a | |
| Wunder et al. (2008a) 1 | *Tilia cordata* | KrelBAI1 | -5.2202 | 1/a | |
| Wunder et al. (2008a) 1 | *Tilia cordata* | KrelBAI2 | -3.64442 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 1 | *Tilia cordata* | KrelBAI3 | -2.87098 | 1/a | |

| Publication | Calibration species | Covariate | Coefficient | Unit | Remarks |
|---|---|---|---|---|---|
| Wunder et al. (2008a) 1+2 | *Betula spec.* | INTERCEPT | 1.073 | - | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | log(DBH) | 0.623 | cm | |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | log(relBAI) | 0.813 | 1/a | |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | log(relBAI)1 | -0.031 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | log(relBAI)2 | 0.073 | 1/a | |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | log(relBAI)3 | -0.042 | 1/a | |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | KrelBAI1 | -5.55349 | 1/a | in communication with the authors, the coefficients for |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | KrelBAI2 | -4.45592 | 1/a | *log(DBH)* and *site* (PL, CH) and the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 1+2 | *Betula spec.* | KrelBAI3 | -3.64797 | 1/a | |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | INTERCEPT | 1.918 | - | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | log(DBH) | 1.105 | cm | |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | log(relBAI) | 1.217 | 1/a | |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | log(relBAI)1 | -0.092 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | log(relBAI)2 | 0.22 | 1/a | |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | log(relBAI)3 | -0.128 | 1/a | |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | KrelBAI1 | -4.8459 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | KrelBAI2 | -3.8672 | 1/a | |
| Wunder et al. (2008a) 2 | *Alnus glutinosa* | KrelBAI3 | -3.16568 | 1/a | |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | INTERCEPT | 1.827 | - | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | log(relBAI) | 0.207 | 1/a | |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | log(relBAI)1 | 0.626 | 1/a | |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | log(relBAI)2 | -1.373 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | log(relBAI)3 | 0.747 | 1/a | |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | KrelBAI1 | -5.5368 | 1/a | |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | KrelBAI2 | -4.37017 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 2 | *Carpinus betulus* | KrelBAI3 | -3.39317 | 1/a | |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | INTERCEPT | 10.009 | - | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | log(relBAI) | 1.743 | 1/a | |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | log(relBAI)1 | -0.113 | 1/a | |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | log(relBAI)2 | 0.328 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | log(relBAI)3 | -0.215 | 1/a | |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | KrelBAI1 | -5.32948 | 1/a | |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | KrelBAI2 | -4.07211 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 2 | *Fagus sylvatica* | KrelBAI3 | -3.40999 | 1/a | |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | INTERCEPT | 5.413 | - | for log-transformed *relBAI*, an additive constant of 0.002531 was used |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | log(DBH) | 1.171 | cm | |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | log(relBAI) | 2.418 | 1/a | |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | log(relBAI)1 | -0.786 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | log(relBAI)2 | 1.444 | 1/a | |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | log(relBAI)3 | 0.658 | 1/a | |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | KrelBAI1 | -4.65255 | 1/a | |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | KrelBAI2 | -3.91917 | 1/a | in communication with the authors, the locations of the knots were correted and thus are different from the original paper |
| Wunder et al. (2008a) 2 | *Fraxinus excelsior* | KrelBAI3 | -3.04359 | 1/a | |

| Publication | Calibration species | Covariate | Coefficient | Unit | Remarks |
|---|---|---|---|---|---|
| Wunder et al. (2008a) 2 | *Quercus robur* | INTERCEPT | -0.465 | - | |
| Wunder et al. (2008a) 2 | *Quercus robur* | log(DBH) | 2.075 | cm | for log-transformed *relBAI*, an additive constant of 0.002531 |
| Wunder et al. (2008a) 2 | *Quercus robur* | log(relBAI) | 1.801 | 1/a | was used |
| Wunder et al. (2008a) 2 | *Quercus robur* | log(relBAI)1 | -0.157 | 1/a | |
| Wunder et al. (2008a) 2 | *Quercus robur* | log(relBAI)2 | 0.382 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the |
| Wunder et al. (2008a) 2 | *Quercus robur* | log(relBAI)3 | -0.225 | 1/a | locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 2 | *Quercus robur* | KrelBAI1 | -5.38701 | 1/a | |
| Wunder et al. (2008a) 2 | *Quercus robur* | KrelBAI2 | -4.41242 | 1/a | in communication with the authors, the locations of the knots |
| Wunder et al. (2008a) 2 | *Quercus robur* | KrelBAI3 | -3.73213 | 1/a | were correted and thus are different from the original paper |
| Wunder et al. (2008a) 2 | *Tilia cordata* | INTERCEPT | -0.847 | - | |
| Wunder et al. (2008a) 2 | *Tilia cordata* | log(DBH) | 1.591 | cm | for log-transformed *relBAI*, an additive constant of 0.002531 |
| Wunder et al. (2008a) 2 | *Tilia cordata* | log(relBAI) | 1.022 | 1/a | was used |
| Wunder et al. (2008a) 2 | *Tilia cordata* | log(relBAI)1 | -0.095 | 1/a | |
| Wunder et al. (2008a) 2 | *Tilia cordata* | log(relBAI)2 | 0.289 | 1/a | *log(relBAI)1-3* refer to the coefficients, *KrelBAI1-3* mark the |
| Wunder et al. (2008a) 2 | *Tilia cordata* | log(relBAI)3 | -0.194 | 1/a | locations of the knots of the restricted cubic splines |
| Wunder et al. (2008a) 2 | *Tilia cordata* | KrelBAI1 | -5.2202 | 1/a | |
| Wunder et al. (2008a) 2 | *Tilia cordata* | KrelBAI2 | -3.64442 | 1/a | in communication with the authors, the locations of the knots |
| Wunder et al. (2008a) 2 | *Tilia cordata* | KrelBAI3 | -2.87098 | 1/a | were correted and thus are different from the original paper |
| Wunder et al. (unpubl.) | low shade tolerance | INTERCEPT | 7.5825 | - | |
| Wunder et al. (unpubl.) | low shade tolerance | DBH | 0.0672 | cm | the influence of relBAI was included via four growth categories: |
| Wunder et al. (unpubl.) | low shade tolerance | DBH^2 | -0.0005 | cm | Very low growth: relBAI = 0 |
| Wunder et al. (unpubl.) | low shade tolerance | low relBAI | 0.581 | - | Low growth: relBAI 0…1.5% |
| Wunder et al. (unpubl.) | low shade tolerance | fast relBAI | 1.1968 | - | Fast growth: relBAI 1.5...3% |
| Wunder et al. (unpubl.) | low shade tolerance | very fast relBAI | 2.0417 | - | Very fast growth: relBAI > 3% |
| Wunder et al. (unpubl.) | low shade tolerance | log(GDD) | -1.0107 | - | |
| Wunder et al. (unpubl.) | intermediate shade tolerance | INTERCEPT | 7.7706 | - | |
| Wunder et al. (unpubl.) | intermediate shade tolerance | DBH | 0.0672 | cm | the influence of relBAI was included via four growth categories: |
| Wunder et al. (unpubl.) | intermediate shade tolerance | DBH^2 | -0.0005 | cm | Very low growth: relBAI = 0 |
| Wunder et al. (unpubl.) | intermediate shade tolerance | low relBAI | 0.581 | - | Low growth: relBAI 0…1.5% |
| Wunder et al. (unpubl.) | intermediate shade tolerance | fast relBAI | 1.1968 | - | Fast growth: relBAI 1.5...3% |
| Wunder et al. (unpubl.) | intermediate shade tolerance | very fast relBAI | 2.0417 | - | Very fast growth: relBAI > 3% |
| Wunder et al. (unpubl.) | intermediate shade tolerance | log(GDD) | -1.0107 | - | |
| Wunder et al. (unpubl.) | high shade tolerance | INTERCEPT | 8.59 | - | |
| Wunder et al. (unpubl.) | high shade tolerance | DBH | 0.0672 | cm | the influence of relBAI was included via four growth categories: |
| Wunder et al. (unpubl.) | high shade tolerance | DBH^2 | -0.0005 | cm | Very low growth: relBAI = 0 |
| Wunder et al. (unpubl.) | high shade tolerance | low relBAI | 0.581 | - | Low growth: relBAI 0…1.5% |
| Wunder et al. (unpubl.) | high shade tolerance | fast relBAI | 1.1968 | - | Fast growth: relBAI 1.5...3% |
| Wunder et al. (unpubl.) | high shade tolerance | very fast relBAI | 2.0417 | - | Very fast growth: relBAI > 3% |
| Wunder et al. (unpubl.) | high shade tolerance | log(GDD) | -1.0107 | - | |

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Draft

Citation,Calibration_Species,Parameter,Coefficient,Unit
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Alenius et al. (2003) 1,Pinus sylvestris,relBAL,2.091,-
Alenius et al. (2003) 1,Pinus sylvestris,1-PBA,2.133,-
Alenius et al. (2003) 1,Pinus sylvestris,qmDBH,-0.128,cm
Alenius et al. (2003) 1,Pinus sylvestris,BA,0.111,m^2/ha
Alenius et al. (2003) 1,Pinus sylvestris,1/DBH,30.884,mm
Bravo-Oviedo et al. (2006),Pinus sylvestris,INTERCEPT,6.8548,-
Bravo-Oviedo et al. (2006),Pinus sylvestris,BAL*CVd,-0.121,m^2/ha
Bravo-Oviedo et al. (2006),Pinus sylvestris,SI,-0.037,m
Bravo-Oviedo et al. (2006),Pinus sylvestris,1/DBH,-9.792,cm
Crecente-Campo et al. (2010),Pinus sylvestris,INTERCEPT,-2.903,-
Crecente-Campo et al. (2010),Pinus sylvestris,relBAL*hdom*sqrtN/100,0.4687,m/ha
Crecente-Campo et al. (2010),Pinus sylvestris,relBAL,-3.214,-
Crecente-Campo et al. (2010),Pinus sylvestris,qmDBH,0.3007,cm
Crecente-Campo et al. (2010),Pinus sylvestris,DBH,-0.4087,cm
Dursky (1997),Fagus sylvatica,INTERCEPT,6.6686,-
Dursky (1997),Fagus sylvatica,h/DBH,-7.6495,m/cm
Dursky (1997),Fagus sylvatica,DBH,-0.261,cm
Dursky (1997),Fagus sylvatica,h,0.2695,m
Dursky (1997),Fagus sylvatica,BAI/DBH,3.0796,cm^2/a/cm
Dursky (1997),Picea abies,INTERCEPT,5.3908,-
Dursky (1997),Picea abies,h/DBH,-5.3998,m/cm
Dursky (1997),Picea abies,SI,-0.0406,m
Dursky (1997),Picea abies,DBH,-0.0089,cm
Dursky (1997),Picea abies,BAI/DBH,1.4802,cm^2/a/cm
Eid and Tuhus (2001),Betula spec.,INTERCEPT,4.8923,-
Eid and Tuhus (2001),Betula spec.,1/DBH,-2.528,cm
Eid and Tuhus (2001),Broadleaf Other,INTERCEPT,5.1575,-
Eid and Tuhus (2001),Broadleaf Other,BAL,-0.0199,m^2/ha
Eid and Tuhus (2001),Broadleaf Other,1/DBH,-7.3544,cm
Eid and Tuhus (2001),Picea abies,INTERCEPT,8.0599,-
Eid and Tuhus (2001),Picea abies,BAL,-0.0281,m^2/ha
Eid and Tuhus (2001),Picea abies,PBA,-0.0132,%
Eid and Tuhus (2001),Picea abies,SI,-0.0264,m
Eid and Tuhus (2001),Picea abies,1/DBH,-6.702,cm
Eid and Tuhus (2001),Pinus sylvestris,INTERCEPT,8.4904,-
Eid and Tuhus (2001),Pinus sylvestris,BAL,-0.0462,m^2/ha
Eid and Tuhus (2001),Pinus sylvestris,SI,-0.0761,m
Eid and Tuhus (2001),Pinus sylvestris,1/DBH,-14.266,cm
Fridman and Ståhl (2001),Betula spec.,INTERCEPT,-2.83,-
Fridman and Ståhl (2001),Betula spec.,BAL,0.0362,m^2/ha
Fridman and Ståhl (2001),Betula spec.,mDBH,15.7,m
Fridman and Ståhl (2001),Betula spec.,BA,-0.0665,m^2/ha
Fridman and Ståhl (2001),Betula spec.,ELV,0.0011,m
Fridman and Ståhl (2001),Betula spec.,DBH,-16.5,m

Fridman and Ståhl (2001),Betula spec.,DBH^2,27.7,m
Fridman and Ståhl (2001),Broadleaf Other,INTERCEPT,-5.4,-
Fridman and Ståhl (2001),Broadleaf Other,BAL,0.0693,m^2/ha
Fridman and Ståhl (2001),Broadleaf Other,BA,-0.0688,m^2/ha
Fridman and Ståhl (2001),Broadleaf Other,ELV,0.00212,m
Fridman and Ståhl (2001),Broadleaf Other,LAT,0.0498,degree
Fridman and Ståhl (2001),Broadleaf Other,<20m clearcut,-0.345,-
Fridman and Ståhl (2001),Broadleaf Other,1/DBH,0.0634,m
Fridman and Ståhl (2001),Broadleaf Southern,INTERCEPT,-3.67,-
Fridman and Ståhl (2001),Broadleaf Southern,BAL,0.168,m^2/ha
Fridman and Ståhl (2001),Broadleaf Southern,BA,-0.14,m^2/ha
Fridman and Ståhl (2001),Broadleaf Southern,DBH,3.34,m
Fridman and Ståhl (2001),Picea abies,INTERCEPT,-4.58,-
Fridman and Ståhl (2001),Picea abies,BAL,0.0282,m^2/ha
Fridman and Ståhl (2001),Picea abies,PIDOM,-0.594,-
Fridman and Ståhl (2001),Picea abies,mDBH,11.2,m
Fridman and Ståhl (2001),Picea abies,BA,-0.0545,m^2/ha
Fridman and Ståhl (2001),Picea abies,<20m clearcut,0.577,-
Fridman and Ståhl (2001),Picea abies,management,0.323,-
Fridman and Ståhl (2001),Picea abies,1/DBH,0.042,m
Fridman and Ståhl (2001),Pinus sylvestris,INTERCEPT,-1.98,-
Fridman and Ståhl (2001),Pinus sylvestris,BAL,0.028,m^2/ha
Fridman and Ståhl (2001),Pinus sylvestris,PIDOM,-0.456,-
Fridman and Ståhl (2001),Pinus sylvestris,mDBH,25.6,m
Fridman and Ståhl (2001),Pinus sylvestris,mDBH^2,-26.6,m
Fridman and Ståhl (2001),Pinus sylvestris,log(BA),-0.739,m^2/ha
Fridman and Ståhl (2001),Pinus sylvestris,moist,0.327,-
Fridman and Ståhl (2001),Pinus sylvestris,DBH,-17.4,m
Fridman and Ståhl (2001),Pinus sylvestris,DBH^2,21.5,m
Holzwarth et al. (2013),Carpinus betulus,INTERCEPT,-2.8,-
Holzwarth et al. (2013),Carpinus betulus,DBH,-0.051,cm
Holzwarth et al. (2013),Fagus sylvatica,INTERCEPT,1.8,-
Holzwarth et al. (2013),Fagus sylvatica,log(DBH),-2.1,cm
Holzwarth et al. (2013),Fagus sylvatica,DI,-1.4,cm/a
Holzwarth et al. (2013),Fagus sylvatica,INTERCEPT,-8.9,-
Holzwarth et al. (2013),Fagus sylvatica,DBH,0.052,cm
Holzwarth et al. (2013),Fagus sylvatica,log(DBH),0,cm
Holzwarth et al. (2013),Fagus sylvatica,DI,0,cm/a
Holzwarth et al. (2013),Fraxinus excelsior,INTERCEPT,1.3,-
Holzwarth et al. (2013),Fraxinus excelsior,log(DBH),-1.6,cm
Monserud and Sterba (1999),Abies alba,INTERCEPT,2.0985,-
Monserud and Sterba (1999),Abies alba,1/DBH,-10.9085,cm
Monserud and Sterba (1999),Abies alba,CR,3.9311,-
Monserud and Sterba (1999),Broadleaf Other,INTERCEPT,2.9223,-
Monserud and Sterba (1999),Broadleaf Other,BAL,-0.0228,m^2/ha
Monserud and Sterba (1999),Broadleaf Other,1/DBH,-8.4877,cm

Monserud and Sterba (1999),Broadleaf Other,CR,2.0609,-
Monserud and Sterba (1999),Fagus sylvatica,INTERCEPT,3.5734,-
Monserud and Sterba (1999),Fagus sylvatica,BAL,-0.0161,m^2/ha
Monserud and Sterba (1999),Fagus sylvatica,1/DBH,-13.9542,cm
Monserud and Sterba (1999),Fagus sylvatica,CR,3.1339,-
Monserud and Sterba (1999),Larix decidua,INTERCEPT,4.407,-
Monserud and Sterba (1999),Larix decidua,BAL,-0.0326,m^2/ha
Monserud and Sterba (1999),Larix decidua,1/DBH,-12.9395,cm
Monserud and Sterba (1999),Larix decidua,CR,2.2039,-
Monserud and Sterba (1999),Picea abies,INTERCEPT,2.1283,-
Monserud and Sterba (1999),Picea abies,BAL,-0.0186,m^2/ha
Monserud and Sterba (1999),Picea abies,1/DBH,-10.0745,cm
Monserud and Sterba (1999),Picea abies,DBH,0.0425,cm
Monserud and Sterba (1999),Picea abies,DBH^2,-0.00081,cm
Monserud and Sterba (1999),Picea abies,CR,3.8251,-
Monserud and Sterba (1999),Pinus sylvestris,INTERCEPT,4.1076,-
Monserud and Sterba (1999),Pinus sylvestris,BAL,-0.0234,m^2/ha
Monserud and Sterba (1999),Pinus sylvestris,1/DBH,-18.9714,cm
Monserud and Sterba (1999),Pinus sylvestris,CR,2.3267,-
Monserud and Sterba (1999),Quercus spec.,INTERCEPT,4.4508,-
Monserud and Sterba (1999),Quercus spec.,1/DBH,-12.0041,cm
Palahí et al. (2003) 2,Pinus sylvestris,INTERCEPT,2.938,-
Palahí et al. (2003) 2,Pinus sylvestris,BAL,-0.02,m^2/ha
Palahí et al. (2003) 2,Pinus sylvestris,DI,2.719,cm/a
Trasobares et al. (2004),Pinus sylvestris,INTERCEPT,2.728,-
Trasobares et al. (2004),Pinus sylvestris,BAL/log(DBH),-0.148,m^2/ha/cm
Trasobares et al. (2004),Pinus sylvestris,ELV,0.067,100m
Trasobares et al. (2004),Pinus sylvestris,CON,-0.006,km
Trasobares et al. (2004),Pinus sylvestris,h,0.107,m
Wunder et al. (2007) 1,Abies alba,INTERCEPT,1.161,-
Wunder et al. (2007) 1,Abies alba,relBAI,29.17,1/a
Wunder et al. (2007) 1,Abies alba,relBAI1,-518.37,1/a
Wunder et al. (2007) 1,Abies alba,relBAI2,1038.53,1/a
Wunder et al. (2007) 1,Abies alba,relBAI3,-505.01,1/a
Wunder et al. (2007) 1,Abies alba,relBAI4,-15.15,1/a
Wunder et al. (2007) 1,Abies alba,KrelBAI1,0.02,1/a
Wunder et al. (2007) 1,Abies alba,KrelBAI2,0.104,1/a
Wunder et al. (2007) 1,Abies alba,KrelBAI3,0.181,1/a
Wunder et al. (2007) 1,Abies alba,KrelBAI4,0.395,1/a
Wunder et al. (2007) 1,Fagus sylvatica,INTERCEPT,-17.63,-
Wunder et al. (2007) 1,Fagus sylvatica,log(DBH),3.57,mm
Wunder et al. (2007) 1,Fagus sylvatica,relBAI,29.17,1/a
Wunder et al. (2007) 1,Fagus sylvatica,relBAI1,-518.37,1/a
Wunder et al. (2007) 1,Fagus sylvatica,relBAI2,1038.53,1/a
Wunder et al. (2007) 1,Fagus sylvatica,relBAI3,-505.01,1/a
Wunder et al. (2007) 1,Fagus sylvatica,relBAI4,-15.15,1/a

Wunder et al. (2007) 1,Fagus sylvatica,KrelBAI1,0.02,1/a
Wunder et al. (2007) 1,Fagus sylvatica,KrelBAI2,0.104,1/a
Wunder et al. (2007) 1,Fagus sylvatica,KrelBAI3,0.181,1/a
Wunder et al. (2007) 1,Fagus sylvatica,KrelBAI4,0.395,1/a
Wunder et al. (2007) 2,Abies alba,INTERCEPT,-0.4,-
Wunder et al. (2007) 2,Abies alba,relBAI,29.17,1/a
Wunder et al. (2007) 2,Abies alba,relBAI1,-518.37,1/a
Wunder et al. (2007) 2,Abies alba,relBAI2,1038.53,1/a
Wunder et al. (2007) 2,Abies alba,relBAI3,-505.01,1/a
Wunder et al. (2007) 2,Abies alba,relBAI4,-15.15,1/a
Wunder et al. (2007) 2,Abies alba,KrelBAI1,0.02,1/a
Wunder et al. (2007) 2,Abies alba,KrelBAI2,0.104,1/a
Wunder et al. (2007) 2,Abies alba,KrelBAI3,0.181,1/a
Wunder et al. (2007) 2,Abies alba,KrelBAI4,0.395,1/a
Wunder et al. (2007) 2,Fagus sylvatica,INTERCEPT,-16.86,-
Wunder et al. (2007) 2,Fagus sylvatica,log(DBH),3.57,mm
Wunder et al. (2007) 2,Fagus sylvatica,relBAI,29.17,1/a
Wunder et al. (2007) 2,Fagus sylvatica,relBAI1,-518.37,1/a
Wunder et al. (2007) 2,Fagus sylvatica,relBAI2,1038.53,1/a
Wunder et al. (2007) 2,Fagus sylvatica,relBAI3,-505.01,1/a
Wunder et al. (2007) 2,Fagus sylvatica,relBAI4,-15.15,1/a
Wunder et al. (2007) 2,Fagus sylvatica,KrelBAI1,0.02,1/a
Wunder et al. (2007) 2,Fagus sylvatica,KrelBAI2,0.104,1/a
Wunder et al. (2007) 2,Fagus sylvatica,KrelBAI3,0.181,1/a
Wunder et al. (2007) 2,Fagus sylvatica,KrelBAI4,0.395,1/a
Wunder et al. (2008a) 1,Alnus glutinosa,INTERCEPT,0.958,-
Wunder et al. (2008a) 1,Alnus glutinosa,log(DBH),1.105,cm
Wunder et al. (2008a) 1,Alnus glutinosa,log(relBAI),1.217,1/a
Wunder et al. (2008a) 1,Alnus glutinosa,log(relBAI)1,-0.092,1/a
Wunder et al. (2008a) 1,Alnus glutinosa,log(relBAI)2,0.22,1/a
Wunder et al. (2008a) 1,Alnus glutinosa,log(relBAI)3,-0.128,1/a
Wunder et al. (2008a) 1,Alnus glutinosa,KrelBAI1,-4.845897,1/a
Wunder et al. (2008a) 1,Alnus glutinosa,KrelBAI2,-3.867198,1/a
Wunder et al. (2008a) 1,Alnus glutinosa,KrelBAI3,-3.165683,1/a
Wunder et al. (2008a) 1,Carpinus betulus,INTERCEPT,5.281,-
Wunder et al. (2008a) 1,Carpinus betulus,log(relBAI),0.643,1/a
Wunder et al. (2008a) 1,Carpinus betulus,log(relBAI)1,-0.056,1/a
Wunder et al. (2008a) 1,Carpinus betulus,log(relBAI)2,0.123,1/a
Wunder et al. (2008a) 1,Carpinus betulus,log(relBAI)3,-0.067,1/a
Wunder et al. (2008a) 1,Carpinus betulus,KrelBAI1,-5.536796,1/a
Wunder et al. (2008a) 1,Carpinus betulus,KrelBAI2,-4.370165,1/a
Wunder et al. (2008a) 1,Carpinus betulus,KrelBAI3,-3.39317,1/a
Wunder et al. (2008a) 1,Fraxinus excelsior,INTERCEPT,-3.3,-
Wunder et al. (2008a) 1,Fraxinus excelsior,log(DBH),1.171,cm
Wunder et al. (2008a) 1,Fraxinus excelsior,log(relBAI),0.333,1/a
Wunder et al. (2008a) 1,Fraxinus excelsior,log(relBAI)1,0.71,1/a

Wunder et al. (2008a) 1,Fraxinus excelsior,log(relBAI)2,-1.305,1/a
Wunder et al. (2008a) 1,Fraxinus excelsior,log(relBAI)3,1.911,1/a
Wunder et al. (2008a) 1,Fraxinus excelsior,KrelBAI1,-4.652545,1/a
Wunder et al. (2008a) 1,Fraxinus excelsior,KrelBAI2,-3.91917,1/a
Wunder et al. (2008a) 1,Fraxinus excelsior,KrelBAI3,-3.04359,1/a
Wunder et al. (2008a) 1,Picea abies,INTERCEPT,4.647,-
Wunder et al. (2008a) 1,Picea abies,log(DBH),-0.384,cm
Wunder et al. (2008a) 1,Picea abies,log(relBAI),0.44,1/a
Wunder et al. (2008a) 1,Picea abies,log(relBAI)1,0.071,1/a
Wunder et al. (2008a) 1,Picea abies,log(relBAI)2,-0.196,1/a
Wunder et al. (2008a) 1,Picea abies,log(relBAI)3,0.125,1/a
Wunder et al. (2008a) 1,Picea abies,KrelBAI1,-5.087314,1/a
Wunder et al. (2008a) 1,Picea abies,KrelBAI2,-3.938754,1/a
Wunder et al. (2008a) 1,Picea abies,KrelBAI3,-3.290959,1/a
Wunder et al. (2008a) 1,Quercus robur,INTERCEPT,-2.785,-
Wunder et al. (2008a) 1,Quercus robur,log(DBH),2.075,cm
Wunder et al. (2008a) 1,Quercus robur,log(relBAI),1.801,1/a
Wunder et al. (2008a) 1,Quercus robur,log(relBAI)1,-0.157,1/a
Wunder et al. (2008a) 1,Quercus robur,log(relBAI)2,0.382,1/a
Wunder et al. (2008a) 1,Quercus robur,log(relBAI)3,-0.225,1/a
Wunder et al. (2008a) 1,Quercus robur,KrelBAI1,-5.387012,1/a
Wunder et al. (2008a) 1,Quercus robur,KrelBAI2,-4.412423,1/a
Wunder et al. (2008a) 1,Quercus robur,KrelBAI3,-3.732127,1/a
Wunder et al. (2008a) 1,Tilia cordata,INTERCEPT,-1.787,-
Wunder et al. (2008a) 1,Tilia cordata,log(DBH),1.591,cm
Wunder et al. (2008a) 1,Tilia cordata,log(relBAI),1.022,1/a
Wunder et al. (2008a) 1,Tilia cordata,log(relBAI)1,-0.095,1/a
Wunder et al. (2008a) 1,Tilia cordata,log(relBAI)2,0.289,1/a
Wunder et al. (2008a) 1,Tilia cordata,log(relBAI)3,-0.194,1/a
Wunder et al. (2008a) 1,Tilia cordata,KrelBAI1,-5.220199,1/a
Wunder et al. (2008a) 1,Tilia cordata,KrelBAI2,-3.644418,1/a
Wunder et al. (2008a) 1,Tilia cordata,KrelBAI3,-2.870975,1/a
Wunder et al. (2008a) 1+2,Betula spec.,INTERCEPT,1.073,-
Wunder et al. (2008a) 1+2,Betula spec.,log(DBH),0.623,cm
Wunder et al. (2008a) 1+2,Betula spec.,log(relBAI),0.813,1/a
Wunder et al. (2008a) 1+2,Betula spec.,log(relBAI)1,-0.031,1/a
Wunder et al. (2008a) 1+2,Betula spec.,log(relBAI)2,0.073,1/a
Wunder et al. (2008a) 1+2,Betula spec.,log(relBAI)3,-0.042,1/a
Wunder et al. (2008a) 1+2,Betula spec.,KrelBAI1,-5.553489,1/a
Wunder et al. (2008a) 1+2,Betula spec.,KrelBAI2,-4.455916,1/a
Wunder et al. (2008a) 1+2,Betula spec.,KrelBAI3,-3.647967,1/a
Wunder et al. (2008a) 2,Alnus glutinosa,INTERCEPT,1.918,-
Wunder et al. (2008a) 2,Alnus glutinosa,log(DBH),1.105,cm
Wunder et al. (2008a) 2,Alnus glutinosa,log(relBAI),1.217,1/a
Wunder et al. (2008a) 2,Alnus glutinosa,log(relBAI)1,-0.092,1/a
Wunder et al. (2008a) 2,Alnus glutinosa,log(relBAI)2,0.22,1/a

Wunder et al. (2008a) 2,Alnus glutinosa,log(relBAI)3,-0.128,1/a
Wunder et al. (2008a) 2,Alnus glutinosa,KrelBAI1,-4.845897,1/a
Wunder et al. (2008a) 2,Alnus glutinosa,KrelBAI2,-3.867198,1/a
Wunder et al. (2008a) 2,Alnus glutinosa,KrelBAI3,-3.165683,1/a
Wunder et al. (2008a) 2,Carpinus betulus,INTERCEPT,1.827,-
Wunder et al. (2008a) 2,Carpinus betulus,log(relBAI),0.207,1/a
Wunder et al. (2008a) 2,Carpinus betulus,log(relBAI)1,0.626,1/a
Wunder et al. (2008a) 2,Carpinus betulus,log(relBAI)2,-1.373,1/a
Wunder et al. (2008a) 2,Carpinus betulus,log(relBAI)3,0.747,1/a
Wunder et al. (2008a) 2,Carpinus betulus,KrelBAI1,-5.536796,1/a
Wunder et al. (2008a) 2,Carpinus betulus,KrelBAI2,-4.370165,1/a
Wunder et al. (2008a) 2,Carpinus betulus,KrelBAI3,-3.39317,1/a
Wunder et al. (2008a) 2,Fagus sylvatica,INTERCEPT,10.009,-
Wunder et al. (2008a) 2,Fagus sylvatica,log(relBAI),1.743,1/a
Wunder et al. (2008a) 2,Fagus sylvatica,log(relBAI)1,-0.113,1/a
Wunder et al. (2008a) 2,Fagus sylvatica,log(relBAI)2,0.328,1/a
Wunder et al. (2008a) 2,Fagus sylvatica,log(relBAI)3,-0.215,1/a
Wunder et al. (2008a) 2,Fagus sylvatica,KrelBAI1,-5.32948,1/a
Wunder et al. (2008a) 2,Fagus sylvatica,KrelBAI2,-4.072114,1/a
Wunder et al. (2008a) 2,Fagus sylvatica,KrelBAI3,-3.40999,1/a
Wunder et al. (2008a) 2,Fraxinus excelsior,INTERCEPT,5.413,-
Wunder et al. (2008a) 2,Fraxinus excelsior,log(DBH),1.171,cm
Wunder et al. (2008a) 2,Fraxinus excelsior,log(relBAI),2.418,1/a
Wunder et al. (2008a) 2,Fraxinus excelsior,log(relBAI)1,-0.786,1/a
Wunder et al. (2008a) 2,Fraxinus excelsior,log(relBAI)2,1.444,1/a
Wunder et al. (2008a) 2,Fraxinus excelsior,log(relBAI)3,0.658,1/a
Wunder et al. (2008a) 2,Fraxinus excelsior,KrelBAI1,-4.652545,1/a
Wunder et al. (2008a) 2,Fraxinus excelsior,KrelBAI2,-3.91917,1/a
Wunder et al. (2008a) 2,Fraxinus excelsior,KrelBAI3,-3.04359,1/a
Wunder et al. (2008a) 2,Quercus robur,INTERCEPT,-0.465,-
Wunder et al. (2008a) 2,Quercus robur,log(DBH),2.075,cm
Wunder et al. (2008a) 2,Quercus robur,log(relBAI),1.801,1/a
Wunder et al. (2008a) 2,Quercus robur,log(relBAI)1,-0.157,1/a
Wunder et al. (2008a) 2,Quercus robur,log(relBAI)2,0.382,1/a
Wunder et al. (2008a) 2,Quercus robur,log(relBAI)3,-0.225,1/a
Wunder et al. (2008a) 2,Quercus robur,KrelBAI1,-5.387012,1/a
Wunder et al. (2008a) 2,Quercus robur,KrelBAI2,-4.412423,1/a
Wunder et al. (2008a) 2,Quercus robur,KrelBAI3,-3.732127,1/a
Wunder et al. (2008a) 2,Tilia cordata,INTERCEPT,-0.847,-
Wunder et al. (2008a) 2,Tilia cordata,log(DBH),1.591,cm
Wunder et al. (2008a) 2,Tilia cordata,log(relBAI),1.022,1/a
Wunder et al. (2008a) 2,Tilia cordata,log(relBAI)1,-0.095,1/a
Wunder et al. (2008a) 2,Tilia cordata,log(relBAI)2,0.289,1/a
Wunder et al. (2008a) 2,Tilia cordata,log(relBAI)3,-0.194,1/a
Wunder et al. (2008a) 2,Tilia cordata,KrelBAI1,-5.220199,1/a
Wunder et al. (2008a) 2,Tilia cordata,KrelBAI2,-3.644418,1/a

Wunder et al. (2008a) 2,Tilia cordata,KrelBAI3,-2.870975,1/a
Wunder et al. (unpubl.),low shade tolerance,INTERCEPT,7.5825,-
Wunder et al. (unpubl.),low shade tolerance,DBH,0.0672,cm
Wunder et al. (unpubl.),low shade tolerance,DBH^2,-5.00E-04,cm
Wunder et al. (unpubl.),low shade tolerance,low relBAI,0.581,-
Wunder et al. (unpubl.),low shade tolerance,fast relBAI,1.1968,-
Wunder et al. (unpubl.),low shade tolerance,very fast relBAI,2.0417,-
Wunder et al. (unpubl.),low shade tolerance,log(GDD),-1.0107,-
Wunder et al. (unpubl.),intermediate shade tolerance,INTERCEPT,7.7706,-
Wunder et al. (unpubl.),intermediate shade tolerance,DBH,0.0672,cm
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