Pitfalls and Hurdles in Site Index Modeling

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Abstract

Site index models play an important part, when deciding on future stand species composition. Most modeling approaches use either Space-for-Time data or research plot data. In a novel approach, we combine both categories. Due to this combination, we are able to identify a number of issues. We found, that basing a model on Space-for-Time data will lead to a distorted growth curve. Moreover, the estimated effects for the dynamic variables, which change over stand life, were flawed, as well. However, the broad coverage of the data is still needed, e.g. when quantifying the influence of the manifold soil categories. We propose a hierarchical chain of models, where each model utilizes a different subset of data. Thus combining the strengths of each subset, while avoiding possible pitfalls. As our research is still ongoing and results are still preliminary, we focus more on the issues we encountered and how to circumvent them.

Keywords: site index model; research plots; inventories; space for time; correlations;

1 Introduction

Site index models play a key role, when assessing the suitability of different tree species for future forest stands. Apart from providing growth and yield estimates, the stand height is also crucial when estimating carbon storage or storm risk, for example.

The data used for those models can be put into two rough categories: Space-for-Time data, which usually refers to inventories, and time series data, which usually refers to long-term research plots. To our knowledge, researchers so far included data from only one category (Antón-Fernández et al., 2016; Nord-Larsen et al., 2007; Schmidt, 2020). For our research, however, we combined data from both categories and from multiple sources. This allowed a thorough assessment of the model results, which would not have been possible otherwise. Since our initial model (Schick et al., 2023), we encountered further issues and gathered additional insight, mostly relating to the characteristics of Space-for-Time data and correlations within the whole data.

Since the modeling process is still ongoing, our results are still preliminary. Thus, we rather want to elaborate on some of the pitfalls we found and the mistakes we made so far.

2 Aim of the research

The aim of this research is, to develop models, which can adequately depict future site index development of different tree species. To be considered adequate, the models have to fulfill a number of criteria. They have to be able to estimate stand height

(1) at any age,
(2) under changing environmental conditions,
(3) for all of Germany,
(4) without the need for existing dendromentric data,
(5) with plausible longitudinal properties,
(6) plausible effects,
(7) without a relevant bias.

In the end, we aim to obtain such models for seven tree species: Oak (*Quercus petraea / robur*), Beech (*Fagus sylvatica*), Spruce (*Picea abies*), Fir (*Abies alba*), Douglas fir (*Pseudotsuga menziesii*), Pine (*Pinus sylvestris*) and European Larch (*Larix decidua*). The site index is represented by the height of the mean quadratic diameter tree (Hq).

3 Material

Our modeling approach is based on using an existing growth curve, i.e. the modified Korf

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function with the four parameters *a*, *b*, *c* and *λ* (Schmidt, 2020).

$$E[log(Hq_{kt})] = a - b * \frac{(age_{kt} + \lambda)^{-c} - (100 + \lambda)^{-c}}{(50 + \lambda)^{-c} - (100 + \lambda)^{-c}}$$

c and *λ* define the basic shape of the curve, *a* is the logarithmic Hq at age 100 and *b* is the logarithmic difference in Hq between age 50 and age 100.

3.1 Dendrometry

The data used for this work combines measurements from inventories and long-term research plots. Three inventories were considered: The national forest inventories of Germany (NFI), 1987 to 2012. The enterprise forest inventories (EFI) of Hessia, Lower Saxony, and Schleswig-Holstein. The carbon stock inventory (CFI) from 2017 from the three aforementioned states including Saxony-Anhalt. Generally, the inventories are characterized by a high number of measured stands with comparably few repeated measurements per stand. Please note, that the word *measurement* henceforth refers to measuring the dendrometry of a whole *stand*, not the individual tree.

Research plot data was gathered from the Northwest German Forest Research Institute (NW-FVA), the Forest Research Institute Baden-Württemberg (FVA), as well as from the state forest enterprises of Brandenburg (BB) and Saxony (SN). Contrary to the inventories, the research plots consist of few plots with a high number of repeated measurements.

The total number of measurements and plots, combined for all seven species, can be found in table 1.

Table 1: Number of plots, measurement occasions and trees per data source.

Source	*n plots*	*n meas.*	*n trees*
Inventories			
NFI	63,531	132,367	1,024,383
EFI	110,506	172,435	2,041,360
CFI	6,169	6,169	41,529
Research Plots			
NW-FVA	1,868	13,188	1,663,106
FVA	1,926	13,436	2,178,749
BB	113	737	173,962
SN	27	127	32,031
Total	184,140	338,459	7,155,120

3.2 Environmental data

The environmental data can be grouped into two main categories: Atmosphere and soil.

3.2.1 Atmospheric data

The atmospheric variables considered here were temperature (Temp), precipitation (Prec) and nitrogen deposition (NDep). Temp and Prec were summed over the stands life span for the dynamically determinded vegetation period (Menzel, 1997; Nuske, 2017), NDep for the whole year. Afterwards, they were interpolated to a 50m x 50m grid for all of Germany. Data is available from 1800 (NDep) or 1900 (Temp, Prec) to 2100. Modeling of Temp and Prec was based on data from the German Meteorological Service (DWD), NDep was based on data from the Umweltbundesamt (Schaap et al., 2018).

3.2.2 Soil data

Soil characteristics were depicted by the rather simple variables water budget category (German: Wasserhaushaltsziffer, WHZ) and nutrient budget category (German: Nährstoffziffer, NZ), since these variables were available for large parts of Germany.

A detailed description of the data, i.e. dendrometry and environmental data, as well as its processing can be found in Schick et al. (2023). Please note, that the modeling approach described there is no longer in use. Additionally, SN and BB data were added and the weighted mean described in equation (3) of said paper was discarded.

4 Pitfalls and Hurdles

When fitting the models and trying to satisfy the criteria defined in ch. 2, several issues became apparent. Almost all of them can be subsumed in simple words: We are missing data.

Although the numbers in table 1 may look comparably large, they become small once they are stratified by species and the environmental variables.

4.1 Space-for-Time

The Space-for-Time Substitution (SFTS) describes the idea, to obtain a so called *false time series* by measuring stands of different age at one point in time. Such data can be obtained from inventories, for example. The use of SFTS data for site index modeling has been recently criticized (Damgaard, 2019; Klesse et al., 2020; Yue et al., 2023). E.g., Yue et al. (2023) authors showed, among others, that a model based on time series data outperformed an SFTS model, as the latter could not accurately capture the effects of the environmental variables. Thus the use of SFTS data for growth and yield modeling is questioned by the authors.

Though our data does not solely contain SFTS data, it still resembles a critical part of the data (cp. table 1). For the whole data, we found an average of 1.8 measurements per plot. Additionally, 41.7% of the plots had only one measurement in total, although these single measurements have not all been taken at the same point in time. However, the inventories were taken in a comparably short time span, i.e. 1987 to 2017, which leads to a high correlation between stand age and germination year. In pure SFTS data, the correlation would be minus one. In our data, it was -0.948 (Pearsons correlation coefficient). Thus we argue, that our *full* data should still be viewed as SFTS data.

The relevance of this correlation becomes apparent, when one considers the change in environmental conditions over the last two centuries. Due to industrialization, the overall nitrogen deposition has increased (cp. Schaap et al., 2018) and, on average, benefited tree growth. Within our data, we observed, that the average site index of the earlier established stands is lower, than the one of more recent ones (see figure 1). For example, one can compare the site index of beech stands established between 1876 and 1900 with beech stands established after 1976: The *median* site index of the older stands equals the *0.6% quantile* of the younger ones. To paraphrase: 99.4% of the younger beech stands grew better than a median old one.

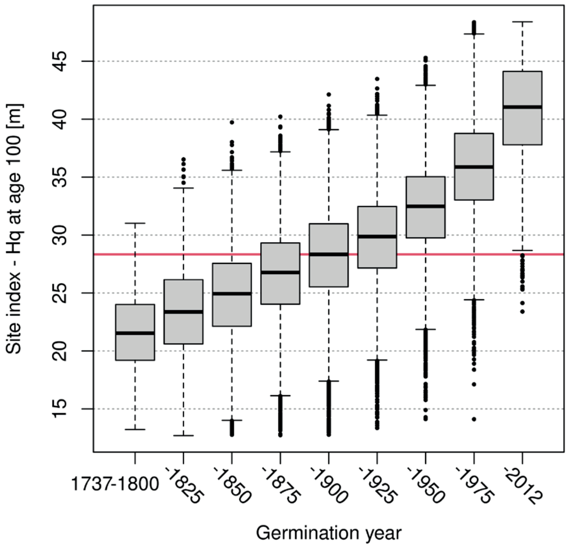

***Figure 1:** The development of site index over germination year for beech. The red line corresponds to the median site index from 1876 to 1900.*

The implications for SFTS data are quite substantial. Consider a theoretical example: Say, we have measured one stand of age 25, 50, 75 and so on to 150, respectively, in the year 2000. Based on our findings above, we can assume, that the site index decreases, the older the measured stands are. For simplicity, we will assume, that each stand grew with a constant site index over stand life. We obtain the corresponding growth curves from yield tables (Nuske et al., 2022) with the Hq_{100} decreasing, e.g., from 34.7m for the youngest stand to 22.1m for the oldest.

If one would estimate a stand growth model on this data, the resulting curve would be distorted and not reflect the real stand growth. This is due to the fact, that only one isolated measurement per stand is present, while the real, individual stand growth remains unobserved. The result can be seen in figure 2.

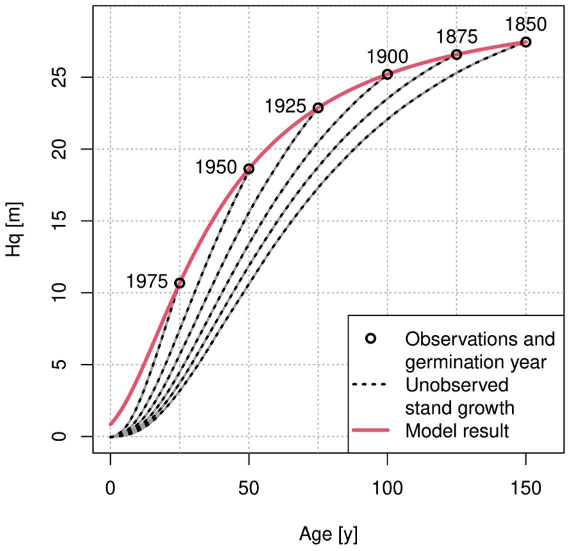

***Figure 2:** The issue with Space-for-Time Substitution data illustrated. Stands growing under shifting conditions result in a distorted growth curve in the model.*

Although the nature of figure 2 is mostly explanatory, it should be stressed, that this is not a purely theoretical example. The red line is obtained from an earlier model version, which is a GAM fitted exclusively on inventory data, but considering all mentioned environmental variables (Schmidt, 2020). For figure 2, all environmental variables have been set to constant values to obtain a constant site index in the model.

It is apparent, that the modeled growth curve has a strong deviation from the yield tables. Moreover, we found, that the modeled curve did not correspond to the time series data of the research plots. Thus there is strong indication, that the resulting curve shape is not plausible and will not be able to properly depict the growth of a stand over time.

It should be pointed out, that said GAM did not show any obvious flaws in the concept or the diagnostics. The environmental variables should have accounted for a changing environment, they showed biologically sound effects, the residuals were normally distributed and without bias. Only with the inclusion of time series data, i.e. the research plots, the issue became apparent.

Thus we argue, that using pure SFTS data for climate sensitive growth and yield models is not advisable. Moreover, one should account for the spatial and temporal structures of the data, e.g. by using a mixed model. This coincides with Yue et al. (2023). However, including the SFTS data at least partially may be necessary to cover a broader environmental spectrum. This will be discussed later on.

4.2 Correlations

During the modeling process, we found different correlation structures within the data, which needed to be accounted for. The most important ones are related to the nitrogen deposition. The temporal correlation, and the connection to the germination year, has been discussed earlier. However, nitrogen is also spatially correlated, with the highest depositions in the northwest of Germany (see figure 3).

In an earlier version of a site index model for beech (Schick et al., 2023), we included a spatial smoother to capture large scale spatial effects, which were not explained by the other environmental variables. The result can be seen in figure 3. An example for such a large scale effect would be wind speed, which would explain the reduced growth in the northwest (cp. figure 3). However, we also found a strong effect for nitrogen in the aforementioned model, with an almost linear increase. During further analysis, it became apparent, that the spatial smoother acted as a counterpart to the spline effect of nitrogen. In a later model formulation without the spatial smoother, we an overall less pronounced effect for nitrogen with an asymptotic shape.

The obvious solution would be a mixed modeling approach. However, we tried fitting different versions of GAMMs in different R-packages. None of them converged, due to the high number of plots with only one measurement.

Thus we would advise caution, when including spatial smoothers and spatially correlated data in one model.

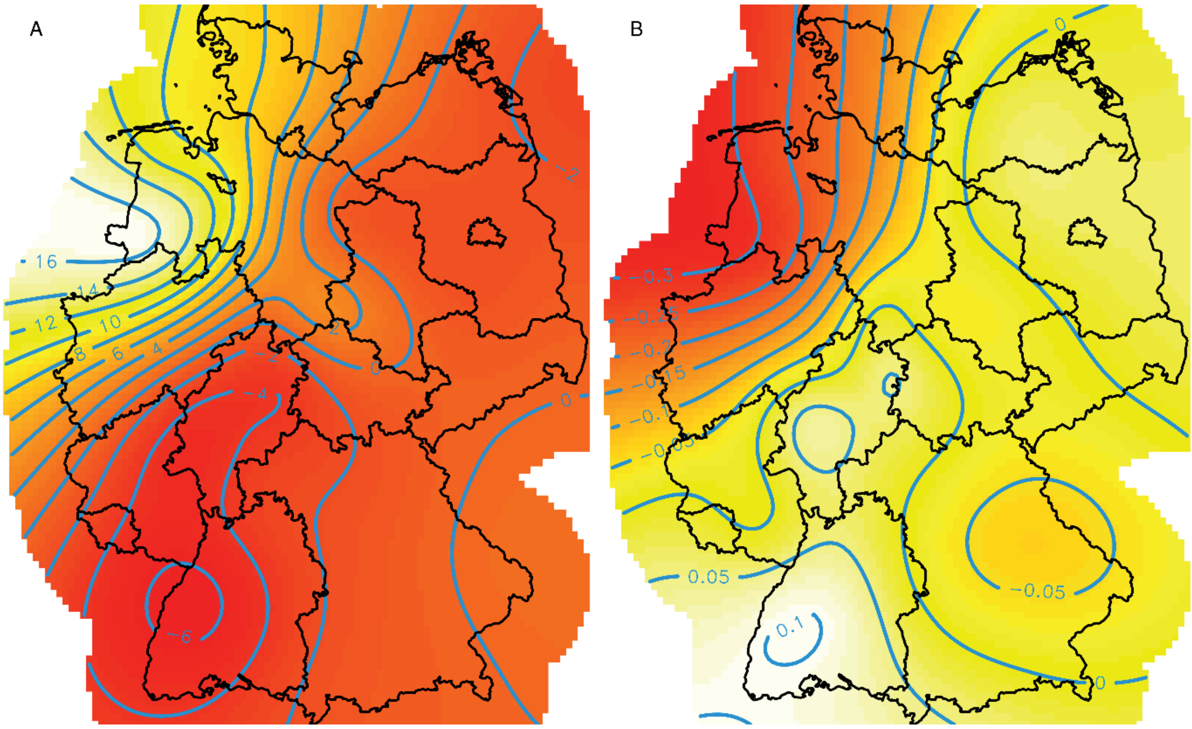

Figure 3: Smoothed deviation of the nitrogen deposition from its mean for Germany (A) and the spatial effect used in Schick et al. (2023) (B). The values in (A) have been aggregated over stand life and do not represent a single point in time.

4.3 Defining the curve shape

As mentioned earlier, our modeling approach is based on the modified Korf function.

Once c and λ are fixed, the function becomes linear, which is desirable for our purposes. During the modeling process it became apparent, that no environmental variable had an effect on b, thus it can also be a fixed value. Hence the basic shape of the curve, i.e. b, c and λ, is defined beforehand and all estimated effects act on the remaining parameter a, i.e. the logarithmic site index.

To be able to correctly estimate the effects, we would argue, that the curve shape should resemble stand growth under constant environmental conditions. However, the respective data from before industrialization is hard to come by. Even most yieldtables, which represent some of the oldest growth and yield data, do not contain values from said era (cp. Schober, 1995). Since there is no data, the effects of the changing environment have to be excluded when determining the basic shape of the curve.

We decided, to use the time series data of the research plots. We then fitted a GAMM with a random intercept on the plot level to the research plot data. The environmental variables are included as spline effects, such that their influence on stand growth is being accounted for. The resulting base curve is shown in figure 4.

Here it can also be seen, that the curve lies between two other modeling approaches without the environmental variables, a GAM and a GAMM, both fit on the same research plot data. The GAM lead to a curve with stronger growth in the youth, the GAMM to a more even growth over stand life.

Since there is no reliable data for stand growth in a constant environment, one cannot assess, which curve is correct. However, during model development, we found, that using the base curve from the GAMM with the environmental variables lead to the best fitting longitudinal patterns in the predictions.

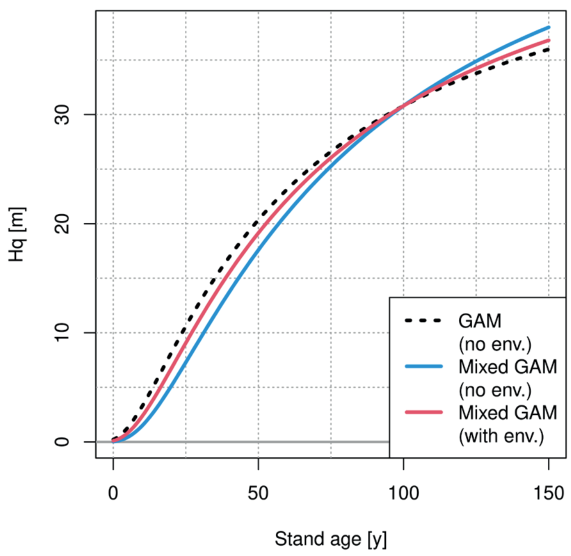

Figure 4: Different base curves for beech obtained from different modeling approaches on research plot data.

5 Combining data strengths

It became apparent, that finding a single model, which satisfies all our criteria, was impossible. The main effects for this being the shifting environmental conditions in combination with a relevant part of our data being SFTS data. Thus, the only feasible solution we could identify, is a hierarchical model chain, where each chain link focuses on a specific task and uses a suitable subset of the data.

First, we use the research plot data to obtain the parameters of the base curve, i.e. b, c and λ, as described earlier.

Second, we generate a subset of the full data, where each plot has at least two measurements (henceforth called *n2 data*). This includes the research plots. Then, a GAMM is used to estimate the effects of the atmospheric variables, i.e. the dynamic variables which change over stand life. With b, c and λ fixed, all effects act on the remaining parameter a of the Korf curve, i.e. the logarithmic site index.

Finally, we use this GAMM to obtain a Hq prediction for the full data. The deviation from the prediction and the actual Hq is then used, to estimate effects for the static environmental variables, i.e. soil parameters and the spatial smoother.

This approach allows us to overcome the obstacles mentioned earlier. The n2 data allowed us to fit a mixed model and thus account for the longitudinal structures within the data. Additionally, the coverage of the dynamic variables in the n2 data is comparable to the full dataset. The loss of information between the two is negligible.

When it comes to the highly varying, categorical soil variables, however, the n2 data would not provide sufficient coverage. Since we assume the effect of the soil to be static over stand life, there is no necessity for a mixed model, such that a GAM with the full data could be used. Moreover, as the effect for nitrogen is already estimated and thus accounted for, the spatial smoother can be included to catch large scale effects. The smoother also serves as a control: When the magnitude of the effect gets too large, the effect for another environmental variable is usually flawed.

6 Conclusions

We combine the time series data from research plots, which reveals longitudinal trends, with SFTS data, which offers a wide spatial coverage. Thus far, both SFTS and time series data have inherent drawbacks. Yet, both are needed to achieve the aims defined earlier and therefore have to be combined (cp. Damgaard, 2019).

By subsetting the data and finding suitable models for different tasks, we are able to circumvent the pitfalls while still utilizing the broad amplitude of our data. Thus, we argue, that operating on subsets of the data rather than the full data is paramount to enable a sound prediction with reliable effects.

It should be stressed, that most of the aforementioned issues and their solutions only became apparent, when verifying the model output against the different data, i.e. SFTS and time series data. The combination of different data from different sources was paramount to identifying and tackling the various issues.

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