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ORIGINAL PAPER

Estimation of Scots pine bark biomass delivered to the wood industry in Northern Germany

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Abstract
Scots pine (*Pinus sylvestris* L.) is the most widely distributed pine species in the world. In Germany, as in many other European countries, it is a very important species both culturally and economically. Few studies have focused on bark volumes being delivered to the wood industry together with the roundwood, being potentially a valuable resource for material or energetic utilization. Therefore, logs from six different forest sites were collected and bark variables including double bark thickness (DBT) in three different categories, diameter, and bark damage (as a degree of missing bark) were measured and analyzed in order to model bark volume (V_{bark}) and bark mass (M_{bark}). The correlation analysis using Pearson's method showed that the highest correlation coefficients were observed from the correlation between DBT and V_{bark}, as well as between DBT and M_{bark}. Also, results demonstrated that with DBT greater than 20 mm, the percentage of V_{bark} exceeded 20%. Finally, different linear regression models were recommended to predict V_{bark} and M_{bark} based on the other variables. The results of this study can be used in different wood industries in order to predict bark volume and bark mass of e.g. truckloads or roundwood stacks.

Key words: bark thickness; bark volume; bark mass; *Pinus sylvestris*; correlation

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1. Introduction

Bark is the boundary between trees and their environment and protects both the cambium and xylem from external environmental influences. The accurate quantification of bark is growing in importance for several reasons including: 1) it is a key variable for assessing wood volumes (Diamantopoulou 2005), 2) to estimate the available resource in terms of bark volume and quantity of extractives for the valorization of tree bark for materials and chemicals (Feng et al. 2013; Bauer et al. 2021), 3) for the calculation of the bark content of energy wood (Liepiņš & Liepiņš 2015), and 4) for the assessment of carbon stocks in tree biomass (Bert & Danjon 2006). The latter is gaining in importance because of the role of managed forests in climate change mitigation due to their capacity to sequester carbon (Klapwijk et al. 2018). Besides the carbon sequestrated in the forest ecosystems, wood products also contribute to climate change mitigation through the carbon stored in harvested wood products and by using wood to substitute more greenhouse gas-intensive materials (Leskinen et al. 2018). Currently, the bark is mostly considered a by-product or even a waste product of the wood industry and therefore mainly incinerated and therewith used as a cheap fuel in e.g. sawmills, board mills, and pulp mills (Feng et al. 2013). However, the use of bark for medicine, construction, clothes, or energy is well documented since ancient times (Pasztory et al. 2016; Leite & Pereira 2017). In the last decades, the interest in the chemical exploration of bark for the extraction of compounds to produce various materials, such as tannin-based biofoams, has increased (Lacoste et al. 2013; Jansone et al. 2017; Pizzi 2019). More recently, simple, and cheap treatments of native Scots pine (*Pinus sylvestris* L.) bark were developed to

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create a leather-like material. For instance, the Scots pine bark was used for panel production or textile production through weaving (Wenig 2022). Through close collaboration between science and design, the material was used to create jackets but possible applications are also seen for the construction of shelters (Wenig et al. 2021). To be able to assess the potentially available bark biomass, it is important to gain knowledge about the amount of bark that is delivered to the wood industry. There, wood and bark are separated by several techniques such as drum debarking or ring debarking. Most bark volume models are based on bark thickness data (Wehenkel et al. 2012; Liepiņš & Liepiņš 2015; Çatal & Saplioglu 2018; Diamantopoulou et al. 2018; Bauer et al. 2021). Thus, bark volumes seem to be overestimated as gaps and cracks are not included. The real bark volume can be obtained through the water displacement technique (Berendt et al. 2021a) or X–ray computed tomography (Stängle et al. 2016). The bark removal due to the rollers and the delimbing knives of the harvester and the grabber of the forwarder is not negligible. Mean bark damage of Scots pine industrial wood at forest road was found to be 12.0% (Berendt et al. 2021b). Thus, it is of importance to consider the bark damages when making an analysis of bark biomass being potentially available from wood industries.

Thus, the aim of this study was to assess the bark biomass which is delivered at the gate of wood industries, and which is therefore potentially available for further utilization and processing. To achieve this, we analyzed the bark mass and bark volume of Scots pine from typical industrial wood assortments used for the production of oriented strand board (OSB).

2. Material and methods

2.1. Site description

The wood originated from six distinct forest sites of the federal state of Brandenburg in north-eastern Germany, and the samples were representative for the supplied wood. The six forest sites are shown in Fig. 1.

2.2. Data collection

The analysis was performed on 317 Scots pine wood discs, which were provided from a OSB manufacturer. Each 4.4 ±0.4 cm thick wood disc was cut from a single 3 m long log at 20 cm from the log end. The advantage of analyzing wood discs instead of logs is that the measurements could be performed under laboratory conditions and that it is much less time intensive. For the characterization of the wood discs, the parameters diameter over bark ($d_{o.b.}$), diameter under bark ($d_{u.b.}$), bark damage, volume over bark ($V_{o.b.}$), volume under bark ($V_{u.b.}$), dry wood disc mass (M_{disc}), and dry bark mass (M_{bark}) were measured and on the basis of this, the following bark parameters were determined:

– Double bark thickness (DBT): both diameters, $d_{o.b.}$ and $d_{u.b}$, were the mean of two perpendicular measurements and DBT was calculated as the difference between $d_{o.b.}$ and $d_{u.b.}$. The $d_{o.b.}$ was between 8.7 and 42.1 cm with a mean of 16.8 ±4.5 cm. The DBT ranged from 0.8 to 33.2 mm and the mean DBT was 10.3 ±6.9 mm. Thus, data were classified based on DBT in three different groups including 0–10, < 10–20 and more than 20 mm as Scots pine bark thickness varies greatly across different stem segments from rough, coarse and furrowed to smooth and thin bark (Durrant et al. 2016; Wilms et al. 2021) (Fig. 2).

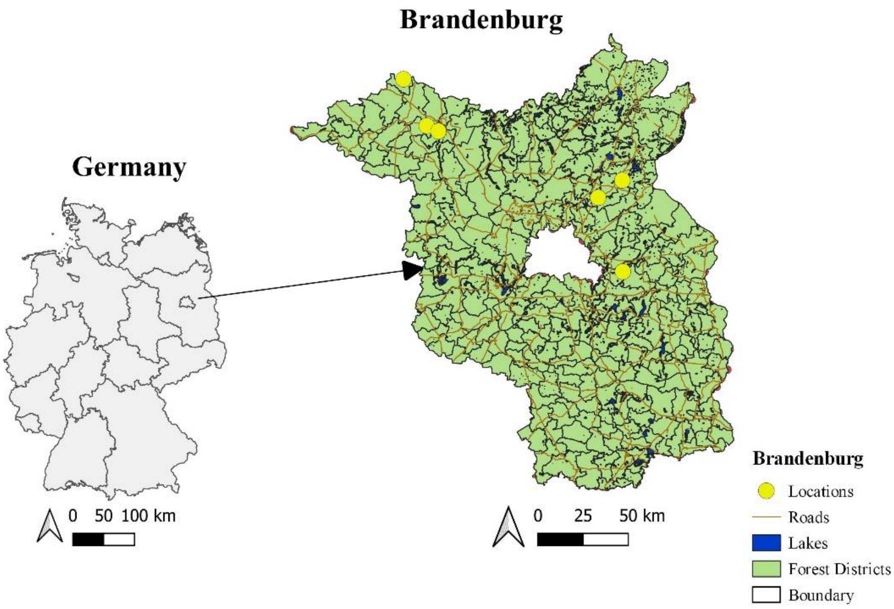

Fig. 1. The origin of the analyzed Scots pine logs.

Fig. 2. Thick, rough and furrowed brown-grey (left) and thin, smooth reddish-orange (right) bark of Scots pine.

- Bark damage was defined as missing bark on the wood discs (see Fig. 3) and calculated as "the ratio of the disc circumference and the length of the bark damages"(Berendt et al. 2021b). In all samples, the mean bark damage was 15.9 ±15.2% with maximal bark damage of 78.2%.
- Bark volume (V_{bark}) was calculated as the difference between $V_{o.b.}$ and $V_{u.b.}$. The volumes of the wood discs were measured using a xylometer with overflow device as described by (Berendt et al. 2021a). In studies, it has been mentioned that the fundamental water displacement technique leads to real volume and is therefore often used to evaluate the accuracy of scaling formulas (Filho et al. 2000; Özçelik et al. 2008; Akossou et al. 2013). The moisture content (MC) of all wood discs was above the fiber saturation point (defined as MC > 30%) and therefore no wood swelling occurred during the immersion.
- M_{disc} and M_{bark} were both oven dry masses and, thus, the masses were determined after drying until constant weight in an oven set at 103 ±2 °C.
- To have the bark biomass in relation to the wood bought by the industries, the analysis was done with 1) the ratio between V_{bark} and $V_{o.b.}$ and 2) the ratio between M_{bark} and the dry wood disc with bark (M_{disc}+M_{bark}). Thus, V_{bark} and M_{bark} were expressed as percentages. The mean volume and dry mass of the wood discs with bark were 1061.7 ±533.1 cm³ and 448.3 ±235.4 g, respectively.

2.3. Statistical analysis

Results of the normality test indicated that the distributions of some variables were not normal. These variables were therefore normalized using Templeton's two-step transformation method (Templeton 2011) before statistical analysis. In the first step of this approach, distributions were converted into ranks, and then the generated ranks to uniform probabilities. In the second step, the inverse-normal transformation was applied to the ranked distributions. In addition, during the normalization of the variables, 13 outliers were removed. Outliers were defined using the IQR method. In this study, data normalization was done using the SPSS ver. 26 statistical software. All other statistical computations were done with R ver. 4.0.3 using the interface RStudio.

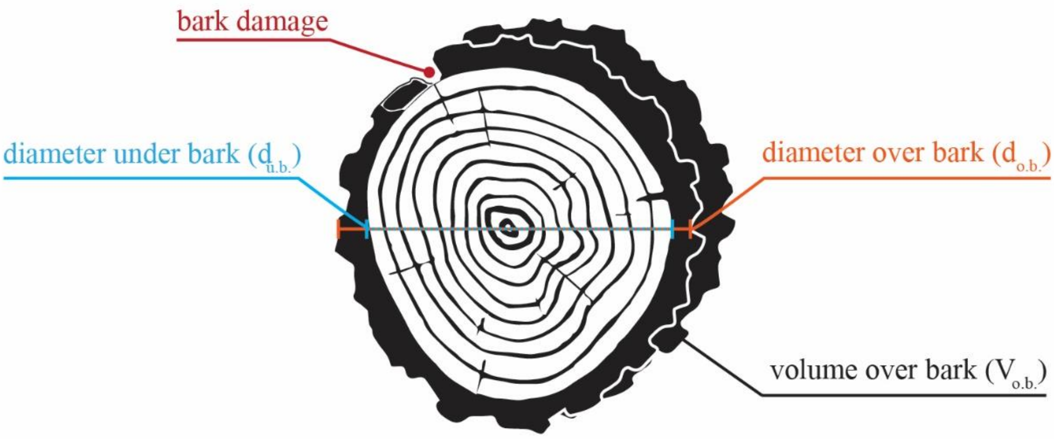

Fig. 3. Representation of diameter over bark ($d_{o.b.}$), diameter under bark ($d_{u.b.}$), volume over bark ($V_{o.b.}$) and bark damage on a wood disc.

During the statistical analysis both V_{bark} and M_{bark} were the response variables. Regression analyses were performed in order to estimate the impact of diameter, DBT, and bark damage on the two response variables (V_{bark} and M_{bark}).

3. Results

3.1. Statistic characterization and correlations

According to the experimental design of this study, 304 wood discs were analysed. Statistical features of the variables including mean, minimum, maximum, and standard deviation for the three different DBT categories are provided in Table 1. The greatest sample size (n = 192) was observed in the first DBT category (0 to 10 mm).

The mean V_{bark} increased from DBT category one (0–10 mm) to the category three (more than 20 mm). The mean V_{bark} was 8.12, 13.92 and 22.10% for the three DBT categories respectively. In addition, the amount of M_{bark} increased (from 4.55 to 13.97%) as the DBT size increased (Table 1).

Table 1. Statistic characterization of all variables.

Variable	Mean	Min	Max	Std. Deviation	N
DBT (0–10 mm)	5.98	0.80	9.98	2.44	192
Diameter [cm]	15.68	8.73	38.89	4.17	192
Damage [%]	20.74	0.00	78.17	15.14	192
V_{bark} [%]	8.12	0.30	0.30	6.01	192
M_{bark} [%]	4.55	0.89	29.24	2.61	192
DBT (10–20 mm)	13.85	10.05	19.70	2.85	75
Diameter [cm]	18.44	11.34	42.12	4.35	75
Damage [%]	11.16	0.00	54.16	10.12	75
V_{bark} [%]	13.93	2.06	38.37	6.40	75
M_{bark} [%]	9.07	3.12	18.85	3.08	75
DBT (> 20 mm)	24.49	20.20	33.20	3.29	37
Diameter [cm]	19.47	14.09	26.12	3.14	37
Damage [%]	3.671	0.00	17.19	4.10	37
V_{bark} [%]	22.11	8.21	47.32	6.00	37
M_{bark} [%]	13.97	6.17	20.57	2.92	37

Sample size (n) = 304 trees.

The relation between different variables in this study was evaluated based on Pearson's correlation (Fig. 4). The correlation matrix demonstrated that there were moderate to significant correlations between most of the variables. Generally, there was a significant positive correlation between M_{bark} and DBT at the 1% probability level. In addition, results indicated that there was a positive significant correlation between V_{bark} and DBT at 1%

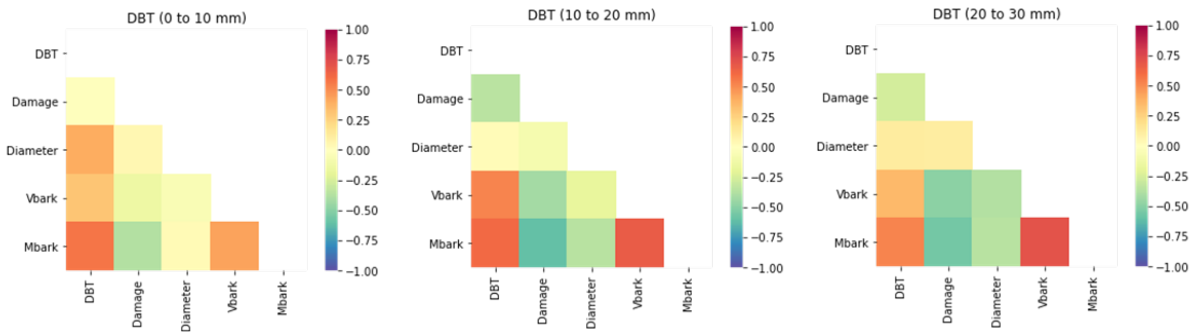

Fig 4. Correlation heatmap of main variables of this study for the three DBT (double bark thickness) categories.

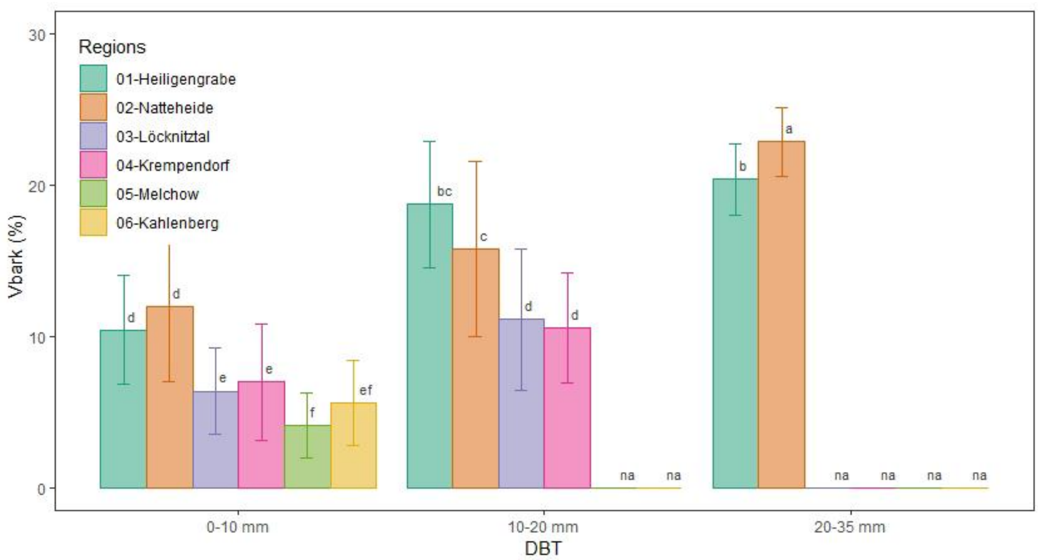

Fig 5. The percentage of V_{bark} in different DBT classes collected from different regions. Means with same letters at the top of bars are not significant ($p \leq 0.05$), na means no data is available.

probability level. This correlation was strongest in the second DBT category (10 to 20 mm) (Fig. 4).

3.2. The percentages of V_{bark} and M_{bark}

In this study, the percentage of V_{bark} and M_{bark} from different regions are shown in Fig. 5 and Fig. 6. Results indicated that the percentage of V_{bark} exceeded 20% in the third DBT category. In addition, the percentage of V_{bark} in Heiligengrabe and Natteheide differed significantly compared to other sites in the first and second DBT categories as well (Fig. 5).

Similar to the V_{bark}, the percentage of M_{bark} was higher in the third DBT category (> 20 mm) than the other classes. It can be clearly seen that also there was a significant difference between some regions. However, similar to the V_{bark} the percentage of M_{bark} in the second DBT category (10 to 20 mm) was significantly higher than the first DBT category. This difference was more evident in the Heiligengrabe and Natteheide regions (Fig. 6).

The main statistical parameters for analysis of variance for V_{bark} and M_{bark} in different DBT categories are reported in Table 2 and Table 3. R^2 is extensively used in different circumstances for both linear and nonlinear regression models (Alexander et al. 2015). Results revealed that the highest and lowest values of R^2 (0.4 and 0.003) for V_{bark} were recorded for DBT in the model without classification and for diameter in the model from the first DBT category. Same results were recorded for M_{bark} (0.678 and 0.001). Adjusted-R^2 (adj-R^2) was used to estimate the quality of the regression models. Similar to R^2, adjusted R^2 varies up to one, where one illustrates the best possible fit (Ohtani 2000). In this study, the highest adj-R^2 for both V_{bark} and M_{bark} were observed in DBT group without DBT categories (0.401 and 0.677, respectively).

Table 2. Results of the analysis of variance for V_{bark} as response variable for all wood discs and for the three DBT categories (0–10; 10–20 and above 20).

DBT	Variable	R^2	Adj_R^2	SE	RSE	RMSE	p-value
0–10 mm	Diameter	0.003	-0.002	0.113	6.917	11.163	0.447
	Damage	0.019	0.014	0.036	6.823	20.504	0.051
	DBT	0.095	0.090	0.104	6.591	7.230	< 0.001
	Diameter	0.031	0.018	0.179	5.450	7.972	0.122
10–20 mm	Damage	0.176	0.165	0.046	5.000	15.749	< 0.001
	DBT	0.275	0.266	0.323	4.689	4.809	7.029e-07
	Diameter	0.136	0.112	0.186	3.714	5.935	0.021
> 20 mm	Damage	0.240	0.220	0.072	3.482	20.932	0.001
	DBT	0.129	0.105	0.227	3.763	3.931	0.027
	Diameter	0.032	0.029	0.098	7.684	9.921	0.001
All	Damage	0.183	0.180	0.028	7.016	19.477	< 0.001
	DBT	0.403	0.401	0.050	6.011	6.366	< 0.001

RSE= Residual standard error; SE= standard error.

As the DBT increased from 0–10 mm to more than 20 mm, standard error (SE) of variables in both cases (V_{bark} and M_{bark}) slowly increased and approximately the highest values were recorded for DBT more than 20 mm. The minimum residual standard error (RSE) of three variables (diameter, damage and DBT) were recorded in more than 20 mm DBT. The RSE values in DBT more than 20 mm for variables of V_{bark} were 3.71, 3.48 and 3.76, respectively. Also, the values for M_{bark} were 2.16, 1.73 and 1.99, respectively (Table 2 and Table 3).

The root mean square error (RMSE) was calculated using the following equation from Chai & Draxler (2014):

$$\mathrm{RMSE} = \sqrt{\sqrt{\frac{1}{n}\sum_{j=1}^{n}(yj-\hat{y}j)^2}}$$

Where n is the number of observations, y is the observed value and $\hat{y}$ is the predicted value.

Results demonstrate that the value of RMSE in DBT 0 to 10 mm was higher than other categories.

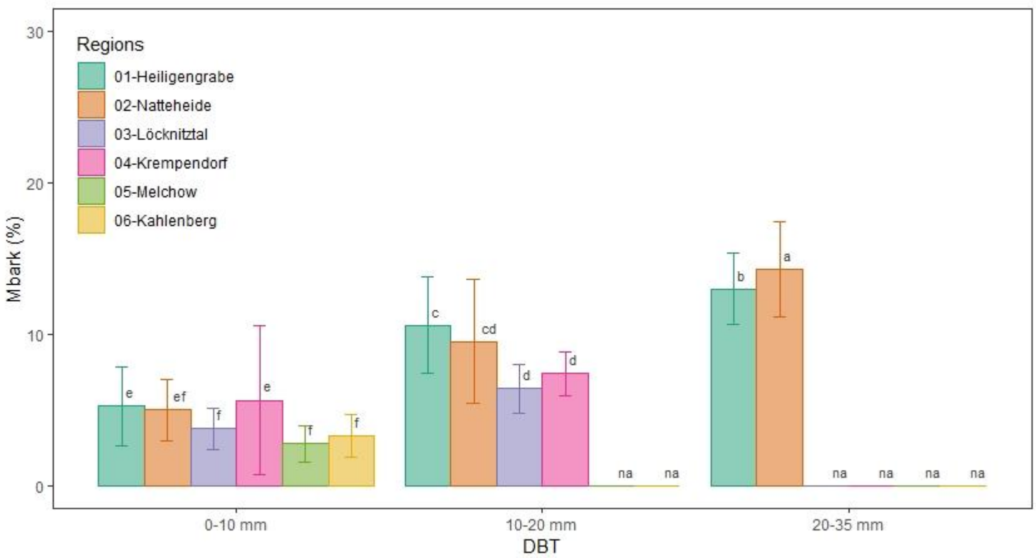

Fig. 6. The percentage of M_{bark} in different DBT classes collected from different regions. Means with same letters at the top of bars are not significant ($p \leq 0.05$), na Means no data is available.

Table 3. Results of the analysis of variance for M_{bark} as response variable for all wood discs and for the three DBT categories (0–10; 10–20 and above 20).

DBT	Variable	R^2	Adj_R^2	SE	RSE	RMSE	p-value
0–10 mm	Diameter	0.001376	−0.004	0.05280	3.226	12.18834	0.604
	Damage	0.1348	0.1304	0.01562	2.942	22.25712	< 0.001
	DBT	0.3341	0.3307	0.04149	2.635	4.08948	< 0.001
10–20 mm	Diameter	0.1273	0.1158	0.07365	2.237	10.18942	0.001
	Damage	0.3677	0.3594	0.0174	1.898	13.92172	< 0.001
	DBT	0.3748	0.3667	0.1302	5.8329	5.832925	< 0.001
> 20 mm	Diameter	0.128	0.105	0.1069	2.169	8.743391	0.023
	Damage	0.3088	0.2906	0.03939	1.731	13.4906	< 0.001
	DBT	0.2821	0.2627	0.1190	1.994	9.025912	< 0.001
All	Diameter	0.07579	0.07284	0.05279	4.153	11.32796	< 0.001
	Damage	0.3541	0.3521	0.01363	3.43	19.49241	< 0.001
	DBT	0.6786	0.6776	0.0201	2.441	5.39242	< 0.001

Results showed that all variables (DBT, diameter and damage) have a significant impact on V_{bark} and M_{bark}. Therefore, predicted models were suggested based on the above results for V_{bark} and M_{bark}, where DBT, diameter and damage were used in our linear regression models as explanatory variables (Table 4).

based on the diameter of trees as well as the bark thickness. Consequently, the calculation of volume and bark is highly influenced by the precise measurement of bark thickness. Several environmental and inherent features can affect bark thickness (Sonmez et al. 2007). In order to provide any predicted model, it is important to see the relation and correlation between these environments and the inherent variables. Results of this study showed there is a moderate to strong correlation between measured variables. In many studies, the correlation between these components have been reported. For instance, Laasasenaho et al. (2005) with providing a model for bark thickness of Norway spruce demonstrated that there is a weak positive correlation between bark thickness and exogenous variables like height and age as well as a strong positive correlation between bark thickness and DBH as endogenous variables. Also, Cellini et al. (2012) showed that there is a correlation between measured variables including bark thickness, DBH, total height of the tree and relative height of 717 different trees from Argentina. Similar results were reported by Kurt et al. (2021) where there was a correlation between bark thickness at breast height and tree diameter of *Pinus brutia* Ten. However, Stängle & Dormann (2018) believed that some environmental characteristics such as geographical elevation, location and rain did not play a significant role on bark thickness of European silver fir (*Abies alba*).

Table 4. Linear regression equations for predicting V_{bark} and M_{bark}.

V&M	DBT class	Predicted model*	R^2	Adj_R^2	RSE	RMSE	p-value
V_{bark}	0–10 mm	y = 7.64574+0.79152×a−0.26470×b−0.01113×c	0.10	0.08	5.892	5.832	< 0.001
	10–20 mm	y = 8.59356+0.88784×a−0.28919×b−0.15509×c	0.36	0.34	5.276	5.140	< 0.001
	> 20 mm	y = 24.0425+0.2517×a−0.3787×b−0.1958×c	0.09	0.01	6.273	5.950	0.341
	All [mm]	y = 8.58384+0.78441×a−0.28140×b−0.04023×c	0.46	0.45	5.819	5.781	< 0.001
	All (No.)*	y = 5.13609+6.70256×a−0.18320×b−0.05440×c	0.39	0.38	6.194	6.154	< 0.001
M_{bark}	0–10 mm	y = 4.3929 + 0.3824 ×a−0.0813×b−0.0435×c	0.19	0.17	2.454	2.428	< 0.001
	10–20 mm	y = 6.7509+ 0.5516×a−0.22638×b−0.11894×c	0.66	0.64	1.986	1.934	< 0.001
	> 20 mm	y = 12.23446 + 0.4157×a−0.40632×b−0.182 ×c	0.56	0.53	1.993	1.890	< 0.001
	All [mm]	y = 5.38502+0.48916×a−0.15686×b−0.06082×c	0.71	0.71	2.372	2.356	< 0.001
	All (No)*	y =3.18791+4.20669×a−0.09607×b−0.06898×c	0.62	0.61	2.703	2.686	< 0.001

Variables: a=DBT (in mm); b=diameter (in cm); c=damage (in %), * In this category, for the variable b, the DBT categories (1, 2 or 3) were used instead of DBT in mm.

Based on the results, the model with the best fit was observed for M_{bark} and without any classification of DBT into categories. These models fitted accounted for 71% of the total variance. Also, R^2 for M_{bark} in the second and third DBT category (10–20 mm and > 20 mm) was 0.66 and 0.56 respectively. Similarly, the highest performance for linear regression of V_{bark} was achieved when all DBT categories were considered with a R^2 of 0.46. In total, it is evident from the results that 1) the models for M_{bark} are more suitable than V_{bark}, 2) the models perform lower for single DBT categories and 3) using the DBT categories instead of DBT in mm resulted in a decrease of model performance for both V_{bark} and M_{bark}.

4. Discussion

Wood as well as bark are renewable resources associated with land use and, thus, become subject to scarcity (Fehrenbach et al. 2017). It is one reason why in recent decades, estimation of biomass and carbon has been an attractive subject in many studies. The biomass of the forest can be determined mostly based on the height, diameter, and density of trees (Vieira et al. 2008). Aboveground biomass assessments include stem wood, stem bark, branches and foliage while total biomass equations consider also stump and roots of the trees (Repola 2008; Li & Zhao 2013). The size and volume of tree barks are

Another important point to note is that the highest percentage of V_{bark} and M_{bark} were observed in the DBT over 20 mm. Previous research also revealed that by increasing the DBT, the percentage of V_{bark} increased (Berendt et al. 2021a). Sonmez et al. (2007) also proposed a positive correlation between DBT and bark volumes of *Picea orientalis* Link. Gea-Izquierdo et al. (2004)

also mentioned that in younger trees the proportion of thickness is lower than in old trees. Results of our study are also in agreement with this idea, where the increase of DBT from zero to more than 20 mm has a significant influence on the percentage of V_{bark}. Furthermore, the increasing of DBT class from 0 to more than 20 mm lead to an increase in the percentage of M_{bark}. Likewise Magalhães (2021) showed that different parameters including DBH class, height, and site, as well as their interactions, have a great influence on both bark mass and bark thickness.

Scots pine is the most widely distributed pine species in the world, "is both commercially and culturally a very important species in a number of European countries" (Durrant et al. 2016; Kozakiewicz et al. 2020) and covers around 70% of forest areas in north-eastern Germany (Bauwe et al. 2013). Therefore, we expected that results on bark thickness, bark volume and bark mass of that tree species is of high interest. The German framework agreement for timber trade (RVR) propose some bark reduction factors to obtain diameter under bark from manual or harvester measurements over bark. The reduction factors for Scots pine, which is equal to the DBT, are based on custom values from practitioners. The reduction factor for diameters up to 20 cm in the RVR is 1 cm (DFWR, DHWR 2020) and, thus, differs from the findings of this study. With mean diameters over bark below 20 cm in all three DBT-categories and with DBT values of 5.98, 13.85 and 24.49 mm, the high variability of bark thickness for similar diameters is obvious. Therefore, more research is recommended in order to define correct bark reduction factors with scientific rigor.

It can be clearly seen that on the one hand, it is so important for the wood industry to estimate different parameters such as M_{bark}, $V_{bark,}$ and DBT precisely and accurately. On the other hand, price and time are often two limiting factors. Therefore, statistical models are needed to allow the wood industry to predict and evaluate the quality of wood, bark, and other parameters. In order to estimate parameter statistical variability, data that characterize the targeted population have to be collected and analyzed (Weiskittel et al. 2011). In this study, DBT, diameter and damage were used respectively to predict M_{bark} and V_{bark}. Results showed that generally the regression models were best fitted to M_{bark} in the unclassified and higher levels of DBT. The better performances of models predicting M_{bark} may be an indication that V_{bark} quantification by immerging a wood disc twice ($V_{bark} = V_{o.b.} - V_{u.b.}$) is susceptible to error. Reasons for that could be water surface tension, sand and dirt or some water absorption despite the green wood condition.

In a few studies, different models have developed to predict various bark quantity parameters including bark thickness, bark area, bark volume, and bark mass. For example, Kozak & Yang (1981) estimated bark volume for 32,000 commercial trees using height, DBH, bark thickness, and DBT. However, height and DBH were the main statistical parameters in their model. In another study, height, site quality, and total volume were introduced as the main parameters for the best equation to predict bark volume of spruce (Dimitrov 1976). In addition, Gordon (1983) developed an equation to estimate bark volume of *Pinus radiata* D. Don using bark thickness. Cellini et al. (2012) mentioned that bark volume highly depends on the bark thickness. In contrast to most of the cited studies which assessed bark thickness and volume from a whole tree at the forest site, the results of the present study considered wood assortments at the wood industry gate. It is the reason why some variables such as DBH or relative height, which showed significant effects in other studies, could not be considered in this study. Mostly, wood industries remove the bark of Scots pine without any further material use. However, it is important to use bark as long, as often and as efficiently as possible, and use it only for energy production at the end of their product lifecycle (Fehrenbach et al. 2017). Therefore, to predict the available bark biomass for further utilization, in terms of V_{bark} and M_{bark}, new models are needed which use variables from wood assortments.

The present study demonstrates that it is possible to use DBT, diameter and bark damage proportion from wood assortments to predict both bark volume and bark mass proportions. As the measurement of bark thickness is labor intensive, it is possible to use DBT class instead of exact DBT measurement. However, it results in lower model performance (see Table 4), which may be acceptable for large quantities such as for entire truck loads. This methodology could easily be applied to other tree species. Nevertheless, it seems that regional or even site-specific factors should be included in the models to increase the performance. However, more data are needed to generate such regional-specific factors and find local applications. Such models can easily find practical applications: 1) to size bark storage capacities when planning new sawmills or wood industry, 2) to assess the energy outcome from bark in incineration plants, 3) to calculate nutrient loss from bark removals for the forest, 4) to quantify bark biomass for chemical extraction or for material production and 5) for carbon sequestration accounting.

5. Conclusion

To achieve the necessary reduction of greenhouse gas emissions, a circular and bio-based bioeconomy plays an essential role. Therefore, raw materials should be used as fully as possible. Currently bark is mostly seen only as a by-product of the wood industry and, it should be of utmost importance to find utilization of bark before incineration. Thus, accurate quantification of bark biomass is necessary, as a potentially valuable resource. This study revealed that it is possible to model the bark volume and bark mass of Scots pine logs delivered to the wood industry. The findings indicated that not only the DBT, diameter, and bark damage have a significant impact on V_{bark} and M_{bark}, but models for M_{bark} are also more suitable than V_{bark}. In final, the results of present study showed that modelling bark volume and bark mass in the wood industry is possible even in moderate model performance. Accordingly, it can be easily extendable to other tree species. This is important for assessing the biomass potential of bark accurately in order to create a functioning cascade use and, thus, to maximize resource effectiveness.

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