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Bark Thickness and Heights of the Bark Transition Area of Scots Pine

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Abstract: The estimation of forest biomass is gaining interest not only for calculating harvesting volumes but also for carbon storage estimation. However, bark (and carbon) compounds are not distributed equally along the stem. Particularly when looking at Scots pine, a radical change in the structure of the bark along the stem can be noted. At the bark transition area, the bark changes from thick and rough to thin and smooth. The aim of our study was (1) to analyze the height of the bark transition area where the bark structure changes and (2) to analyze the effect of cardinal direction on the bark thickness. Regression analyses and forward selection were performed including measured tree height, DBH, bark thickness, crown base height and upper and lower heights of the bark transition areas of 375 trees. While the cardinal direction had no effect on bark thickness, DBH was found to have a significant effect on the heights of the bark transition areas, with stand density and tree height having a minor additional effect. These variables can be used to estimate timber volume (without bark) with higher accuracy and to predict the carbon storage potential of forest biomass according to different tree compartments and compounds.

Keywords: bark structure; *Pinus sylvestris*; forward selection; bark types

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1. Introduction

Scots pine (*Pinus sylvestris*, L.) is one of the main tree species in Central and Northern European forests. In addition, it is often planted in pure stands due to its short rotation time [1] and its low site and climate requirements. In the total forest area of Germany, the proportion (by area) of pine stands amounts to 22%. In the federal state of Brandenburg, this proportion increases to up to 70% according to the last Federal Forest Inventory in 2012 [2]. Thus, Scots pine is the second most represented tree species in Germany after Norway spruce (*Picea abies*, L.) [2]. Suitable for use as construction timber and sawlogs, as well as for pulp and chipboard, this tree species is very important for forestry, especially in Eastern Europe [3]. Currently, the focus of the timber industry lies mostly on the processing of wood. The bark is often considered as an industrial by-product and is primarily used for energy production [4]. However, due to its unique chemical composition, bark can be used to produce biomaterials with the potential to replace fossil fuel-based products. Interest in these new value-added products made from the valuable compounds of tree bark is increasing steadily [5–7].

Regardless of whether bark is being used as high-value raw material or treated as a by-product, there is a real need to determine the proportions of bark accurately. The bark of most woody plants is defined as all tissues located outside the vascular cambium, divided into the inner (phloem) and the outer bark [8]. As the correct determination of the bark proportion is of great importance when calculating the volume of wood without bark, it has a substantial economic impact [9,10]. The accurate recording of the ratio between wood and bark biomass can also be used for other purposes such as carbon inventory [11] or to determine the fire-adaptedness of tree species [12,13]. Generally, bark factors based on bark thickness models are used to predict the diameter under bark in order to further estimate the wood volume [14,15]. Since bark percentage varies among different tree species from 4% to 30% [16,17], bark thickness has to be determined at the species level. Additionally, the respective growing region has to be considered [18]. Several bark types (e.g., smooth bark, white bark, fissured bark and scaly bark) with different bark rugosities (ridges and furrows) increase the complexity of precise and accurate estimations of tree bark allometry or volume [11,19–21].

The bark of Scots pine poses additional challenges to the development of bark deduction factors, as its thickness varies greatly across different stem segments: (i) rough, coarse and furrowed bark that is brown to gray-brown, (ii) a transitional phase, and (iii) smooth bark with a distinct reddish-orange color [22–25]. In addition to the difference in structure and color (Figure 1), these various bark types within a tree have different thicknesses and proportions [26–29]. Thus, the heights of the bark transition area from one bark type to another have to be determined in order to relate these to other growth parameters.

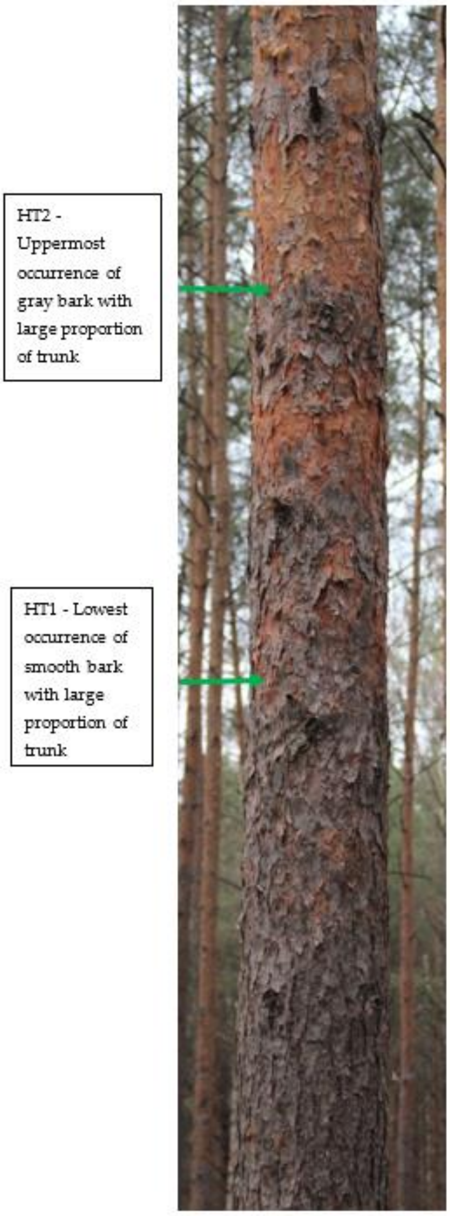


Figure 1. Bark transition phases along the stem of Scots pine, with HT1: bark transition height 1 and HT2: bark transition height 2.

Therefore, the purpose of this study was to determine the tree height at which Scots pine bark changes from thick and rough to thin and smooth. Several growth parameters were analyzed in order to reliably predict the bark type proportion of standing Scots pines. Consequently, it could be expected that the heights of the bark transition area would increase with increasing DBH, increasing tree height and decreasing stand density. A second purpose was to analyze the influence of the cardinal direction on the bark thickness. We hypothesized that bark thickness would increase with increasing DBH and tree height and that the bark thickness would be affected by the cardinal directions. Precise estimations on the heights of the bark transition area and of bark thickness may further be used for a wood volume estimation of standing trees, carbon inventories of forests and for developing new bark deduction factor algorithms, e.g., for harvesters.

2. Materials and Methods

2.1. Site Description

The research area is situated near Eberswalde in the German federal state of Brandenburg. The analyzed forest stands were all located within the forest district Heegermuehle. The mean precipitation and the mean annual temperature (for the period between 2010 and 2020) recorded by the German weather service were 498 mm/a and 10.0 °C, respectively [30]. Across the research area, cambisols are prevalent, with podzols being present in the vicinity of stand 3 [31].

2.2. Research Design

The measurements were carried out during November 2020. In total, 375 Scots pines (*Pinus sylvestris*, L.) originating from three single-aged, monoculture stands were measured. The three stands had different ages and diameters at breast height (DBH): the age of stand 1 was 64 years and the trees had a mean DBH of 18.5 ± 5.2 cm; DBH of stand 2 (69 years) was higher at 27.8 ± 4.9 cm; and stand 3 (84 years) had a mean DBH of 34.5 ± 5.3 cm (Table 1). In each stand, three distinct plots were chosen with approximately 70–100 m distance between the plot centers. Within a specific radius around the center of the plot, all Scots pine trees were measured. To ensure a minimum sample size of 30 trees per plot, the plots' radii (r) were 12.62 m (corresponding to an area (A) of 500 m^2), 15.45 m (A = 750 m^2) and 17.84 m (A = 1000 m^2) for stands 1 to 3, respectively. The radii were increased according to stand age in order to balance out the lower stand density. In stand 1, the densities were 1020, 1300 and 800 trees/ha for the three plots, in stand 2 they were 480, 507 and 587, and in stand 3 the densities were 330, 360 and 320 trees/ha.

Table 1. Characteristics of the forest stands, with DBH: diameter at breast height, BT: bark thickness, H: tree height, HC: crown base height, HT1: transition height 1 and HT2: transition height 2.

Characteristic	Stand 1	Stand 2	Stand 3	All
WGS84 Coordinates	13.762056, 52.818503	13.752174, 52.82378	13.744799, 52.815309	
Plot radius (in m)	12.62	15.45	17.84	
Cumulative plot area (in m^2)	1500	2250	3000	
Stand age (in years)	64	69	84	
Trees measured (N)	156	118	101	375
Stand density (N/ha)	1040	524	337	
Mean DBH ± SD (in cm)	18.5 ± 5.2	27.8 ± 4.9	34.5 ± 5.3	25.7 ± 8.4
Mean BT ± SD (in cm)	1.24 ± 0.41	1.68 ± 0.39	1.99 ± 0.39	1.58 ± 0.50
Mean H ± SD (in m)	18.9 ± 2.8	25.5 ± 2.0	26.8 ± 1.9	23.1 ± 4.3
Mean HC ± SD (in m)	14.1 ± 2.2	19.2 ± 2.2	19.1 ± 2.3	17.0 ± 3.3
Mean HT 1 ± SD (in m)	3.0 ± 0.9	4.3 ± 1.5	5.8 ± 1.7	4.2 ± 1.8
Mean HT2 ± SD (in m)	5.6 ± 1.8	7.1 ± 2.2	9.1 ± 2.5	7.0 ± 2.5

The DBH was measured at 1.3 m tree height with a slide caliper and two measurements were taken at a 90° angle for every analyzed tree. The bark thickness was measured with the Swedish bark gauge (SUUNTO, 60 mm, Vantaa, Finland) at 1.3 m tree height. As proposed by Stängle et al. [32] five bark thickness measurements were taken to reduce errors. The first bark thickness measurement was always taken from the cardinal position south, with the following measurements moving clockwise around the stem.

The height parameters tree height (H), crown base height (HC) and both heights of the bark transition area (transition height 1 and 2: HT1 and HT2) were measured using a VertexIV hypsometer (Haglöf AB, Bromma, Sweden) to a precision of 0.1 m. HC was defined as the height of the lowest knot with three or more living branches and without any dead branches upwards, which is also known as the analytical crown base height [33–38]. The height of the first bark transition (HT1) was defined as the lowest occurrence where smooth bark occupied at least half of the stem circumference (Figure 1). Smaller single patches of smooth bark farther downwards were not considered as representative for HT1. For the second bark transition height (HT2), the height measurement was performed at the uppermost end of rough bark that is connected to the stem base (Figure 1). Freshly formed patches of gray or rough bark around knots, which were separate from the interconnected rough bark portion, were not considered as the upper bark transition point HT2.

2.3. Data Analysis and Statistics

To identify the best model to determine HT1 and HT2 for several variables, a forward selection was performed [39]. The analyzed response variables were: DBH, H, HC, stand density (StD) and plot density (PD). While PD is the number of trees/ha in a single circle plot, StD is the average of the three respective PD figures in the stand. The forward regression analysis was carried out with the R-packages *caret* [40] and *MASS* [41]. The forward selection selects the best model for a certain amount of n predictors out of a set pool of variables [39]. The model whose single predictor represents the best fit (with lowest RMSE and highest R^2) was defined as the base linear model. Subsequently, the next model was formed with an additional variable, keeping the first predictor. This was performed using k-fold cross-validation, meaning that the total sample was divided into 10 subsets (folds), as far as possible of the same size. Out of these ten subsets, nine were then used to build the model and one was used as a test set in order to minimize RMSE. Prior to regression analysis, some trees were removed from the analysis due to obvious measurement errors in the height measurements or because DBH and/or H of trees were significantly different from the respective stand, resulting in N = 366 trees being analyzed for HT1 and HT2 and N = 373 for bark thickness.

As the Shapiro–Wilk Test did not confirm a normal distribution ($p \leq 0.05$) for DBH, H and HC, all vectors were transformed to their natural logarithm. As a result, both transformed response variables ln(HT1) and ln(HT2) followed a normal distribution. The correlation of each predictor to ln(HT2) followed the same order as with ln(HT1), but with a generally weaker Spearman-ρ by ca. 0.1. Regarding collinearity, a Spearman-rank-correlation test was executed for all transformed predictor variables (Table 2). The highest collinearity of predictors was found between ln(DBH) and ln(H) with a Spearman-ρ of 0.8486. ln(HC) was also found to correlate strongly with ln(H) as both are height parameters. ln(StD) and ln(PD) naturally correlate highly as they provide the same information but on different scales. Moreover, for comparability reasons, StD and PD [N/ha] were divided by 100 to have a similar scale as DBH, HC and H. Consequently, a model with multiple predictors including StD and/or PD can be plotted without the point cloud being separated by stands with high x-axis difference.

Table 2. Combined correlation matrix (Spearman-ρ) of logarithm-transformed variables, with HT1: transition height1, HT2: transition height2, DBH: diameter at breast height, H: tree height, HC: crown base height, StD: stand density and PD: plot density.

Variables	ln(HT1)	ln(DBH)	ln(H)	ln(HC)	ln(StD)	ln(PD)	Variables
	1	0.7293	0.6391	0.4975	−0.6675	−0.6668	**ln(HT1)**

Table 2. *Cont.*

Variables	ln(HT1)	ln(DBH)	ln(H)	ln(HC)	ln(StD)	ln(PD)	Variables
ln(HT2)	1	1	0.8486	0.6238	−0.8104	−0.8135	**ln(DBH)**
ln(DBH)	0.6553	1	1	0.8393	−0.8250	−0.8120	**ln(H)**
ln(H)	0.5532	0.8486	1	1	−0.7063	−0.6960	**ln(HC)**
ln(HC)	0.4157	0.6238	0.8393	1	1	0.9439	**ln(StD)**
ln(StD)	−0.5409	−0.8104	−0.8250	−0.7063	1	1	**ln(PD)**
ln(PD)	−0.5461	−0.8135	−0.8120	−0.6960	0.9439	1	
	ln(HT2)	**ln(DBH)**	**ln(H)**	**ln(HC)**	**ln(StD)**	**ln(PD)**	

All statistical computations were executed with R 4.0.3 [42] using the interface RStudio [43]. The quality of linear regression models was assessed using the adjusted coefficient of determination, Adjusted-R^2 (adj-R^2). Whereas R^2 of a linear regression model increases just by adding predictors [44], adj-R^2 compensates by including the degrees of freedom into the equation. The root mean square error (RMSE) was used to calculate the mean square deviation of residuals from the regression line. By subtracting the number of predictors p in the denominator of the RMSE function, the residual standard error (RSE) accounts for additional predictors in multiple regression analysis [44]. After confirming DBH as the single best predictor, a non-linear regression analysis for HT1 and HT2~DBH was performed with the R-package *minpack.LM* [45].

The significance level (α) was set to 5 %, with $\alpha < 1\%$ considered as highly significant.

3. Results

3.1. Bark Thickness

The mean bark thickness increased from stand 1 to stand 3. The mean bark thickness was significantly different with 1.2 + 0.4 cm, 1.7 $\pm$ 0.4 cm and 2.0 $\pm$ 0.4 cm for stands 1, 2 and 3, respectively. The mean proportion of bark (as the ratio between the double bark thickness and DBH) was 12.5% $\pm$ 2.3%. The bark proportion decreased with increasing age from 13.4% $\pm$ 2.4% in stand 1 (64 years) to 11.7% $\pm$ 1.83% in stand 3 (84 years).

The analysis showed that the two independent variables DBH and H had a significant effect on the bark thickness with $p = 2.2 \times 10^{-16}$ and $p = 0.036$, respectively. The bark thickness model using a multiple linear regression showed an adj-R^2 of 0.705 when considering DBH and H. According to the following equation, for a given DBH, the bark thickness decreases with increasing tree height:

$$y = 0.0564 \times \text{DBH} - 0.0134 \times \text{H} + 0.439 \quad (1)$$

where y is the bark thickness in cm, DBH the diameter at breast height in cm and H the tree height in m.

Through an ANOVA, the influence of the cardinal direction on the bark thickness was tested. The result showed that no significant effect of the cardinal direction was observed when considering all stands with a *p*-value of 0.538 (Figure 2). Similarly, when looking at single stands, no significance of the cardinal direction was found for stand 1 (*p*-value = 0.444), stand 2 (*p*-value = 0.64) or stand 3 (*p*-value = 0.328).

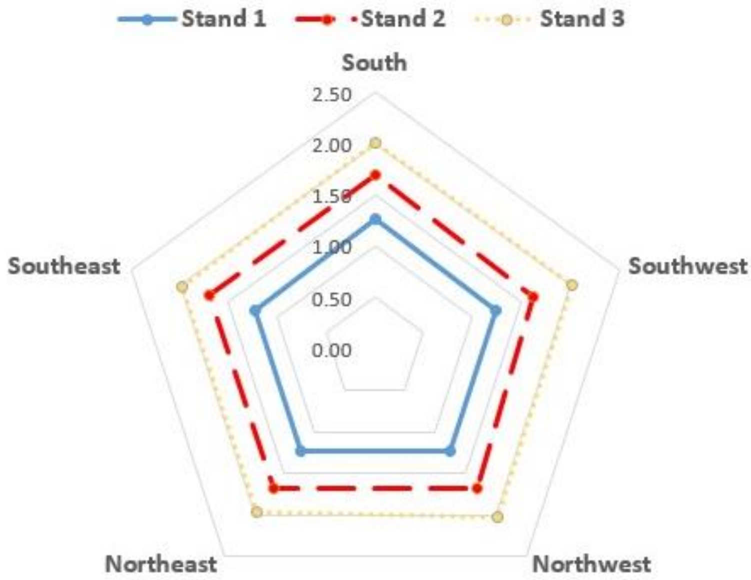


Figure 2. Bark thickness for different cardinal directions for the three stands.

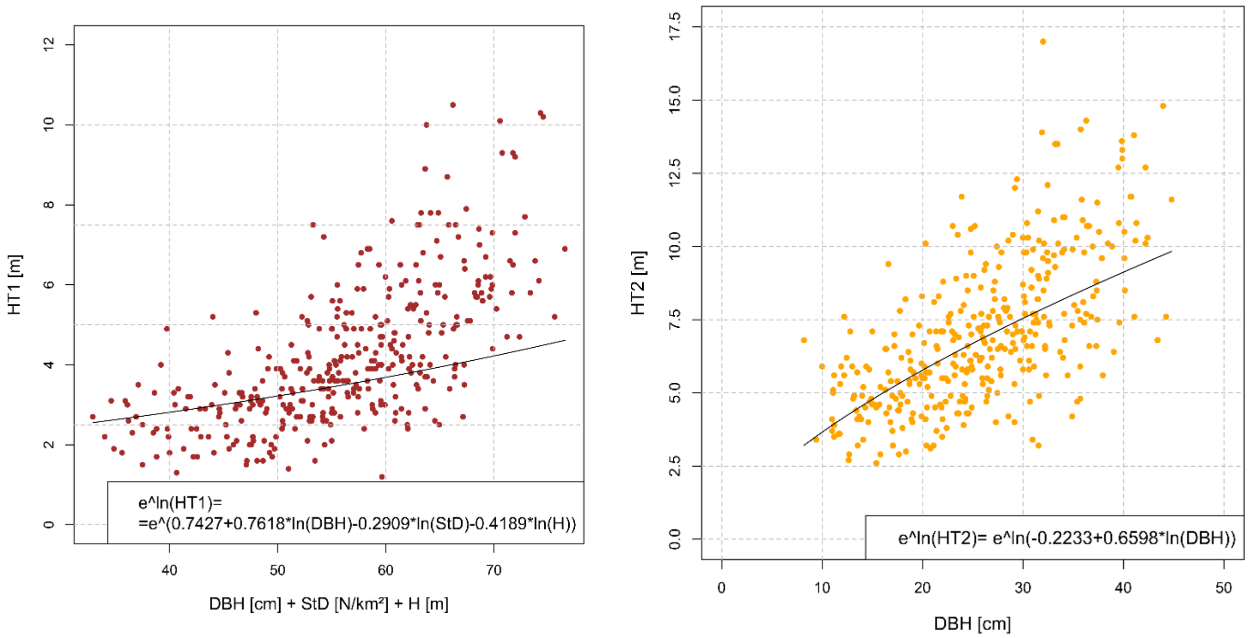
3.2. Bark Transition Heights

A multiple linear regression analysis was carried out separately for ln(HT1) and ln(HT2) by using a forward selection algorithm. The variable ln(DBH) was identified as the strongest single predictor for both ln(HT1) and ln(HT2) with adj-R^2 values of 0.4833 and 0.3935, respectively. By adding ln(StD) as the second predictor to the regression, an additional 1.5% of explained variance was observed for ln(HT1). When including the third predictor ln(H) in the model, adj-R^2 reached 0.5153 for ln(HT1). In the case of ln(HT2), only ln(DBH) had a significant effect upon the regression. As ln(PD) showed a lower adj-R^2 than ln(StD), ln(PD) was not further analyzed. Moreover, the variable ln(HC) was found to be not significant. Table 3 provides the estimates and model statistics. According to the Shapiro–Wilk Test, the residuals of both models are normally distributed.

Table 3. Model statistics for bark transition heights 1 (HT1) and 2 (HT2), with DBH: diameter at breast height, StD: stand density and H: tree height.

Variable	Estimate	SE	*p*-Value	Adj-R^2	RSE
ln(HT1)				0.5135	0.2965
Intercept	0.7427	0.5469	0.175		
Coef. ln(DBH)	0.7618	0.0999	2.11×10^{-13}		
Coef. ln(StD)	−0.2909	0.1985	0.0355		
Coef. ln(H)	−0.4189	0.0586	1.07×10^{-6}		
ln(HT2)				0.3935	0.2781
Intercept	−0.2233	0.1378	0.106		
Coef. ln(DBH)	0.6598	0.0428	1.19×10^{-41}		

The scatter plots after back transformation into metric values are displayed in Figure 3. The regression of the transformed log values for HT2 shows a similar image to HT1, with a metric regression curve which does not follow the exponentially shaped scatter. Naturally, the measured values and the value range of HT2 are higher than those of HT1, resulting in a worse regression according to the lower R^2 and higher RSE.



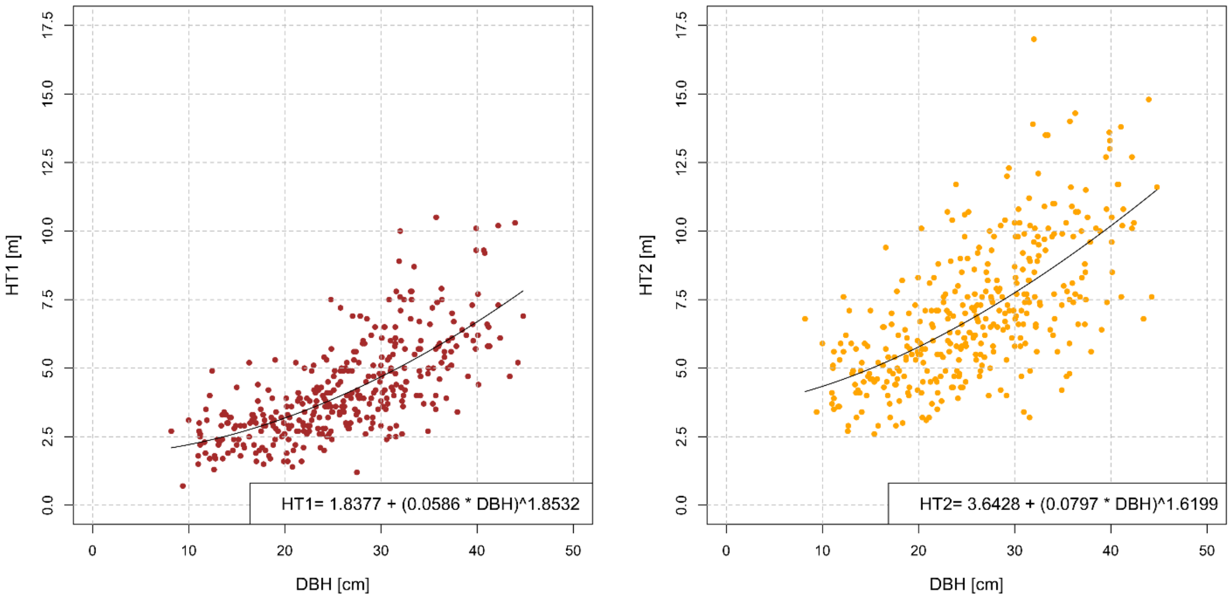
(**left**) (**right**)

Figure 3. Scatter plot of the bark transition heights (HT) after back transformation into metric value for the HT1 regression (**left**) and the HT2 regression (**right**).

Since only a minimal gain in explained variance and decrease in error was achieved by adding independent variables to the linear regression of logarithmically transformed values, DBH was considered the main predictor for HT1 and HT2. In order to fit the non-linear relationship of HT1 or HT2 to DBH, a non-linear regression fit was applied. While $\text{HT1} \sim a + (b \times \text{DBH})^c$ reached an RSE of 1.2527, the RSE of $\text{HT2} \sim a + (b \times \text{DBH})^c$ increased by about 54% to 1.9323 (Table 4 and Figure 4).

Table 4. Model statistics for bark transition heights 1 (HT1) and 2 (HT2) with the non-linear regression.

Variable	Estimate	SE	*p*-Value	RSE
HT1				1.2527
Intercept a	1.8376	0.3766	1.59×10^{-6}	
b	0.0586	0.0102	1.85×10^{-8}	
c	1.8532	0.3121	6.79×10^{-9}	
HT2				1.9323
Intercept a	3.6428	0.7179	6.23×10^{-7}	
b	0.0797	0.0247	1.38×10^{-3}	
c	1.6199	0.3613	9.84×10^{-6}	



(left) **(right)**

Figure 4. Scatter plots of the non-linear regressions of the bark transition heights (HT) with HT1 regression (**left**) and HT2 regression (**right**).

4. Discussion

4.1. Bark Thickness

The analysis showed that DBH and tree height significantly affect bark thickness at a height of 1.3 m in Scots pine trees. The strong influence of DBH and the weak influence of tree height on bark thickness for Scots pine were in line with earlier studies [46,47] which stated that DBH was the most relevant independent variable for estimating bark thickness at 1.3 m for Norway spruce (*Picea abies*, H. Karst) and Turkish pine (*Pinus brutia*, Ten.), respectively. Moreover, a strong correlation between DBH and bark thickness was also found for Oriental spruce (*Picea orientalis*, Link) [48] and Radiata pine (*Pinus radiata*, D.Don) [49]. While for Norway spruce the tree height did not have an effect on bark thickness [46], smaller trees had a thicker bark when looking at Radiata pine. The regression analysis showed that tree height was negatively correlated with bark thickness. Thus, similar to the results of Gorden [49], for Scots pine higher trees had a thinner bark than smaller trees. This could be because smaller trees use more energy on bark production compared to height growth, or there may be genetic or site influences [12,21,46]. The measurement showed a mean bark thickness of 1.2 cm for a mean DBH of 18.5 cm, and a bark thickness of 2.0 cm for trees with a mean DBH of 34.5 cm. Compared with available data on Scots pine bark thickness from the literature, the results from this study were of similar dimensions and they were only slightly higher compared to bark thicknesses from 0.85 cm to 1.35 cm [26], between 0.75 cm and 1.4 cm [27] and between 1.14 cm and 1.54 cm [28]. However, even if the measurements from both Gorden [49] and Kahriman [47] were performed on logs with thick and gray bark from the lower part of the tree, the results are only partially comparable with the bark thickness at DBH. Another study found that, at a relative height of 5%, the bark proportion is 14.7% for Scots pine [50]. A relative height of 5% corresponds to a height of 1.3 for a 26 m tall tree and, thus, is comparable with the bark proportions found in this study, which were between 11.7% and 13.4%.

The bark thickness measurements were performed with a bark gauge. Different authors note that the use of a bark gauge may lead to biased measurements [32,46,49]. Moreover, the time of year affects the measurements. Penetration of the bark gauge into the growing annual rings was observed for the relatively soft early growth, especially during spring and summer [46]. As the field work occurred during November and was performed by the same person, and as five bark thickness measurements were taken for each tree, the possible risks of measurement errors were minimized. This method is non-destructive as opposed to more precise methods such as measuring the diameters over and under bark [51] or computed tomography for highly accurate measurements [32], which can only be achieved by analyzing logs or wood discs. When analyzing the influence of the cardinal direction on bark thickness, no significant differences were found. Nevertheless, some factors may influence the bark thickness around the stem, as shown with sun radiation on the bark thickness of Oriental spruce [48].

4.2. Bark Transition Heights

All analyzed trees were from homogeneous pure Scots pine stands. An original study on smooth bark proportions on Scots pine was described by Dengler [22] in 1937, noting a positive relation between the smooth bark onset height and greater DBH. Based on the above-mentioned initial findings of Dengler, Wagenknecht [23] carried out similar measurements two years later. Furthermore, in 1963, Erteld [24] directly referred to Wagenknecht's findings. His criticism was that Wagenknecht only listed mean values of the diameter steps, which Erteld took as an opportunity to establish, among other things, linear regression functions between the smooth bark onset height and DBH. These three authors also confirmed additional positive influences on the smooth bark onset height: age, lower stand density, branchiness and tree height.

The main result of HT1 and HT2 regression analysis is that DBH has the strongest significant influence among all the investigated parameters. This is underlined by the small gain of the explained variance when adding additional predictors. The variance of the back-transformed values corresponds to e^RSE = e^0.30 ≈ 1.35. Thus, there is already an average range of at least ±1.35 m for the explained variance. While the RSE values of non-linear regression analysis are higher compared to the linear equations for transformed parameters, the a + (b × DBH)^c regression curve clearly shows a better fit to the exponential relationship of HT1 and HT2~DBH. Due to a possible over- or underestimation of the location of the bark transition area, these models give an estimation of both bark transition heights. However, it should be mentioned that the mean length of the bark transition areas was 2.87 m ± 1.42 m over all trees. Thus, it could be expected that the bark transition area can be accurately located even if this was not possible for the two distinct bark transition heights. For an accurate prediction of the tree height where the bark structure is changing, the model should be improved. In order to improve the models, further data acquisition on the Scots pine bark transition area should include a wider range of plots with a more incremental variety of stand characteristics, such as DBH, heights or tree age classes.

Erteld's findings of the linear regression functions of a single bark transition height correlating to DBH could not be replicated in this study [24]. On visual inspection of the scatter plots, HT1 and HT2 seem to correlate linearly with DBH on a stand scale. Nevertheless, a linear regression of HT = a + b × DBH was not possible due to residuals not being normally distributed. Another drawback of the more complex models is the negative correlation between DBH and stand density. In other words, stand density depends on thinning measures, which aim to improve the diameter and crown growth of the remaining stand. In addition, DBH and tree height are correlated, so the combined use of both variables as predictors does not necessarily improve the model. An older stand has the largest DBH but has most often been thinned accordingly. In summary, additional collinear predictors have only minuscule influences supplementing DBH.

5. Conclusions

The unusual bark structure of Scots pine along the stem, divided in two distinct bark types and a transition area, poses a key challenge when the ratio between wood and bark is calculated, or when looking at bark deduction factors. Such factors are used to predict the diameter under the bark in order to estimate the timber volume without bark. For Scots pine, some general bark functions are available for lower and for upper stem parts. However, by modelling the respective heights of the bark transition area, the bark proportion and thus also the bark volume of standing trees can be determined. This non-destructive method may be useful for both timber and carbon inventory purposes: For estimating Scots pine timber volume, new algorithms can be developed according to our findings and, thus, result in more differentiated bark factor models for the two distinct bark structures. Such models may be included in the analysis of forest inventory data to provide a more accurate estimation of, e.g., carbon sequestered by trees. As well, our results can be used as a basis for a more correct estimation of the bark proportion of harvested trees, or even in wood stacks. Therewith, a better economic valuation of logs and stacks is possible, according to the purchaser's demands. Furthermore, the valuable raw material bark that is important for a developing bioeconomy can be valued on a more reliable basis, to support a shift from fossil to renewable raw materials in the coming years.

Author Contributions: F.W., N.D. and F.B. conceived and designed the study, with contributions from T.C.; F.W. and N.D. collected the data; F.W. and N.D. analyzed the data, with contributions from F.B.; F.W., N.D., F.B. and T.C. wrote the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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