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An analysis of Norway spruce stem quality in Baden-Württemberg: results from the second German national forest inventory

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Abstract Additional information concerning the quality of growing stock in forests has been obtained for the first time in Baden-Württemberg and Rheinland-Pfalz during the course of Germany's second national forest inventory (BWI 2; conducted during the period 2001–2002). In this article, the quality assessment—called stem quality rating method—is described with a special focus on its potential to provide the basis for a more detailed investigation of the growing stock's quality distribution. As a main result, the article presents and illustrates a model-based quantification of single tree and stand/site variable effects on the quality distribution of Norway spruce. Single tree variables showing a significant effect are diameter at breast height (DBH), height–DBH-ratio (*h*/*d*-value), age and distance to forest edge. Additional stand/site variables which have a significant effect are altitude, terrain slope, stand type and inventory team. Due to the ordinal type of the response variable, a categorical regression model is applied. Non-linear effects of predictor variables were detected and modeled by integration of smoothing spline terms. Validating model predictions with regard to expert knowledge in forestry led to the integration of simple constraints in the linear predictor, which controls whether category-specific effects are fitted or not. The resulting model could be described as a vector generalized additive non-proportional odds regression model. This improved insight into the determination of stem quality could be applied in optimization studies to derive optimal silvicultural treatments and in the setting up of management guidelines. Assuming constant relationships between predictor and response variables over time, the combined application with growth simulators allows for a prediction of future joint quality and size class assortment distributions. Finally, the model would allow for a sustainability control of stem quality over time if a consecutive inventory will be conducted during the course of the third German national forest inventory (BWI 3).

Keywords German national forest inventory · Norway spruce · Stem quality rating method · Categorical regression · Non-proportional odds model

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Introduction

In line with the second national forest inventory (BWI 2), a state-level enquiry concerning the quality of growing stock was conducted in Baden-Württemberg and Rheinland-Pfalz. The procedure of classifying stem quality within the framework of a large scale inventory has not been carried out in Germany to date and for the first time has permitted a simultaneous assessment of the quality distribution of growing stock at a federal state level (Leenen and Schmidt 2005). Austria has a longer tradition in both, a national forest inventory and the assessment of stem quality within this large scale inventory (Gabler and Schadauer 2006). A stem quality rating has been conducted during the course of the first national forest inventory in Switzerland also (Stepien et al. 1998). For a comprehensive overview and comparison of several stem quality rating approaches, see Wiegard (1998).

The so-called "stem quality rating method" of the BWI 2 assigns one of six grades to the tree's stem, which cover the range from excellent to very poor quality. Admittedly, a large scale inventory restricts opportunities for assessing quality insofar as the methods should not be too complex or labor intensive. However, even if cutbacks in the differentiation of stem quality have to be accepted, it is to be expected that the quality rating allows for estimates of biological production possibilities and the evaluation of possible site influences and silvicultural concepts. In addition, information concerning quality distribution may be employed for purposes of strategic focus in forest production planning and in the timber processing chain.

However, simple descriptions by univariate quality distributions are not sufficient for several management objectives but a model-based analysis of the quality distribution is needed. Hence, the analysis presented in this article aims at the identification of potential influencing factors and the quantification of their effects using a specific regression model. The analysis to date has been conducted for Norway spruce only. The main application areas of such a model are (1) the prediction of the future stem quality distribution, (2) a support of forest management optimization and (3) a support of sustainability control with respect to stem quality.

Concerning application area (1). For a prediction of the future stem quality distribution, it must be implied that the derived statistical relations are approximately stable over time. Under this assumption, the model can be used in joint log quantity and quality forecasting by differentiating predicted size class distributions into quality classes.

Concerning application area (2). The quantification of effects which are open to silvicultural control and effects which could not be influenced by silviculture enables for optimizing silvicultural management regimes. Additionally, maps of the predicted spatial stem quality distribution could be provided for optimizing round wood supply.

Concerning application area (3). Exactly the same model structure could be parameterized using data from a consecutive stem quality rating in the BWI 3. Comparing both, the models from BWI 2 and BWI 3 would allow for a more detailed analysis of changes in the quality distribution than just comparing simple histograms.

For the later interpretation of the model's behavior, it is important to explain in advance the method of stem quality rating within the BWI in more detail.

Materials and methods

The German national forest inventory is a systematic sample plot inventory with a two-stage cluster-design (BMVEL 2001), which in Baden-Württemberg is carried out on a sample grid of 2 × 2 km (Kändler et al. 2005) oriented on the Gauß–Krüger coordinate system. The primary sample unit is a quadratic tract with a side length of 150 m. The actual sample plots (tract corners) are located at the corners of this quadratic tract and will be treated as secondary sample units. Data are only assessed if the corner center hits forest. For the inventory concerning growing stock, the sampling of trees took place, based on callipered angle count sampling using a basal area of 4 m^2 ha^{-1}.

Stem quality rating method

An extensive description of the stem quality rating method conducted within the second national forest inventory is given by Willmann et al. (2001a, 2001b). In developing the main concept, fundamental experiences from the Swiss national forest inventory (Stepien et al. 1998) were considered. The procedure of quality classification is carried out on sample trees with a minimum diameter of 30 cm at breast height (DBH). The method for assessing the quality of the standing stem employs a classification method whereby six quality classes are used. Class 1 corresponds to "very good" while class 6 corresponds to "very poor" (only conditional allowance for sawing) quality. The chosen six-grade classification allows a finer differentiation of quality compared to the Swiss national forest inventory. Data were collected for the tree species with the greatest economic importance, namely Norway spruce, Silver fir, Scots pine, Douglas fir, European larch, Common beech and Oak species. The quality class of conifer stems was assessed up to a height of 10 m. An exception was made for pine, for which assessment was carried out to a height of 7 m, as it shows a tendency for shorter useable stem length. Concerning broadleaved species, quality was assessed to a height of 5 m. For each tree species, every quality class was supplemented with a photo-catalog.[1] The photos aid practical classification and give an overall picture of the individual classes. Alongside the photo series, sorting criteria for classifying the quality classes of broadleaves and conifers were devised (Table 1).

All externally identifiable bark and branch attributes as well as damages were accounted for in their entirety. A quality adjustment and, therefore, a devaluation or a revaluation is possible depending on the overall impression.

[1] The photo-catalog for all tree species is available under http://www.fva-bw.de/indexjs.html?http://www.fva-bw.de/forschung/bwi_gueteanspr/einleitung.html.

Table 1 Sorting criteria and rules used to rate the stem quality of standing conifer trees in the BWI 2, Baden-Württemberg

Sorting criteria and rules for softwoods (Norway spruce, Silver fir, Douglas fir, Scots pine, European larch)

Grade	1	2	3	4	5	6
Bark characteristics	Even, smooth, fine textured bark without other bark features, on the whole length without branches and knobs	Even; in the upper stem part slight knobs and larger branch scars acceptable (not too prominent, i.e., when too late pruned than grade 3)	Slightly coarse, uneven bark; larger knobs above 5 m and slight knobs in lower 5 m acceptable	Coarse, uneven bark texture acceptable; knobs on whole stem length (in particular, pine); several bark features	Coarse, uneven bark texture acceptable; knobs acceptable; numerous bark features accepted	Coarse bark; knobs
Branches	Lower 5 m branch-free, apparently pruned, no branch scars, above branch-free (no particular cause); single epicormic branch allowed at very top end of stem (only fir)	Lower 5 m branch-free without bark scars, above branch-free, but slight knobs; above 5 m branch-free, but slight knobs and larger branch scars accepted; single epicormic branches (small diameters) in the upper parts (above 5 m) accepted for fir, but no black knots and epicormic branches	Up to 5 m largely branch-free; above that slender-branched (thin live branches) accepted; for fir: accumulation of thin epicormics above 5 m and single epicormics up to 5 m accepted	Branch scars and thin, live branches evenly distributed on the whole stem length accepted, if slender-branched (at least in the bottom stem length)	Strong-branched on whole stem length	Strong-branched to the stem's butt end
Damages	Not accepted	Fissure, frost ribs and other larger damages excluded, small damages accepted	Damages (bark damages) above 5 m and few small damages below 5 m accepted	Few damages (bark damages) on whole stem length accepted	Larger felling damage, frost damage and other bark damages on the whole length of the stem accepted	Extensive felling damages and logging damages accepted
Stem form	Straight, cylindric, bottleneck and sweep excluded	Straight, cylindric, bottleneck and sweep excluded	One-sided, slight sweep accepted, largely cylindric, bottleneck excluded	One-sided sweep and ovality accepted, slight bottleneck accepted	Multiple sweep accepted	Strongly bent
Other features	On whole stem length defect-free (10 or 7 m), excluded are fir cancer, mistletoe, wavy grain (fiddle back grain) in fir	Few minor externally visible features (such as branch scars): fir cancer, mistletoe on stem, wavy grain excluded	Average quality; mistletoe on stem excluded (except at very top end and apart of that defect-free, fir); slightly wavy grain in fir accepted	Slightly wavy grain in fir accepted stem quality below average; in upper section mistletoe accepted for fir	Stem sawable; wavy grain accepted for fir, mistletoe on fir over 5 m and bottleneck in spruce accepted	Stem not completely usable; rot all features accepted

An exception is the first quality class in which only stems of exceptionally good quality occur. An assessment of stem quality to a height of 10 m is associated with some uncertainty. Therefore (e.g., when assessing branch dimensions), only a differentiation in light and heavy branching is made. The differentiation into quality classes gives an impression of the present status, independent of the particular growth phase of the tree. The actual possible uses and tree dimensions do not play a role in the differentiation, rather the development potential of the smaller dimensions is considered.

Altogether, 25,534 Norway spruce trees have been quality rated in Baden-Württemberg during the course of the second German national forest inventory. These trees display a wide range of parameters that potentially influence the stem quality distribution (Table 2).

Within the scope of the BWI 2 in Baden-Württemberg, the stand type was determined using permanent sample plots with a radius of 25 m from the sample plot center. In this case a variety of stand types are distinguished according to dominant and admixed tree species present. The different stand types had to be stratified before using them as predictors. Hence, the rarer stand types were pooled according to their dominant tree species. During the model selection, further stratification was conducted to ensure a concurrence of the model predictions with forest expert knowledge. This finally resulted in only three stand type groups (Table 2).

The terrestrial data assessment of the BWI 2 including the stem quality rating was carried out in Baden-Württemberg by eight inventory teams. Special training was provided so that the most uniform assessment concerning the quality of the stem could be guaranteed.

Categorical regression model

Regression analysis is the most commonly used modeling approach in forest growth and yield research. However, a standard-regression requires that the response variable is homogeneously and normally distributed. In the case of the stem quality rating, the response variable “quality class” is neither continuous nor normally distributed. However, because it is rank-scaled, it can be described as ordered with six categories (Fahrmeir et al. 2007). The description of this variable type is made possible with the help of a generalized linear regression model assuming a multinomial distribution, whereby the approach of the so-called cumulative logit is frequently used (McCullagh 1980; Anderson and Philips 1981) (Eqs. 1, 2a). The well-known proportional odds model is the simplest case of the cumulative logit regression model whereby only the intercept varies depending on the responding category (Eqs. 2b, 3, 4). When applying these models, also termed categorical regression, the vector of probabilities on single tree level for the various quality classes can be estimated depending on arbitrary values of the independent variables

Table 2 Mean characteristics of 25,534 Norway spruce trees which have been quality rated during the course of the BWI 2 in Baden-Württemberg

Quality class	1	2	3	4	5	6
Number of quality-rated trees by quality class	22	505	8,215	14,253	2,449	90

Inventory team	1	2	3	4	5	6	7	8
Number of quality-rated trees by inventory team	1,080	2,132	1,936	3,841	5,731	2,403	3,749	4,662

Stand type group (by dominating species)	Spruce, beech or other broadleaves with high lifespan	Silver fir	Light-demanding tree species or Douglas fir
Number of quality-rated trees by stand type	23,647	1,206	681

Quantiles (%)	0	10	20	30	40	50	60	70	80	90	100
DBH (cm)	9.4	32.1	34.3	36.6	39.0	41.5	44.2	47.5	51.5	57.6	111.7
h/*d*-value (cm/cm)	34.2	56.3	61.6	65.5	68.9	72.0	75.2	78.4	82.2	87.3	132.0
Age (year)	27	50	60	70	76	85	95	100	110	125	282
Altitude (m)	102	430	500	565	610	660	700	760	850	955	1,370
Terrain slope (%)	0	1	3	5	6	9	12	16	21	27	80

Quantiles (%)	0	1	2	3	4	5	6	7	8
Distance to forest edge (m)	0.0	2.6	4.3	6.8	9.6	12.8	16.6	21.3	40

(the quality classes 1 and 2, respectively, 5 and 6 have been combined as a result of the small number of observations especially in the classes 1 and 6). The individual observations are (conditional) multinomially distributed

$$y_{ir}|x_i \sim M(1, \pi i),\ \ \pi_i = (\pi_{i1}, \ldots, \pi_{iR})'$$
$$\mathrm{Cov}(y_{ir}, y_{is}) = y_{ir}(1 - y_{is}), r \leq s.$$

$$g_r(\gamma_i) = \ln \frac{\sum_{j=1}^{r} \pi_{ij}}{1 - \sum_{j=1}^{r} \pi_{ij}} = \beta_{0r} + x_i' \beta_r,$$
$$\text{with } \gamma_{ir} = \pi_{i1} + \ldots + \pi_{ir} \text{ and } \gamma_{iR} = 1,$$
$$r = 1, \ldots, R - 1. \tag{1}$$

$$P(y_i \leq r|x_i) = \sum_{j=1}^{r} \pi_{ij} = \frac{\exp\left(\beta_{0r} + x_i'\beta_r\right)}{1 + \exp\left(\beta_{0r} + x_i'\beta_r\right)} \tag{2a}$$

$$P(y_i \leq r|x_i) = \sum_{j=1}^{r} \pi_{ij} = \frac{\exp\left(\beta_{0r} + x_i'\beta\right)}{1 + \exp\left(\beta_{0r} + x_i'\beta\right)} \tag{2b}$$

or

$$P(y_i \leq r|x_i) = \frac{\exp\left(\beta_{0r} - \sum_{k=1}^{q} x_{ik}\beta_k\right)}{1 + \exp\left(\beta_{0r} - \sum_{k=1}^{q} x_{ik}\beta_k\right)} \tag{3}$$

$$P(y_i = r|x_i) = \frac{\exp\left(\beta_{0r} - \sum_{k=1}^{q} x_{ik}\beta_k\right)}{1 + \exp\left(\beta_{0r} - \sum_{k=1}^{q} x_{ik}\beta_k\right)} - \frac{\exp\left(\beta_{0,r-1} - \sum_{k=1}^{q} x_{ik}\beta_k\right)}{1 + \exp\left(\beta_{0,r-1} - \sum_{k=1}^{q} x_{ik}\beta_k\right)} \tag{4}$$

with:

$g_r(\gamma_i)$ transformed probability expectation value (single tree level) for categories equal or less r for the ith combination of characteristics (independent variables), the logistic function g is used as link function,

y_{ir} empirical proportion of category r for the ith combination of characteristics, assuming a multinomial distribution with $\sim M(1,\pi_i)$, $\pi_i = (\pi_{i1},\ldots,\pi_{iR})'$,

$\pi_{ir} = E(y_{ir})$ expectation value of the (conditional) probability (single tree level) for category r for the ith combination of characteristics,

x_i' vector of independent variables,

β_{0r} vector of category-specific intercepts,

β_r vector of regression coefficients, whereby all coefficients depend on the response category r,

r rth category of the 1 to $R - 1$ categories, whereby R equals the total number of categories and

q total number of independent (predictor) variables

However, the presence of an ordinal structure of the response variable is not sufficient when deciding whether the proportional odds model is the adequate model to be applied. It has to be tested whether the use of this relatively simple model results in an inadequately strong data reduction (Armstrong and Sloan 1989; Peterson 1990). Further special cases can be formulated in such a way within the cumulative logistic approach so that all or only subsets of the covariates are dependent on particular response categories. Additionally, the integration of additive terms offers the opportunity to consider possible non-linear effects in generalized additive models. In doing so, linear terms are substituted by splines, and in this process various types of splines (smoothing splines, regression splines and penalized regression splines) can be used. In the case of the *VGAM*-Software, so-called vector smoothing splines are used as default, which are multivariate extensions of univariate cubic smoothing splines (Yee and Wild 1996). The model type can be described as a (vector generalized) additive non-proportional odds model according to Yee and Wild (1996). When substituting all linear terms with additive terms, which depend on the response categories, the following extension results starting from the proportional odds model:

$$g_r(\gamma_i) = \ln \frac{\sum_{j=1}^{r} \pi_{ij}}{1 - \sum_{j=1}^{r} \pi_{ij}} = \frac{\exp\left(\beta_{0r} - \sum_{k=1}^{q} f_{kr}(x_{ik})\right)}{1 + \exp\left(\beta_{0r} - \sum_{k=1}^{q} f_{kr}(x_{ik})\right)}, \tag{5}$$

In general, the so-called deviance statistics and the Akaike information criterion (AIC) and Bayesian information criterion (BIC; Burnham and Anderson 2004) are used as model selection criteria, as the underlying estimation procedure is based on the maximum likelihood approach. In all tested model structures, the following variables were identified and integrated as significant predictor variables:

- DBH (cm)
- *h*/*d*-value as measurement for taper/slenderness (HD) (cm/cm)
- Age (*A*) (year)
- Distance to forest edge (DF) (m);
- Altitude (AL) (m);
- Terrain slope (TS) (%);
- Stand type (ST): three categories defined by dominating species: (1) spruce, beech or other broadleaves with high lifespan, (2) Silver fir and (3) light-demanding species or Douglas fir and
- Inventory team (IT): inventory team responsible for stem quality rating

The model selection process displayed the proportional odds model as less suitable and an additive non-proportional odds regression model was chosen. It could be demonstrated on the basis of the BIC and the testing of the deviance statistics using the likelihood ratio test that there was a highly significant superiority of the finally selected model (Table 3). However, the substitution of the linear terms by additive terms only for the covariates *h*/*d*-value, age, distance to forest edge and altitude improved the model. Model terms dependent on categories of the response variable were admitted for the variables age and DBH.

Two additional constraints were defined in order to ensure a concurrence with expert forestry knowledge. (1) The predicted quality distribution of spruce should decrease from stand types with dominant shade-tolerant species to dominant semi-shade-tolerant species to dominant light-demanding species if all other predictors are set constant. (2) Within these groups, the predicted quality distribution of spruce should decrease from stand types with dominant conifer species toward those with dominant broadleaved species if all other predictors are set constant. The constraints are based on the expert knowledge, that the natural pruning of spruce takes place at a slower rate, when there is less competition from light-demanding tree species than when there is higher competitive pressure from shade-tolerant tree species. The poorer natural pruning of spruce when mixed with broadleaved tree species is explained by the absence of shade in the winter months.

Other more complex model structures which were examined are superior under purely statistical evaluation criteria. However, in this case, implausible model behavior occurs without exception, especially near the marginal areas of the distributions of independent variables. These led to a somewhat less flexible model during model selection. Thus, the established model shows a significantly higher goodness of fit (AIC, BIC, likelihood ratio test; Table 3) when compared with the proportional odds model, and has a plausible model behavior over the whole range of predictor variables when compared with more complex model approaches.

Table 3 Statistical test values and the result of the likelihood ratio test for the proportional odds model and the finally selected additive non-proportional odds model

	Proportional odds model	Additive non-proportional odds model
Residual deviance	46530.67	44847.34
AIC	46566.67	44923.36
BIC	46712.95	45060.01
Likelihood-ratio-test	Highly significant superiority of the more complex model	

In two cases the use of an additive term brought no significant improvement (DBH, terrain slope). In both cases a more exact distribution of the deviance statistic was derived using the bootstrap method. For this, 1,500 data sets from the more parsimonious model were generated while keeping the predictor variables constant. Both the more parsimonious and the more complex model are fitted 1,500 times to these generated data and each time the deviance statistic is calculated. The resulting distribution of the deviance statistic represents the null hypothesis. This method is recommended by Yee and Wild (1996) for the validation of multivariate generalized additive models and has been described in more detail by Hastie and Tibshirani (1990).

In conclusion, for the special application of modeling the quality class distribution of Norway spruce, the final model structure can be described as follows:

$$P(y_i \le r|x_i) = \frac{\exp\left(\beta_{0r} - f_{1r}(A_i) - f_2(\mathrm{HD}_i) - f_3(\mathrm{DF}_i) - f_4(\mathrm{AL}_i) - \beta_{5r=2,3}\cdot \mathrm{BHD}_i - \beta_6\cdot \mathrm{TS}_i - \mathrm{ST}_i^T\cdot\beta_7 - \mathrm{IT}_i^T\cdot\beta_8\right)}{1+\exp\left(\beta_{0r} - f_{1r}(A_i) - f_2(\mathrm{HD}_i) - f_3(\mathrm{DF}_i) - f_4(\mathrm{AL}_i) - \beta_{5r=2,3}\cdot \mathrm{BHD}_i - \beta_6\cdot \mathrm{TS}_i - \mathrm{ST}_i^T\cdot\beta_7 - \mathrm{IT}_i^T\cdot\beta_8\right)} \quad (6)$$

where ST_i and IT_i are indicator vectors for stand type and inventory team, respectively, and β_7 and β_8 are vectors of coefficients. For further clarification, the model can be described by its linear predictor as follows:

$$g_1(\gamma_i) = \beta_{01} + f_{11}(A_i) + f_2(\mathrm{HD}_i) + f_3(\mathrm{DF}_i) + f_4(\mathrm{AL}_i) + \beta_6\cdot\mathrm{TS}_i + \mathrm{ST}_i^T\cdot\beta_7 + \mathrm{IT}_i^T\cdot\beta_8$$

$$g_2(\gamma_i) = \beta_{02} + f_{12}(A_i) + f_2(\mathrm{HD}_i) + f_3(\mathrm{DF}_i) + f_4(\mathrm{AL}_i) + \beta_{52}\mathrm{DBH}_i + \beta_6\cdot\mathrm{TS}_i + \mathrm{ST}_i^T\cdot\beta_7 + \mathrm{IT}_i^T\cdot\beta_8$$

$$g_3(\gamma_i) = \beta_{03} + f_{13}(A_i) + f_2(\mathrm{HD}_i) + f_3(\mathrm{DF}_i) + f_4(\mathrm{AL}_i) + \beta_{53}\mathrm{DBH}_i + \beta_6\cdot\mathrm{TS}_i + \mathrm{ST}_i^T\cdot\beta_7 + \mathrm{IT}_i^T\cdot\beta_8$$

In order to parameterize the categorical regression model, the statistical package *R* was used (R Development Core Team 2003). In addition, to adjust the proportional odds model, the program library *MASS* (Venables and Ripley 2002) was employed. Furthermore, the program library *VGAM* (Yee 2005) was used for fitting various types of the cumulative logistic regression model and all generalized additive model variants in the model selection process.

Results

The covariates which influence the quality class distribution can be subdivided into tree and stand/site (sample plot) parameters. In doing so, the influence of the stand/site parameters (altitude, terrain slope, stand type and inventory team) and that of the distance of the single tree to the forest edge can be more easily interpreted than the influence of the other tree parameters (DBH, *h*/*d*-value and age), as only the latter ones are highly correlated with one another. The description of the model behavior with the aid of predictions executed under "ceteris paribus" conditions (sensitivity analysis) is, therefore, firstly carried out for the stand/site and then for the tree parameters. The predictor variable, whose influence on the prediction is to be examined, is varied in the process across a wide range of values. The values of all other continuous variables are fixed to their means within the database and a particular category for the categorical variables is determined. A deviating approach is chosen for the variables DBH, *h*/*d*-value and age. In order to take the correlation of these variables in the prediction process into account, value combinations of certain model trees are used. In this way, for all predictions in which the DBH, *h*/*d*-value and the age are held constant, the values of the average mean quadratic diameter tree (D_g) over all sample plots of the BWI 2 are used which contain spruce of a site index of 12 m^3 ha^{-1} a^{-1} and an age of 100. Site index is defined as the mean annual increment at age 100 (MAI_{100}). A mean annual increment at age 100 of 12 m^3 ha^{-1} a^{-1} is equivalent to a mean-height-based site index of 33.2 m (reference age 100). For site index system, the yield tables for forest management in Baden-Württemberg are used (Ministry of Rural Affairs, Food, Agriculture and Forestry Baden-Württemberg 1993). In doing so, the mean quadratic diameters (Norway spruce) of 237 sample plots are included in the calculation. Concerning the categorical variables, the model was initialized applying the stand type "spruce, beech or other long living broadleaved species" and an inventory team which shows an "average" effect on the quality class distribution. From a silvicultural perspective, the stratification of the stand types is very rough and due to guaranteeing a biologically plausible order of the variable effects. This specific stratification results in a predicted quality of spruce in all stand types with dominant shade/semi-shade-tolerant tree species that is higher compared to stands where light-demanding trees dominate.

Terrain slope

With increasing slope, the model forecasts an increase in the less favorable quality classes 4 and 5 + 6 and a decrease in the quality classes 3 and 1 + 2 (Fig. 1a). In this case, a linear model term is sufficient to describe the data structures. Thereby, the observed deviance statistic is clearly smaller than the 95% quantile of the bootstrap distribution (Fig. 1b). It also becomes obvious that the distribution estimated by the bootstrap method is only roughly approximated by a χ^2-distribution with 2.74 degrees of freedom. However, in this case the null hypothesis would not be rejected even if using the χ^2-distribution (with a significance level of 5%).

The negative influence of insufficient side shade in hillside situations on pruning can be seen as the main reason for the pattern of the conditional quality proportions.

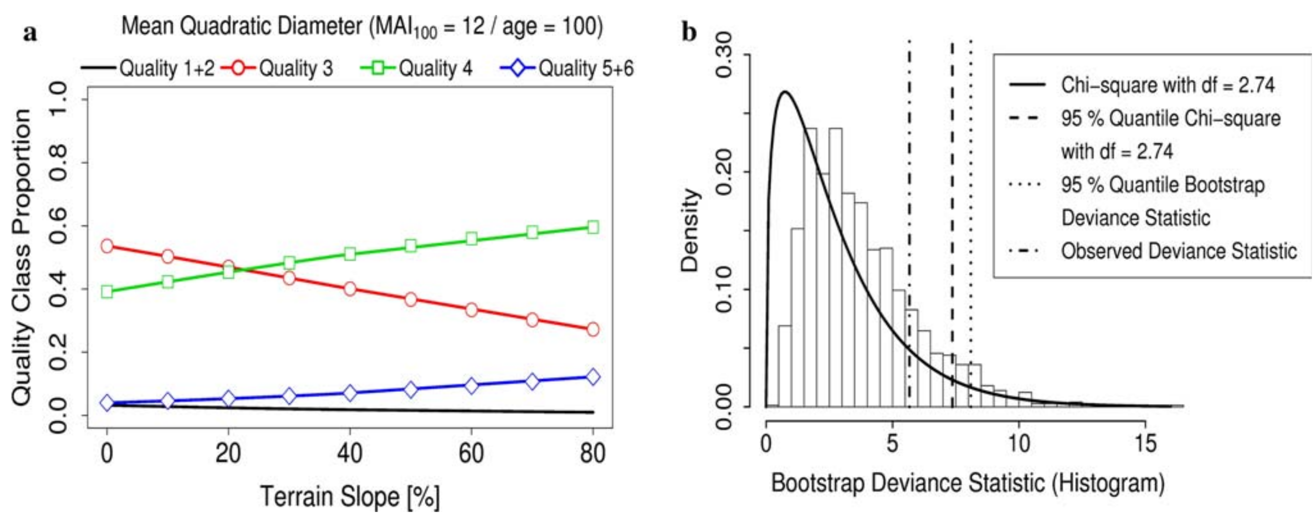

Fig. 1 **a** Predicted conditional quality distributions for varying terrain slopes under ceteris paribus conditions for the average mean quadratic diameter tree of ~100-year-old spruce stands with a site index of MAI_{100} ~12 m^3 ha^{-1} a^{-1} (mean height-based site index ~33.2 m), taken from data base BWI 2. **b** Comparison of the deviance statistic distribution using a bootstrap simulation with its approximation using the χ^2-distribution to test the significance of an additive model term for terrain slope

It increases consistently with gradient and certainly does not commence at a certain threshold value. However, above a gradient of 40% only a small number of data sets are located. Between 0 and 40% gradient, where 99% of the assessed spruce is located, the proportion of the quality class 3 decreases by 13%, while the proportion of the quality class 4 increases by 11% and that of the quality class 5 + 6 by 3%.

It is not possible to determine to what extent various (terrain dependent) harvesting methods (i.e., felling and skidding damages) have influenced the quality distribution. However, no significant difference arises between the quality of trees from sample plots which were harvested between 1987 and 2002, and those from sample plots where no harvesting occurred when the terrain gradient was already used as a predictor. In this regard, it can be generally assumed that the static model approach is problematic in identifying the effect of a periodic harvest and thinning intensity on stem quality as the initial status cannot be considered.

Altitude

In contrast to the slope gradient, a non-linear term as opposed to a linear term leads to a significant model improvement with respect to altitude. Thereby, the function pattern hardly shows any influence of altitude up to height of 800 m (Fig. 2a). From an altitude of approximately 800 m, the proportion of the quality class 3 decreases with increasing altitude, while the proportions of the quality classes 4 and 5 + 6 increase with altitude. The use of a linear term to quantify the influence of altitude would have not adequately represented this trend with a clear "break" at approximately 800 m. At an altitude of between 800 and 1,100 m, where 24% of the assessed spruce can be found, the proportion of the quality class 3 decreases by about 11% and the proportions of the quality classes 4 and 5 + 6 increase by 9 and 3%, respectively. The trend continues further above an altitude of 1,100 m whereby this area only concerns about 2% of the recorded spruce. The illustration of the effect of altitude on the scale of the linear predictor once again clarifies the non-linear relation (Fig. 2b). The two times pointwise standard error of the mean curve identifies areas of lower prediction accuracy (Fig. 2b).

Distance to forest edge

In order to quantify the influence of distance to the outer forest edge, the non-linear model term proves to be superior (Fig. 3a). For the quality classes 5 + 6 and 1 + 2, approximately monotone decreasing, respectively, increasing proportions are predicted by the model. This seems biologically plausible. The quality classes 3 and 4 also show increasing, respectively, decreasing proportions across almost the whole range of distances. However, in principle, non-monotone processes may also be plausible for the "medium" classes of the quality distribution as a result of interactions between the quality classes. Thereby, a clear influence concerning the outer forest edge can be identified for the quality classes 3, 4 and 5 + 6 up to a distance of 10 m. In this case, the interpretation might be that the proximity to the outer forest edge has a negative impact primarily due to stronger branching. From a distance of approximately 10 m and farther, the curves seem

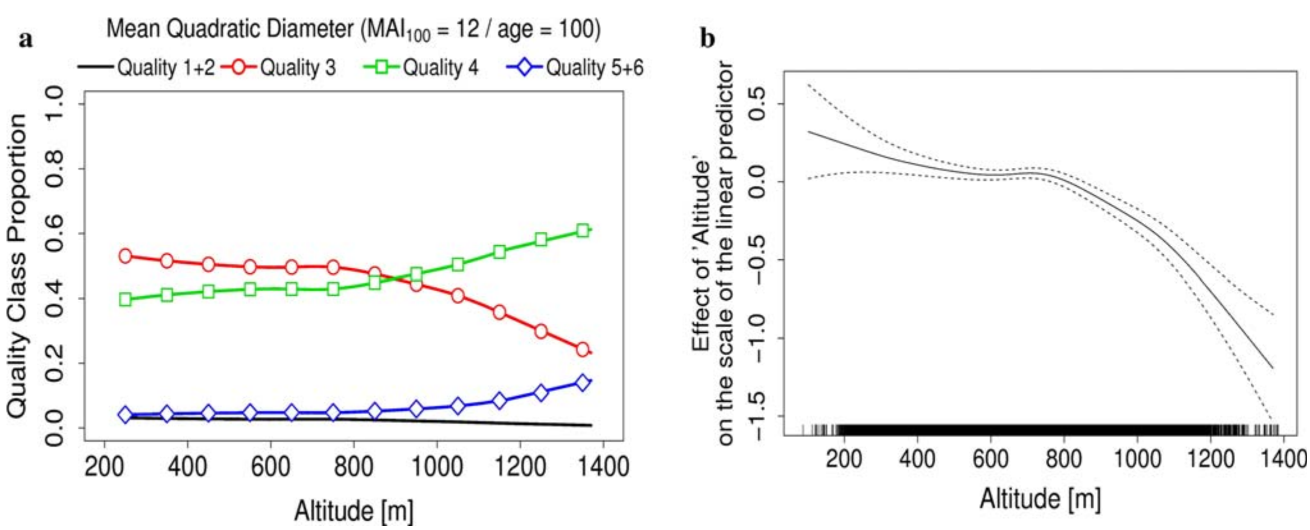

Fig. 2 **a** Predicted conditional quality distributions at varying altitude under ceteris paribus conditions for the average mean quadratic diameter tree of ~100-year-old spruce stands with a site index of $MAI_{100} \sim 12\ m^3\ ha^{-1}\ a^{-1}$ (mean height-based site index ~33.2 m), taken from data base BWI 2. **b** Effect of altitude and two times pointwise standard error curves on the scale of the linear predictor

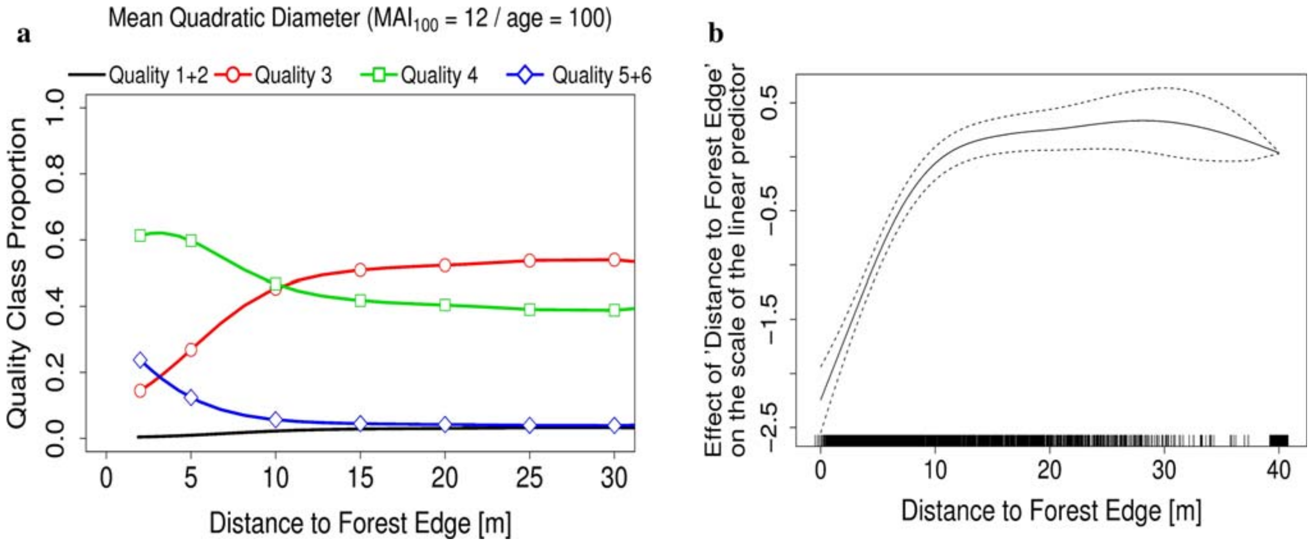

Fig. 3 **a** Predicted conditional quality distributions with varying distance to the outer forest edge under ceteris paribus conditions for the average mean quadratic diameter tree of ~100-year-old spruce stands with a site index of MAI_{100} ~12 m^3 ha^{-1} a^{-1} (mean height-based site index ~33.2 m), taken from data base BWI 2. **b** Effect of distance to the outer forest edge and the two times pointwise standard error curves on the scale of the linear predictor

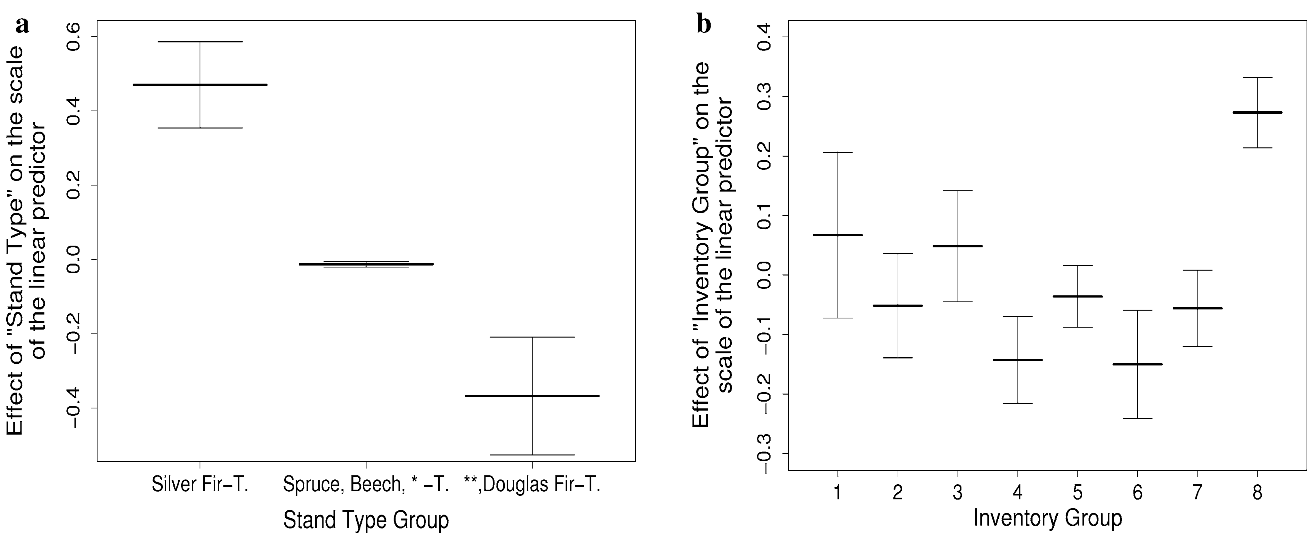

Fig. 4 **a** Effect of stand type group and two times pointwise standard errors on the scale of the linear predictor. **b** Effect of inventory group and two times pointwise standard errors on the scale of the linear predictor

to approach asymptotes, resulting from the decreasing influence of the outer forest edge. From a biological perspective, the asymptote is plausible. However, all these processes show trends in a slightly opposite direction at a distance of more than 25 m, which might be the result of randomness in the database.

In principle, the prediction error has the tendency to increase with increasing distance to the forest edge. However, at a distance of 40 m which covers all trees for which no distance was measured (94% of the database) the error decreases to a very small value as can be seen in Fig. 3b.

Stand type

During model selection it becomes evident that the order of the original stand type groups resulting from the associated coefficients only partially corresponds with specifications derived from expert knowledge. A plausible order could only be guaranteed by a very rough stratification into three groups: (1) fir types, (2) types with dominant spruce, beech or other long living broadleaved species and (3) types with dominant light-demanding tree species or Douglas fir (Table 2). In this classification, the stem quality of spruce decreases from species group 1–3 (Fig. 4a). In this case only the effects on the scale of the linear predictor are presented.

When categorical predictor variables are used, it is of particular interest to know if the various categories differ among themselves in reference to their effects in a statistical sense. Looking at the stand type groups it is apparent that the effects on the scale of the linear predictor do vary. This is because the intervals of the two times standard error do not overlap for any of the categories (Fig. 4a).

Inventory team

Assuming a uniform assessment, one would expect that no improvement in the goodness of fit would be achieved using the variable “inventory team” in addition to the predictor variables already identified as significant. Surprisingly, the variable “inventory team” was identified as significant. However, serious differences arise only for the inventory team 8 (Fig. 4b). As the estimate for inventory team 8 is based on a relatively large data set, the two times pointwise standard error is relatively small and there is no overlap with the error intervals of other inventory teams (Fig. 4b).

It is necessary to integrate the variable “inventory team” into the model to guarantee unbiased estimates of the model effects. In contrast, its effect can only be interpreted in a non-restrictive manner if no spatial trend exists within the database. Spatial trends are often caused by spatially varying factors that have not been identified. This limitation in the interpretation of the model behavior is of particular importance concerning the variable “inventory team”, because for logistical reasons each inventory team assessed a spatially coherent area of Baden-Württemberg. Hence, the team effect could also represent a spatial trend not captured by the other predictors included.

Tree variables: DBH, *h*/*d*-value

The tree variables DBH, *h*/*d*-value and age were not yet used independently as predictors in our considerations due to their high correlation. However, these variables were used in the form of value combinations of a representative model tree. If these variables are to vary under otherwise constant conditions across a wide range of values, then their correlation structure has to be considered for the generation of plausible pairs of variates also. Hence, single tree variate pairs were generated starting from the mean quadratic diameter of site index $\mathrm{MAI}_{100} = 8$, $\mathrm{MAI}_{100} = 12$ and $\mathrm{MAI}_{100} = 16\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$ at a reference age of 100 years. The quadratic mean diameter (D_g) was calculated from the database as described at the beginning of this chapter. The associated height (H_g) results from the predetermined age and mean-height-based site index. Subsequently, the variable DBH varied across a value range of 25–90 cm and the associated tree heights were estimated using generalized height–diameter curves. Consequently, these pairs of variates describe typical tree characteristics, which might occur within a stand of the respective site index. For reasons ensuring a wide diameter range, pairs of variates are generated in the area of extrapolation also whereby the correlation structure is always taken into consideration. Consequently, the following diagrams depict the prediction of conditional quality distributions within model stands, whereby all other metric predictors were set constant at a data base average. The categorical predictors again were set to the stand type “spruce, beech or other long living broadleaved species” and the previously applied inventory team which shows an “average” effect on the quality class distribution.

In order to demonstrate the influence of varying silvicultural scenarios on the quality distribution, two further variants were generated based on the model stand using the average empirical D_g. In doing so, two different D_g at age 100 were used at the same average stand height (which means the same mean-height-based site index) to calibrate the generalized height–diameter curve, respectively, to generate pairs of height and diameter. On the one hand, the yield table D_g at age 100 was used. On the other hand, a D_g that is 10 cm higher than the empirical D_g was used. This variant is interpreted as the result of hypothetical silvicultural scenarios applying more heavy thinnings compared to the empirical 100-year-old stands (sample plots).

Independently of the three silvicultural scenarios and site indices, it becomes clear that with an increase in DBH, the model predicts monotonously decreasing proportions in the quality classes 1 + 2 and monotonously rising proportions in the quality class 5 + 6 (Fig. 5a). In contrast, the trends for the quality class 3 indicate a maximum which is all the more distinct, as site index decreases. With increasing site index, this maximum lies at the level of a larger DBH. The trend of quality class 4 shows a minimum in the maximum of quality class 3, and also a maximum in the area of larger diameters which shifts more toward larger diameters with increasing site index. These trends are plausible if one accepts branching as the dominant quality criterion. It can be assumed that more dominant trees within a stand will form larger branches as there is less pressure from competition or better growth due to their own genetic make up (Schmidt 2001; Schmidt and Weller 2006). In such an interpretation, stronger conversions over time within the stand size class distribution are excluded as the quality rating only concerns the stem up to 10 m. A comparison of the conditional quality distributions for the empirical average D_gs ($\mathrm{MAI}_{100} = 8\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$: 37.5 cm, $\mathrm{MAI}_{100} = 12\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$: 44.7 cm and $\mathrm{MAI}_{100} = 16\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$:49.4 cm) demonstrate a decreasing quality

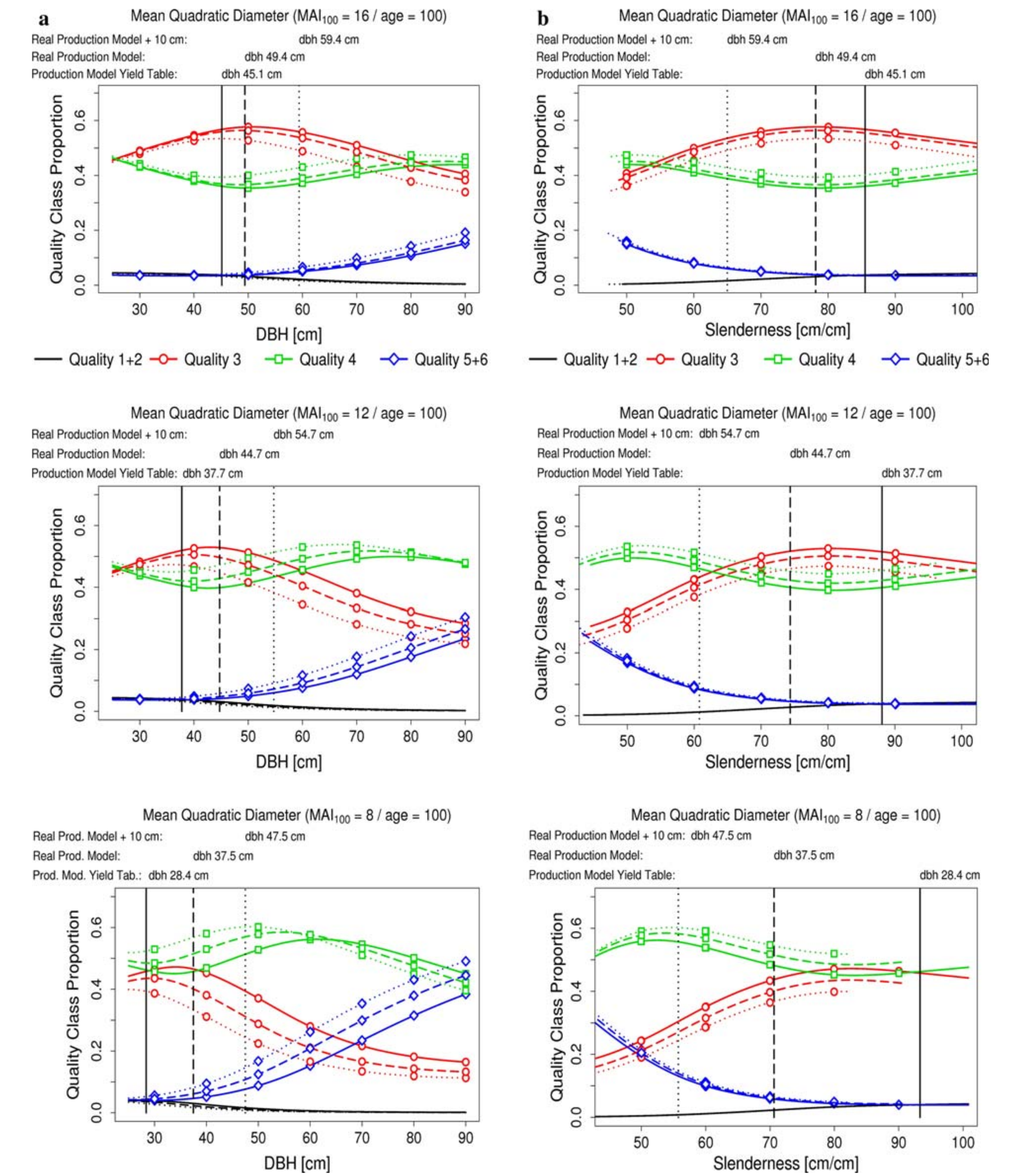

Fig. 5 a, b Predicted conditional quality distributions within 100-year-old model stands of the site indices $\mathrm{MAI}_{100} = 8$, 12 and 16 $\mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$ over the DBH (*left*, **a**) and the *h*/*d*-value (slenderness) (*right*, **b**) under ceteris paribus conditions. In addition, the effects of various mean quadratic diameters on the quality structure are shown as the potential result of varying silvicultural scenarios: *vertical lines* mark the values of the mean quadratic diameters. The *continuous line* indicates the D_g according to the yield table, the *long dashed line* indicates the D_g according to the real situation and the *dotted line* indicates the D_g increased by 10 cm at an age of 100 as opposed to the real situation. The associated functional trends which illustrate the specific quality class proportions determined by D_g and site index, are in each case encoded in the same line type

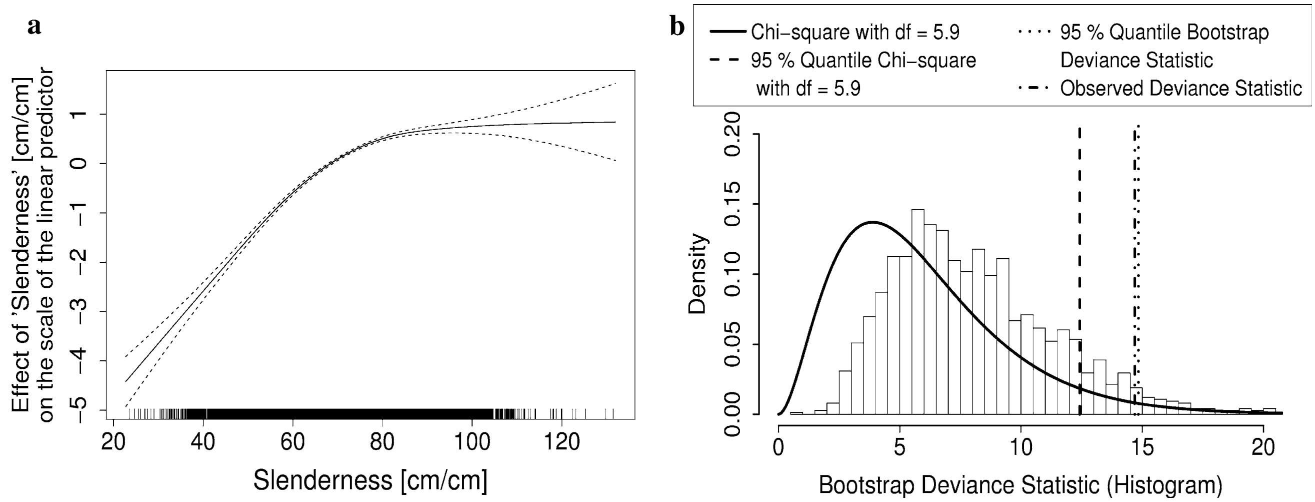

Fig. 6 **a** Effect of slenderness and two times pointwise standard error curves on the scale of the linear predictor. **b** Comparison of the deviance statistic distribution using a bootstrap simulation with its approximation using the χ^2-distribution to test the significance of an additive model term for DBH

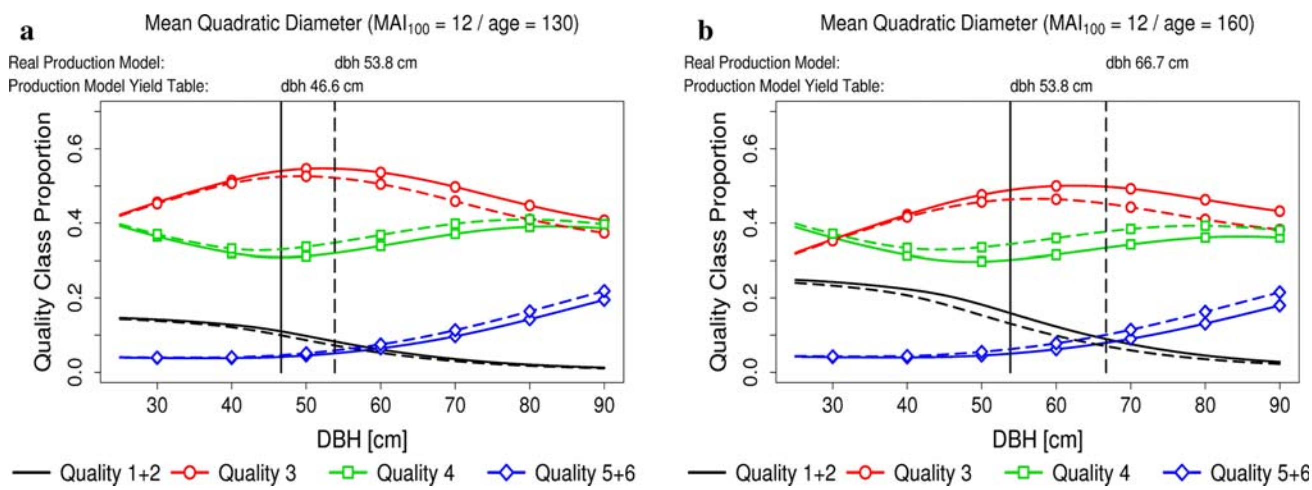

Fig. 7 **a, b** Predicted conditional quality distributions within a 130 (**a**, *left*) and a 160-year-old (**b**, *right*) model stand with the site index $MAI_{100} = 12\ m^3\ ha^{-1}\ a^{-1}$ over the DBH under ceteris paribus conditions. In addition, the effects of various mean quadratic diameters are illustrated as the potential result of different silvicultural scenarios on the quality structure: *vertical lines* indicate the values of the mean quadratic diameters, whereas the *continuous line* indicates the D_g according to the yield table and the *long dashed line* indicates the D_g according to the real situation. The associated functional trends which illustrate the specific quality class proportions determined by D_g and age are in each case encoded in the same line type

distribution from good to poor site indices. When interpreting these particular model predictions it is very important to consider that these are quality distributions relating to three stands of equal age. Therefore, generalized statements concerning the differences in quality composition, e.g., comparing medium-sized logs with large-sized logs cannot be derived from this particular analysis.

If one compares the different D_gs for a given site index as a potential result of various silvicultural scenarios, it becomes evident that the lower the site index, the more clearly the empirical values differ from the values obtained in the yield table. Therefore, with decreasing site index the associated differences in the quality distributions are even more evident. However, it can be seen that even equally strong manipulations of the D_g, as assumed in the progressive scenarios "empirical D_g + 10 cm", have a different effect depending on the site index. Thus, it is evident that the more the site index decreases the more an increase of D_g causes a shift toward less favorable quality distributions.

The effects of "silvicultural impacts" on the D_g for the various site indices can now be explained as follows: for a potential increase in the D_g by 10 cm at an age of 100, where site index is low, stem number reductions along with the promotion of future crop trees have to be conducted earlier than where the site index is average or good. The best site indices, in contrast to the poorer growing sites, allow for a longer juvenile phase, with lower intervention intensities because after this phase a more pronounced increase in diameter growth can still be realized. In this consideration, the focus is only on quality aspects not regarding, e.g., stability or increment.

When interpreting the model behavior, one must take into account that this is a static approach. It cannot, therefore, be used in forecasting the development of the quality distribution over time as a result of silvicultural development pathways. However, it can be used successfully in predicting the most likely quality distribution of a stand with specified characteristics. When the effects of various silvicultural scenarios are interpreted, one has to take into account that apart from a shift in conditional quality distribution at a given DBH, there is also a movement in the diameter distribution due to a shift in the D_g. In most cases this effect might have much stronger impacts on the quality structure of a stand than the shift in the conditional quality distribution. The illustration of the quality distributions plotted against the *h*/*d*-values of the single trees for the same model stands shows again plausible model behavior across the whole range of values (Fig. 5b).

The following important conclusion can be drawn from the illustrations (Fig. 5a): for a given site index an increase in diameter growth usually leads to a decrease in quality distribution. At the same time, two effects must be considered. On the one hand, the conditional quality distribution degrades for a given DBH. On the other hand, the shift in the diameter distribution leads to larger diameters and a less favorable quality structure. When considering the empirical D_gs, large differences in the site indices arise. When looking at the site index $\mathrm{MAI}_{100} = 8\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$, it can be seen that due to certain silvicultural practices a further increase in the diameter growth would lead to a significant decrease in the stem quality. It can also be observed that the scope for the site indices $\mathrm{MAI}_{100} = 12\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$ and especially $\mathrm{MAI}_{100} = 16\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$ is significantly larger. In the latter case even the hypothetical increase of the D_g by 10 cm at an age of 100 would not lead to significant changes in the conditional quality distribution (of the D_g). However, the influence of the shift in the whole diameter distribution has yet to be considered in greater detail.

As an example for the tree variables, the effect of the additive term for the variable *h*/*d*-value is illustrated (Fig. 6a). A clear linear trend can be observed below a value of about 70, whereas an asymptotic functional trend suggests virtually no influence above this value.

Initially, it was pointed out that the deviance statistic shows only low values when it comes to the significance testing of addititve terms concerning the covariates slope and DBH. Owing to poor approximation by the χ^2-distribution (Figs. 1b, 6b), the distribution of the deviance statistic representing the null hypothesis was estimated with the bootstrap method to test the significance of an additive term for the variable DBH. In this case, the null hypothesis is not rejected only when the bootstrap distribution is used. This underlines the necessary use of the resampling method.

Tree variable: age

Finally, the effect of age on stem quality will be illustrated (Fig. 7). A large portion of spruce-dominated forests in Baden-Württemberg are still composed of even aged stands. Therefore, we will analyze the stem quality for even-aged stands of different stand-age. Once again it must be pointed out that the illustration is not about a time series of the same model stand, but rather a prediction of three model stands differing in age which could have undergone various silvicultural treatments. As a starting point the 100-year-old stand with the site index $\mathrm{MAI}_{100} = 12\ \mathrm{m}^3\ \mathrm{ha}^{-1}\ \mathrm{a}^{-1}$ is used (Fig. 5a, center).

The previous illustrations of the model behavior have shown that the (conditional) quality distributions decline within even aged stands with increasing DBH and decreasing *h*/*d*-value. In contrast, older spruce stands show a more favorable quality distribution than younger stands if the marginal conditions are the same. In this way, the proportion of quality class 3 increases significantly with increasing age, with a DBH larger 60 cm (Fig 5a, center; Fig. 7). At the same time, the proportion of quality class 4 declines consistently across the whole diameter range, while the proportion of quality class 5 + 6 primarily declines with a DBH larger 60 cm. The quality classes 1 + 2 are increasing with increasing age mainly below a DBH of 60 cm.

We must consider the fact that one cannot conclude from these differences directly how much of a certain log quality class will be produced under certain conditions. For such forecasting, the quality distributions must be supplemented by estimates of the diameter distribution. For example, it is possible that the increase in quality over age can be explained by the fact that the lower quality classes are harvested earlier and more frequently. If at the same time there is a strong decrease in growing stock, it might be possible that despite a higher proportion at an age of 160 (Fig. 7), the quality class 3 would yield less than at an age of 100 (Fig. 5a, center).

Discussion and conclusions

The modeling approach presented in this paper is more flexible compared to standard ordered categorical regression models which are often used in the direct modeling of stem wood, round wood or sawn wood quality (Gobakken 2000; Uusitalo 1995). At the same time the integration of simple constraints is possible which can be used to achieve plausible prediction patterns corresponding with forest expert knowledge. The presented model type is also superior to an approach employing a set of regression models with binary response (Sterba et al. 2003). Applying a set of independent models disregards the covariance structure between quality classes.

Various conclusions may be drawn from this analysis for decision support within the context of practical forestry. One of the most important conclusions relate to the site index dependence of differences in the conditional quality distributions and the (according to site index) varying influence of the (thinning dependent) increase of diameter growth. We have been able to show that with reference to the effects on stem quality, there is more scope for an increase in diameter growth (which is dependent on thinning), on the better growing sites. These findings are qualitatively consistent with single tree model approaches for modeling branch diameter which is one of the most important properties that influences wood quality of Norway spruce. Schmidt (2001) uses *h*/*d*- value additionally to DBH as a predictor that has a negative effect on branch diameter. Assuming that for a predefined DBH and age combination, the average tree height is higher at good sites would lead to better qualities compared to poor sites. Maguire et al. (1991) presented a single tree model for the prediction of maximum branch diameter in Douglas fir where site index has a negative effect with DBH already integrated in the model.

Furthermore, sites could be subdivided into different value categories related to the predictors terrain slope, altitude and site index, which cannot be influenced by management. As a result, a ranking of the stands or the stand strata could be derived and the management intensity could be adjusted accordingly. However, it must be taken into account that the 100-year-old stands of today have not been treated in the past using the current silvicultural concepts. A classification of stands according to value categories can be used in a meaningful way, when supply contracts require the delivery of particularly high proportions of high- or low-quality logs. In principle, it would be possible to transfer the basic model structure to other tree species.

However, further improvement will be possible in the case of a consecutive stem quality rating in the course of the BWI 3 by parameterization of dynamic models. Dynamic models allow for forecasting change rates in the quality distribution (Sterba et al. 2003). Hence, they enable to set up on the initial stem quality distribution found in a previous inventory. Additionally, they are sensitive to harvesting and thinning scenarios, which take stem quality into account, i.e., by removing poor qualities first.

The usefulness of the model predictions for practical management is limited also by the fact that the quality rating of the standing stem cannot be directly equated to the round wood and sawn wood quality. The connection of the stem quality rating with the round wood and sawn wood quality through statistical models would clearly increase the usefulness of the provided information (Sterba et al. 2003). The data requirement for evaluating such connections is extensive in terms of cost and time input if the investigation is on the single tree level (Leenen 2006). As a result only smaller data sets are available than those that can be used for the modeling of stem quality (Leenen 2006; Gobakken 2000; Uusitalo 1995). Therefore, the model presented in this paper can be seen as a sub model (developed from an extensive database) within a comprehensive round wood and/or sawn wood forecasting system based on standard inventory parameters.

But to date the investigations dealing with the connection between stem quality rating and round/sawn wood quality are rare. Stepien et al. (1998) and Leenen (2006) found the correlations between the quality rating of spruce and fir stems and the related sawn wood to be significant but weak. Results from Uusitalo (1995) and Gobakken (2000) are more promising. However, they use more detailed information about external stem characteristics. Uusitalo (1995) additionally uses bucking information and the location of the timber within the stem as predictors. Another difference is due to the specific definition of timber grades which is partly depending on the stem's dimension (Uusitalo 1995). Teeter and Zhou (1999) successfully predict the proportions of different timber product classes from large scale inventory data. But the used product classes are rather size than quality classes.

The correlations between stem quality and round wood quality appear to be slightly higher (Leenen 2006), especially when focusing on stems of poor and high quality. In this investigation the correlations were higher applying regional customer-oriented sorting rules than applying European standards (DIN EN 1998). Leenen (2006) investigated 771 single stems and the related round wood and sawn wood in a detailed manner. However, a problem results from non-assessed cuts of stem sections showing stem rot which confounded the actual correlation structure. The slightly higher correlations between stem and round wood quality are confirmed by an investigation by Sterba et al. (2003). The correlations thereby were higher in enterprises dominated by softwoods than in those dominated by hardwoods. In this investigation harvested assortments were only available on forest district level. Overall, the link between stem quality and round/sawn wood quality must be improved in the future. Further investigations are needed in both areas of forest utilization research, the original stem quality rating and the development of adequate models. However, to allow comparisons, any changes in the stem quality assessment methods must be compatible with the quality rating method of the BWI 2.

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