Understanding bark thickness variations for *Araucaria angustifolia* in southern Brazil

Emanuel Arnoni Costa[1,2] · Veraldo Liesenberg[1] ·
César Augusto Guimarães Finger[3,4] ·
André Felipe Hess[1] · Cristine Tagliapietra Schons[3]

Abstract This study aimed to understand bark thickness variations of *Araucaria angustifolia* (Bertol.) Kuntze trees growing in natural forest remnants in southern Brazil, and their relationship with quantitative and qualitative attributes. Bark thickness must be accurately estimated in order to determine timber volume stocks. This is an important variable for the sustainable management and conservation of araucaria forests. In spite of its importance and visibility, bark thickness variations have not been evaluated for this key species in southern Brazil. A total of 104 trees were selected, and their qualitative and quantitative attributes such as diameter at breast height (D_{BH}), height (H), crown base height (C_{BH}), crown length (C_L), social position (S_P), stoniness (S_T), position on the relief (P_R), vitality (V_T) and branch arrangement (B_A) were measured. The trees were categorized into two groups: red bark or gray bark. Regression analysis and artificial neural networks (ANN) were used for modelling bark thickness. The results indicate that: (1) bark thickness showed good correlation to D_{BH}, with 0.76 as coefficient of determination (R^2), 0.540 as Mean Absolute Error (M_{AE}) and 22.4 root-mean-square error in percentage ($R_{MSE\%}$); (2) the trend changed according to bark colour, with significant differences for the intersection (β_0 – Pr > F: $p = 0.0124$) and slope (β_1 – Pr > F: $p = 0.0126$) of bark thickness curves between groups; (3) the highest correlation of bark thickness was found with: D_{BH} ($\rho = 0.88$), H ($\rho = 0.58$), C_{BH} ($\rho = 0.46$), S_P ($\rho = -0.52$), and B_A ($\rho = -0.32$); (4) modelling with ANN confirmed high adjustment ($R^2 = 0.99$) and accuracy ($R_{MSE\%} = 3.0$) of the estimates. ANN is an efficient and robust technique for the modelling of various qualitative and quantitative attributes commonly used in forest mensuration. The effective use of ANN to estimate araucaria bark in natural forests reinforces its potential, besides the possibility of application for other forest species.

Keywords Dendrometry attributes · Crown characteristics · Prediction models · Bark factor · Parana-pine

✉ Emanuel Arnoni Costa
emanuelarnonicost@hotmail.com

1　Graduate Program in Forest Engineering, Santa Catarina State University (UDESC), Lages, SC 88520-000, Brazil

2　Department of Forest Engineering, Federal University of Uberlândia (UFU), Monte Carmelo, MG 38500-000, Brazil

3　Graduate Program in Forest Engineering, Federal University of Santa Maria (UFSM), Santa Maria, RS 97105-900, Brazil

4　Graduate Program in Agroecosystems, Federal Technological University of Paraná (UFTPR), Dois Vizinhos, PR 85660-000, Brazil

Introduction

Forest inventory is used to obtain information about the quantity, quality and condition of the resource components of a forest, particularly tree species, and other land characteristics (Kershaw et al. 2017). With the advancement of technology by industries that handle forest products and the

growing demand for alternative products and energy sources, tree bark volume estimates have become relevant (Kozak and Yang 1981).

To provide accurate and timely information on current and future growing stock, forest managers need to estimate both volume and tree taper. Since inner bark volume and taper—required for accurately estimating bark volume—are based on the diameter measured for bark, bark thickness needs to be determined or predicted. As such, bark thickness is an important variable in forest mensuration (Muhairwe 2000), and in order to convert outside-bark diameters into inside-bark diameters, several equations for bark thickness and volume have been developed for many species worldwide (Li and Weiskittel 2011).

The bark is a vital woody component close to the surface but its characteristics and thickness have been only recently considered in the context of communities and biomes (Pausas 2015). The bark includes all tissues outside the cambium—the inner living phloem and dead outer tissues or rhytidome. The phloem plays an essential role translocating carbohydrates, while the periderm or outer bark tissue reduces water loss and provides protection from both biotic and abiotic injuries (Kozlowski and Pallardy 1996). Trees with a thick bark have vital tissue protection against attack from pathogens, herbivores, frost and drought. Thick bark characteristics are vital in large trees subjected to surface fires (Pausas 2015). However, bark thickness and texture vary significantly from extremely rough to soft according to the species (West 2015) and the environment (Zeibig-Kichas et al. 2016).

Regression models are commonly used to model forest attributes. However, artificial neural networks (ANN) have been applied in various fields of science due to their learning ability from using a dataset, and the generalization capability of this learning with unknown data has very accurate estimates (Haykin 2007). The use of ANN as an estimate method in forest science is promising for acquiring values for height (Binoti et al. 2013; Castaño-Santamaría et al. 2013), volume (Gorgens et al. 2009; Silva et al. 2009; Castro et al. 2013a; Binoti et al. 2014a; Leal et al. 2015), diameter distribution (Binoti et al. 2014b), bark (Diamantopoulou 2005, 2006), and relative diameter, as well as studies on stem shape (Leite et al. 2011; Soares et al. 2011; Souza 2013; Schikowski et al. 2015; Sanquetta et al. 2017), growth and production models at individual tree level (Castro et al. 2013b), and allows for the modelling of various qualitative and quantitative attributes simultaneously.

Araucaria (*Araucaria angustifolia*), also known as Brazilian pine, is an important tree species in southern Brazil of considerable economic importance due to its exceptional wood quality (Carvalho 1994). This species originally covered 200,000 km^2 in the south of the country in early 1900s (Hueck 1972). Due to intensive and often indiscriminate harvesting, its area has been reduced significantly. However, it still has potential to be used sustainably, combined with strategic conservation (IUNC 2006). A pioneer study by Reitz and Klein (1966) revealed the natural occurrence of some Araucaria varieties whose major characteristics are related to the maturation of edible seeds that are palatable to both fauna and humans. However, due to annual climatic variations that determine maturation time, this differentiation is a challenging task. As an alternative, it is easy to categorize bark colour into red or gray while in the field (Fig. 1).

To identify factors that influence changes associated with bark thickness and might serve as support tools for silvicultural activities, this study was developed with the following hypotheses: H_1—there are differences in bark thickness of Brazilian pines according to their colour (Fig. 1); H_2—qualitative variables of the crown and site are important to bark thickness; and, H_3– ANN can estimate accurately bark thickness of Araucaria.

Fig. 1 Illustrative bark colour characteristics: (a) gray, (b) red
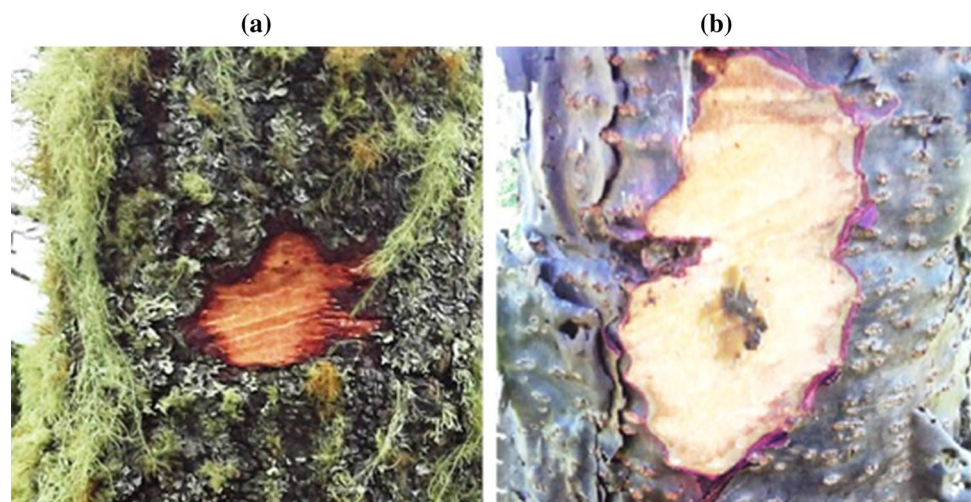
Given this context, this study aimed to model bark thickness for diameter at breast height (D_{BH}) of araucaria growing in a natural forest in southern Brazil. The specific objectives were: (1) to characterize the in situ measured variables by qualitative and quantitative means; (2) to compare the bark thickness of gray- and red-coloured trees; (3) to develop a regression model of bark thickness in D_{BH} function; (4) to verify the dendrometric, qualitative variables of crown, and local site variables associated with bark thickness; (5) to model the bark thickness using ANN; and, (6) to compare regression and ANN estimators.

Methods and materials

Characteristics of the species

Araucaria angustifolia (Bertol.) Kuntze belongs to the genus *Araucaria*, family Araucariaceae consisting of 16 species, exclusive to the southern hemisphere with two in South America. Other species are found in Oceania. It is an evergreen species and a heliophyte pioneer, adapted to intensive solar isolation, typical of high altitude regions, with rectilinear or cylindrical, rarely forked stems, containing four to eight verticils or whorls upon insertion of branches which stand out with age. As a dioecious plant—rarely monoeciousonly by trauma or disease— it has reproductive structures in male and female strobiles (Carvalho 2003).

Araucaria can reach heights of 20 to 50 m and up to two m in diameter. The crowns have cylindrical primary branches curved upwards, with the lower ones curved more than the upper ones; both branch types with secondary branches (grimpas), alternating and grouped at the apex (Reitz and Klein 1966). The trunk has thick, gray, rough, and deeply cracked bark, peeling off in rectangular plates and blades at the top of the trunk (Marchiori 2005). The species has a bark thickness between 5–10 cm (Ceccatto 1943), accounting for an average 32.6% of the total tree volume (Silva et al. 1975).

Study area

The study was conducted in a natural forest on a rural property in the municipality of Lages (27º48′S and 50º19′W), in the state of Santa Catarina (SC). The local climate is humid subtropical with no dry season and with a temperate summer (Cfb) (Alvares et al. 2013) according to the Köppen climate classification. The forest is predominantly Araucaria, with over 300 trees of this species per hectare, and with an average basal area of 21.9 m^2 ha^{-1}. Thus the local climate (Cfb) is favoured to this species in southern Brazil (Silveira et al. 2018).

Data collection

The attributes measured were based on 104 sample trees within the natural forest as a representation of population characteristics (Table 1). A detailed description of the field measurements can be found in Costa (2011).

Crowns were categorized into geometric formats: cone, umbel, hemisphere or champagne glass; these

Table 1 Description of the qualitative and quantitative attributes obtained from each individual tree

Parameter	General description
Diameter at breast height (D_{BH})	D_{BH} was measured with a diameter tape (cm), 1.30 m above the soil surface
Bark thickness (B_T)	This is defined as the mean between two measurements; the first was taken from the North position and the other was perpendicular (90°) (E or W). With Pressler's increment borer, cores were extracted with their respective bark, directly measured. Two groups of trees were distinguished, one with gray-coloured bark (Fig. 1a), the other with red-coloured bark (Fig. 1b)
Height (H)	Measured with Vertex hypsometer, accurately in tenths of a meter
Crown base height (C_{BH})	Measured with Vertex hypsometer, accurately in tenths of meters, from ground level up to the insertion point of the crown
Crown length (C_L)	Calculated by the difference between height and crown base height
Social position (S_P)	Classified according to the tree position at the vertical strata and its respective light exposure degree: S_{P1}—dominant trees: occupy the upper stratum with high light exposure; S_{P2}—co-dominant trees: occupy the intermediate stratum with average light exposure; S_{P3}—dominated trees: occupy the lower stratum with low light exposure
Stoniness (S_T)	Describes the presence of rocky outcrops on the site that are classified in: (0) no visual outcrop; (1) outcrop lower than 33.3%; (2) outcrop from 33.3% to 66.6%; (3) outcrop higher than 66.6%
Tree position on the relief (P_R)	Classified into four types: (1) lower hillside, (2) average hillside, (3) upper hillside and (4) plateau.
Vitality (V_T)	Amount of live leaves and their distribution in the crown were determined visually, as well as health class: (1) high vitality; (2) average vitality and (3) low vitality
Branch arrangement (B_A)	Assessed as: (1) well-spread branches over all four quadrants homogeneously; (2) distributed into three quadrants; (3) branches distributed into one or two quadrants.

characteristics are caused by the ontogenetic alteration of the crowns, a characteristic of the species as described by Seitz (1986), and by competition with other trees (Costa and Finger 2017).

Statistical analysis

Descriptive statistics characterized the measured variables. A *t* test verified the existence of differences in mean between bark thickness measured in the north position and in the perpendicular measurement. The same test verified differences between the gray- and red-coloured bark groups. The following logarithmic model (Silva et al. 1975) was used to describe the relationship between bark thicknesses:

$$B_T = \beta_0 + \beta_1 \ln(D_{BH}) \tag{1}$$

where B_T = Bark thickness; D_{BH} = Diameter at breast height; β_0, β_1 = estimated regression coefficients.

An analysis of covariance (ANCOVA) was used to verify differences between trends [intercept (β_0) and slope (β_1)] of the adjusted regression lines (Milliken and Johnson 2002) for bark thickness for the tree groups between gray- and red-coloured bark.

Spearman's rank correlation assessed the association between bark thickness and dendrometry, crown qualitative attributes, and site variables in addition to diameter. The variables with the highest correlation were also examined for their contribution to improve estimates of bark thickness. In addition to other advantages of using ANN, it is possible to model with categorical variables (qualitative) aside from numeric variables (quantitative) (Vieira et al. 2018).

The perceptron-type neural network from multiple layers (Haykin 2007) was architecture: n–n-1. Linear normalization of numeric variables was set between 0 and 1. The input variables were: D_{BH}, H, H_{CB}, S_P, B_A, G_r and B_{Tpred}; the continuous output variable was bark thickness. The group (G_r) variable expressed the differentiation between gray- (1) and red-barked trees (2). B_{Tpred} was the bark thickness estimate: $B_T = -6.3248 + 2.4908 \cdot \ln(D_{BH})$, considering both bark colour groups (Table 3—All). In the hidden layer and in the output layer, the logistic activation and identity activation functions were applied.

To assess the performance of the adjusted models, the most appropriate being the one that presented the highest value of the coefficient of determination (R^2) (Eq. 2), the lower mean absolute error (M_{AE}) (Eq. 3) and root-mean-square error in percentage ($R_{MSE\%}$) (Eq. 4), and a regular and good waste distribution graphic. Statistical analyses used the statistical program R, version 3.5.2 (http://cran.r-project.org).

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \right] \tag{2}$$

$$M_{AE} = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \tag{3}$$

$$R_{MSE}\% = \frac{\sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}}{\bar{y}} \times 100 \tag{4}$$

where R^2 is coefficient of determination, M_{AE} the mean absolute error, $R_{MSE\%}$ the root-mean-square error in percentage, y_i the observed values, $\hat{y}_i$ the estimated values; $\bar{y}$ the average of the observed values, and *n* is number of observations.

Results

Qualitative and quantitative characteristics

The sample trees had a wide range of D_{BH}, (17.0–117.8 for gray- and 14.7–79.3 for red-barked trees), and heights ranging from 11.8 to 32.9 for gray- and 9.1 to 24.9 for red-barked trees, and covered a wide variability of dendrometric characteristics such as C_{BH}, C_L, S_T, P_R and bark thickness (Table 2).

Trees were located in different positions throughout the site ('1' had 30 trees; '2', 41; '3', 17; '4', 16), with different levels of stoniness ('0' = 55 trees; '1' = 27; '2' = 17; '3' = 5). A similar trend was observed for these variables within the gray- and red- barked groups. The three social positions analyzed were also representative (S_{P1} = 79 trees; S_{P2} = 10; S_{P3} = 15) and the tree frequency according to the classification pertaining to the branch arrangement was: '1' = 60 trees; '2' = 31; '3' = 13. No red-barked tree was class 3 of branch arrangement. The irregularities in the branch arrangement of dominant Brazilian pines in these quadrants are the result of competition and wind intensity, confirmed by fallen branches. No trees with low vitality were identified but 19 were classified as average vitality. This is especially related to the effect of intra-interspecific competition between individuals and the amount of light that reaches the understory.

Bark thickness variations between groups

After assessing the average bark thickness of the north position (2.96 cm) and its perpendicular E or W measurement (2.99 cm), according to the *t* test, there were no significant differences ($t = -0.14$; $p < 0.8867$). There were also no differences between the gray- (2.94 cm) and red-coloured bark

Table 2 Statistical summary of measured variables for gray- and red-barked trees

Variables	Bark	Units	Mean	Minimum–Maximum	Standard deviation
D_{BH}	Gray	cm	47.2	17.0–117.8	24.7
H		m	18.8	11.8–32.9	4.5
C_{BH}		m	14.6	3.0–30.3	4.6
C_L		m	4.2	0.6–9.0	1.9
B_T		cm	2.9	0.4–7.1	1.5
S_P		–	1.6	1–3	0.8
S_T		–	0.7	0–3	0.9
P_R		–	2.2	1–4	1.0
V_T		–	1.3	1–2	0.5
B_A		–	1.8	1–3	0.8
D_{BH}	Red	cm	46.0	14.7–79.3	17.8
H		m	16.6	9.1–24.9	3.8
C_{BH}		m	10.7	4.3–17.6	4.1
C_L		m	5.9	2.9–9.9	1.7
B_T		cm	3.0	0.9–5.2	1.1
S_P		–	1.0	1–1	0.0
S_T		–	0.8	0–3	0.9
P_R		–	2.1	1–4	1.0
V_T		–	1.0	1–2	0.2
B_A		–	1.2	1–2	0.4

D_{BH} Diameter at breast height, *H* is Height, C_{BH} Crown base height, C_L Crown length, B_T Bark thickness, S_P Social position, S_T Stoniness, P_R Tree Position on the relief, V_T Vitality, B_A Branch arrangement

Table 3 Adjustment and precision statistics of the regression models

Characteristic of bark	β_0	β_1	R^2	M_{AE}	R_{MSE}(%)
Gray	−7.1905	2.7204	0.83	0.507	21.4
Red	−4.3795	1.9758	0.61	0.515	22.3
All	−6.3248	2.4908	0.76	0.540	22.4

β_0 and β_1 are estimated regression coefficients; R^2 is coefficient of determination; M_{AE} is mean absolute error; R_{MSE} (%) is root-mean-square error in percentage

trees (3.02 cm) ($t = -0.31$; $p < 0.7557$). These results reflect only the central value comparison between groups.

Adjustments and comparison of the regression model

The three adjustments of the logarithmic model, according to bark characteristics, demonstrated all regression coefficients to be significant ($p < 0.0001$; Table 3). The largest value of R^2 and smallest M_{AE} and $R_{MSE\%}$ were for trees with gray bark.

Covariance analysis (F = 115.02; Pr > F: < 0.0001) showed significant differences for the intersection (β_0 – Pr > F: $p = 0.0124$) and slope (β_1 – Pr > F: $p = 0.0126$) of
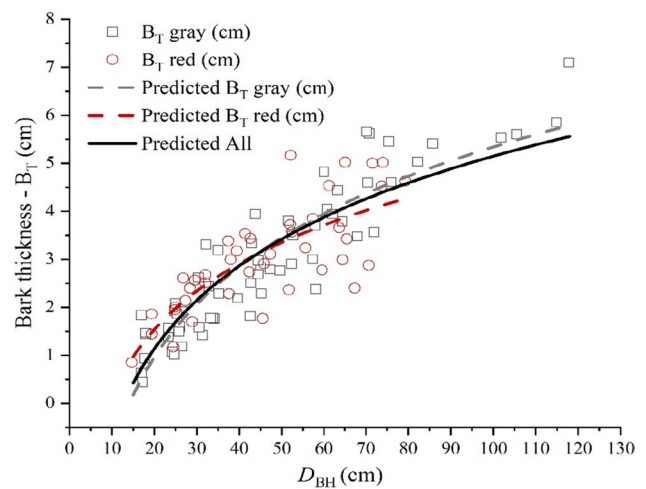

Fig. 2 Observed and estimated values of bark thickness (B_T) with diameter at breast height (D_{BH})

Table 4 Correlation analysis of bark thickness (B_T) between qualitative and quantitative variables

BT	ρ	*p*-value
D_{BH}	0.88	< 0.0001
H	0.58	< 0.0001
C_{BH}	0.46	< 0.0001
C_L	0.16	0.1007
S_P	−0.52	<0.0001
S_T	−0.06	0.5505
P_R	−0.24	0.0150
V_T	−0.12	0.2391
B_A	−0.32	0.0009

D_{BH} diameter at breast height, *H* height, C_{BH} crown base height, C_L crown length, S_P social position, S_T stoniness, P_R tree position on the relief, V_{TH} vitality; B_A branch arrangement

bark thickness curves between bark colour groups. Based on these results, it was necessary to use specific equations for each group. Graphic analysis of observed and estimated values showed that red bark trees smaller than 40.0 cm D_{BH} have the thickest bark and, as such, they become the thinnest bark trees (Fig. 2). During data collection, we did not find red bark trees with $D_{BH} > 80.0$ cm.

Variables related to bark thickness

Correlation analysis of bark thickness with qualitative and quantitative variables are shown in Table 4. The more representative variables were D_{BH} ($\rho = 0.88$; $p < 0.0001$); H ($\rho = 0.58$; $p < 0.0001$); and C_{BH} ($\rho = 0.46$; $p < 0.0001$), all with well-distributed points, similar to a straight line, followed by the qualitative variables S_P ($\rho = -0.52$;

$p < 0.0001$); and B_A ($\rho = -0.32$; $p = 0.0009$). P_R, C_L, S_T and V_T were not significantly correlated ($p > 0.01$).

Modelling using artificial neural networks

The architectures of 3500 trained artificial neural networks are shown in Table 5. A total of 500 networks of each type (1–7) were trained, according to the evaluated input variables and differing number of neurons in the hidden layer (2–12), to obtain single bark thickness estimation (B_T) in the output layer.

The number of trained networks in accordance with the input variables and neurons of the hidden layer ranged from a minimum of 41 to a maximum of 97 (Fig. 3a). Thus, mean values were calculated for statistics R^2 (Fig. 3b), M_{AE} (Fig. 3c) and $R_{MSE\%}$ (Fig. 3d) according to each of the trained networks (1–7). With the inclusion of independent variables during network modelling (1–7), they showed, on average, increased adjustment and accuracy compared to the previous network architecture: D_{BH}–H ($\Delta R^2 \approx 7.7\%$ and $\Delta R_{MSE\%} \approx -5.2$); D_{BH}–H–C_{BH} ($\Delta R^2 \approx 3.9\%$ and $\Delta R_{MSE\%} \approx -3.4$), D_{BH}–H–C_{BH}–S_P ($\Delta R^2 \approx 1.3\%$ and $\Delta R_{MSE\%} \approx -1.2$), D_{BH}–H–H_{BC}–S_P–B_A ($\Delta R^2 \approx 3.2\%$ and $\Delta R_{MSE\%} \approx -4.0$), D_{BH}–H–C_{BH}–S_P–B_A–G_r ($\Delta R^2 \approx 0.8\%$ and $\Delta R_{MSE\%} \approx -1.2$), D_{BH}–H–C_{BH}–S_P–B_A–G_r–B_{Tpred} ($\Delta R^2 \approx 1.1\%$ and $\Delta R_{MSE} \approx -2.3$), respectively, considering the largest number of neurons in the hidden layer (Fig. 3b–d).

Table 6 shows neural networks selected to describe bark thickness (B_T) according to the variation of neurons in the hidden layer. In the input layer, the introduction of other independent variables increased network adjustment and accuracy criteria. Network type 7, which included the input variables: D_{BH}–H–C_{BH}–S_P–B_A–G_r–B_{Tpred}; showed better performance, with an increase in R^2 from 0.924 to 0.997, whereas the $R_{MSE\%}$ was reduced from 14.9 to 3.0 in accordance with the number of neurons obtained in the hidden layer.

The networks with the best performance were those that included 8 to 12 neurons in the hidden layer, represented, respectively, by the networks 138, 501, 1432, 1813, 2286, 2747 and 3157, for each variable inclusion. Figure 4 shows the predicted values *versus* the measured values for each of these networks.

Discussion

The purpose of this study was to develop models for predicting bark thickness at arbitrary diameter levels of Araucaria growing in natural forests. The development of a logarithmic regression proved that there is a strong correlation between bark thickness and stem diameter (Table 3). The same relationship has been investigated for other species such as *Pinus radiata* D. Don (Johnson and Wood 1987), *Picea abies* (L.) H. Karst. (Laasasenaho et al. 2005), *Pinus patula* Schiede ex Schltdl. & Cham. (Laar 2007), tropical rain forest species of French Guiana (Paine et al. 2010) and *Quercus* spp. (Schwilk et al. 2013). Different trends were found in bark thickness estimates between red bark and gray bark trees in our study (Fig. 2).

It is not yet known which factors influence each group that leads to such specific dendrological characteristics. Field observations show that gray- barked trees were older and had, on average, shorter crown lengths compared with red- barked trees (4.2 m and 5.9 m, respectively). It was initially hypothesized that the distinct bark colours were associated with the light intensity inside the forest (Reitz and Klein 1966). However, this hypothesis was rejected during the forest inventory, as Brazilian pines from the two groups were subjected to low, medium and high light incidence.

Dendrological features such as bark colour, size of pine nuts and maturation time have been reported in the literature and used to differentiate Araucaria varieties (Reitz and Klein 1966). In addition, in popular knowledge, the crown architecture differentiates between male and female pines. The dendrometrical and morphological characteristics of the

Table 5 Architecture of networks trained to estimate bark thickness (B_T) of Brazilian pines

Type	Input	Train	Number of neurons		Activation function	
			Hidden	Output	Hidden	Output
1	D_{BH}	500	2–8	1	Logistic	Identity
2	D_{BH}–H	500	3–9	1		
3	D_{BH}–H–C_{BH}	500	3–10	1		
4	D_{BH}–H–C_{BH}–S_P	500	3–10	1		
5	D_{BH}–H–C_{BH}–S_P–B_A	500	3–11	1		
6	D_{BH}–H–C_{BH}–S_P–B_A–G_r	500	3–11	1		
7	D_{BH}–H–C_{BH}–S_P–B_A–G_r–B_{Tpred}	500	4–12	1		

D_{BH} diameter at breast height, H height, C_{BH} crown base height, S_P social position, B_A branch arrangement, G_r group, B_{Tpred} bark-thickness-regression model prediction
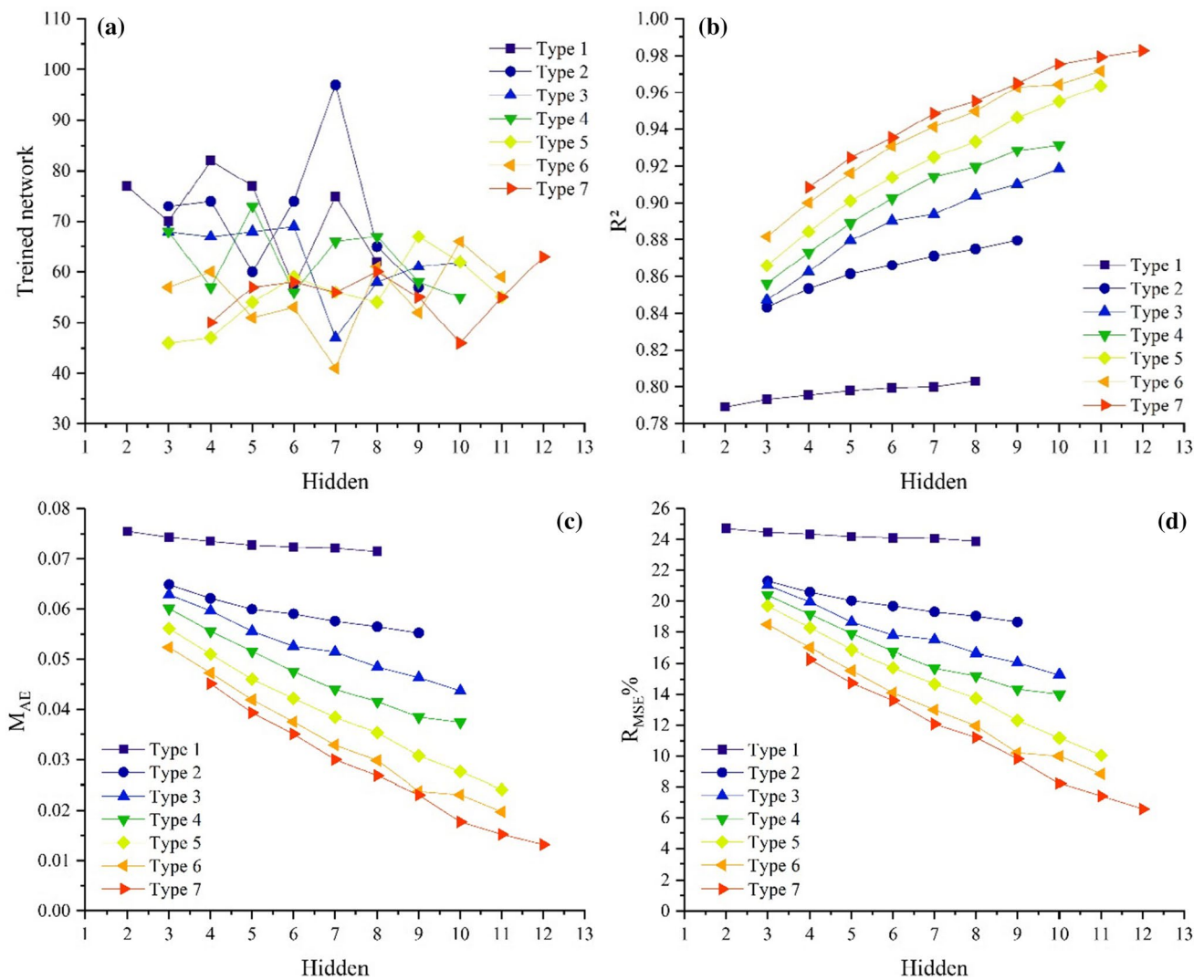
Fig. 3 Trained networks: **a** Amount of trained networks with different input variables and neurons in the hidden layers; Average of R^2 values (**b**); Average M_{AE} (**c**); and $R_{MSE}(\%)$ (**d**) calculated for the trained networks with different input variables and number of neurons in the hidden layer to estimate the bark thickness (B_T) of Brazilian pines. (Network types 1–7 considered the input variables D_{BH}; D_{BH}–H; D_{BH}–H–C_{BH}; D_{BH}–H–C_{BH}–S_P; D_{BH}–H–H_{BC}–S_P–B_A; D_{BH}–H–C_{BH}–S_P–B_A–G_r; D_{BH}–H–C_{BH}–S_P–B_A–G_r–B_{Tpred} respectively. D_{BH} Diameter at breast height, *H* Height, C_{BH} Crown base height, S_P Social position, B_A Branch arrangement, G_r group, B_{Tpred} bark-thickness-regression model prediction)

species are reflections of its relationship with its environment, and should be analyzed for a better understanding of the factors that operate throughout its life.

As an attempt to improve bark thickness estimates, the contribution of other quantitative and qualitative variables as inputs beyond diameter are also investigated. In this context, among other advantages of using artificial neural networks, is the possibility of modelling with categorical variables (qualitative) such as sociological position (S_p), branch arrangement (B_A), and group (G_r), beyond numeric variables (quantitative) (Vieira et al. 2018).

Overall, classifications of qualitative attributes in natural forests should be assessed carefully and with defined

standards to allow other researchers to follow the same procedures. Standardization of criteria is one of the greatest challenges in forest surveys when using attributes of this character. Barbosa (2018) described the current state of tree competition in natural forests by crown classification attributes, and proposed new metrics with different classification levels to describe characteristics related to the vertical crown form, the distance between pseudo-whorls, percentage of green leaves and crown size. This permitted a good explanation of Araucaria basal area growth.

Considering the data in Table 6, the Figs. 3a–d and the Fig. 4, it is clear that the use of ANN is a feasible technique to estimate bark thickness of Araucaria. There

Table 6 Networks selected to estimate the bark thickness (B_T) of Brazilian pines

Network	Type	Input	Number of neurons		Activation function		Statistics		
			Hidden	Output	Hidden	Output	R^2	M_{AE}	R_{MSE} (%)
–	Regression	D_{BH}	–	–	–	–	0.761	0.540	22.6
89	1	D_{BH}	2	1	Logistic	Identity	0.790	0.075	24.7
371	1		3	1			0.800	0.072	24.1
132	1		4	1			0.802	0.072	24.0
24	1		5	1			0.814	0.070	23.3
311	1		6	1			0.817	0.069	23.1
22	1		7	1			0.817	0.068	23.0
138	1		8	1			0.821	0.067	22.8
676	2	D_{BH}–H	3	1	Logistic	Identity	0.851	0.065	20.8
589	2		4	1			0.869	0.058	19.5
862	2		5	1			0.876	0.057	19.0
912	2		6	1			0.881	0.056	18.6
985	2		7	1			0.885	0.054	18.2
522	2		8	1			0.887	0.052	18.1
501	2		9	1			0.895	0.051	17.5
1418	3	D_{BH}–H–C_{BH}	3	1	Logistic	Identity	0.854	0.062	20.6
1475	3		4	1			0.884	0.052	18.3
1427	3		5	1			0.899	0.050	17.1
1328	3		6	1			0.911	0.049	16.1
1285	3		7	1			0.913	0.047	15.9
1283	3		8	1			0.924	0.044	14.8
1158	3		9	1			0.934	0.038	13.8
1432	3		10	1			0.941	0.038	13.1
1658	4	D_{BH}–H–H_{BC}–S_P	3	1	Logistic	Identity	0.876	0.054	19.0
1582	4		4	1			0.896	0.052	17.4
1909	4		5	1			0.906	0.046	16.5
1533	4		6	1			0.918	0.042	15.4
1523	4		7	1			0.935	0.037	13.7
1840	4		8	1			0.942	0.033	13.0
1711	4		9	1			0.946	0.031	12.5
1813	4		10	1			0.946	0.032	12.5
2398	5	D_{BH}–H–C_{BH}–S_P–B_A	3	1	Logistic	Identity	0.880	0.053	18.7
2088	5		4	1			0.902	0.051	16.9
2194	5		5	1			0.923	0.040	14.9
2021	5		6	1			0.938	0.036	13.5
2306	5		7	1			0.950	0.032	12.1
2059	5		8	1			0.957	0.028	11.1
2302	5		9	1			0.966	0.024	10.0
2476	5		10	1			0.980	0.018	7.7
2286	5		11	1			0.980	0.017	7.6

Table 6 (continued)

Network	Type	Input	Number of neurons		Activation function		Statistics		
			Hidden	Output	Hidden	Output	R^2	M_{AE}	R_{MSE} (%)
2575	6	D_{BH}–H–C_{BH}–S_P–B_A–G_r	3	1	Logistic	Identity	0.901	0.044	17.0
2871	6		4	1			0.913	0.044	15.9
2914	6		5	1			0.932	0.036	14.1
2883	6		6	1			0.947	0.033	12.4
2552	6		7	1			0.951	0.030	11.9
2923	6		8	1			0.969	0.024	9.5
2829	6		9	1			0.978	0.017	7.9
2857	6		10	1			0.983	0.017	7.0
2747	6		11	1			0.990	0.013	5.5
3216	7	D_{BH}–H–C_{BH}–S_P–B_A–G_r–B_{Tpred}	4	1	Logistic	Identity	0.924	0.040	14.9
3251	7		5	1			0.938	0.036	13.4
3446	7		6	1			0.954	0.031	11.6
3244	7		7	1			0.969	0.026	9.5
3350	7		8	1			0.980	0.016	7.6
3499	7		9	1			0.984	0.013	6.8
3323	7		10	1			0.989	0.013	5.7
3089	7		11	1			0.995	0.007	3.9
3157	7		12	1			0.997	0.006	3.0

R^2 is coefficient of determination; M_{AE} mean absolute error, R_{MSE} (%) is root-mean-square error in percentage, D_{BH} diameter at breast height, H height, C_{BH} crown base height, S_P social position, B_A branch arrangement, G_r group, B_{Tpred} bark-thickness-regression model prediction

was more accuracy projecting bark thickness compared to the use of regression models. Moreover, an increase in predictive accuracy was also obtained using variables that consider both qualitative and quantitative information of tree and site. Other researchers have reported the influence of environmental factors on bark thickness such as fire regime (Van Mantgem and Schwartz 2003; Lawes et al. 2011), climate conditions (Pellegrini et al. 2017), and frost events (Molina et al. 2016) which are evidence of the importance of site variables, in addition to those intrinsic to the tree itself.

The last variable tested for inclusion in the artificial neural network was the regression model prediction itself (Type 7). The concept is to attribute applicability to previous regression models, for instance, under certain conditions, to allow the readjustment to current variations and to provide greater flexibility to the models. Finally, the possibility of variation in the number of neurons with the artificial neural networks has also resulted in prediction improvements to some extent, where it seems to stabilize (Fig. 3b, 3c and 3d). Approximately eight neurons, regardless of network type, were shown to be sufficient with a tendency to maintain both R^2 and $R_{MSE\%}$ constant. The continuous addition of neurons may result in overfitting and consequently, lower generalization power (Theodoridis and Koutroumbas 1999; Goodfellow et al. 2016).

Conclusions

There is evidence of statistically significant differences between the regression of gray- and red- barked trees in accordance with Araucaria D_{BH}. This variable can be estimated for a wide range of diameter distributions using adjusted regression equations for both bark colour groups.

Qualitative variables are important in the modelling of several artificial intelligence techniques. Such variables can distinguish characteristics inherent to the data that would be difficult to distinguish with conventional regression modelling.

Artificial neural networks are an efficient and robust technique for various qualitative and quantitative attribute models commonly used in forest mensuration. For this reason, its accuracy, applicability and usability were confirmed in this study for modelling biometric variables in natural forests of high complexity and variability.
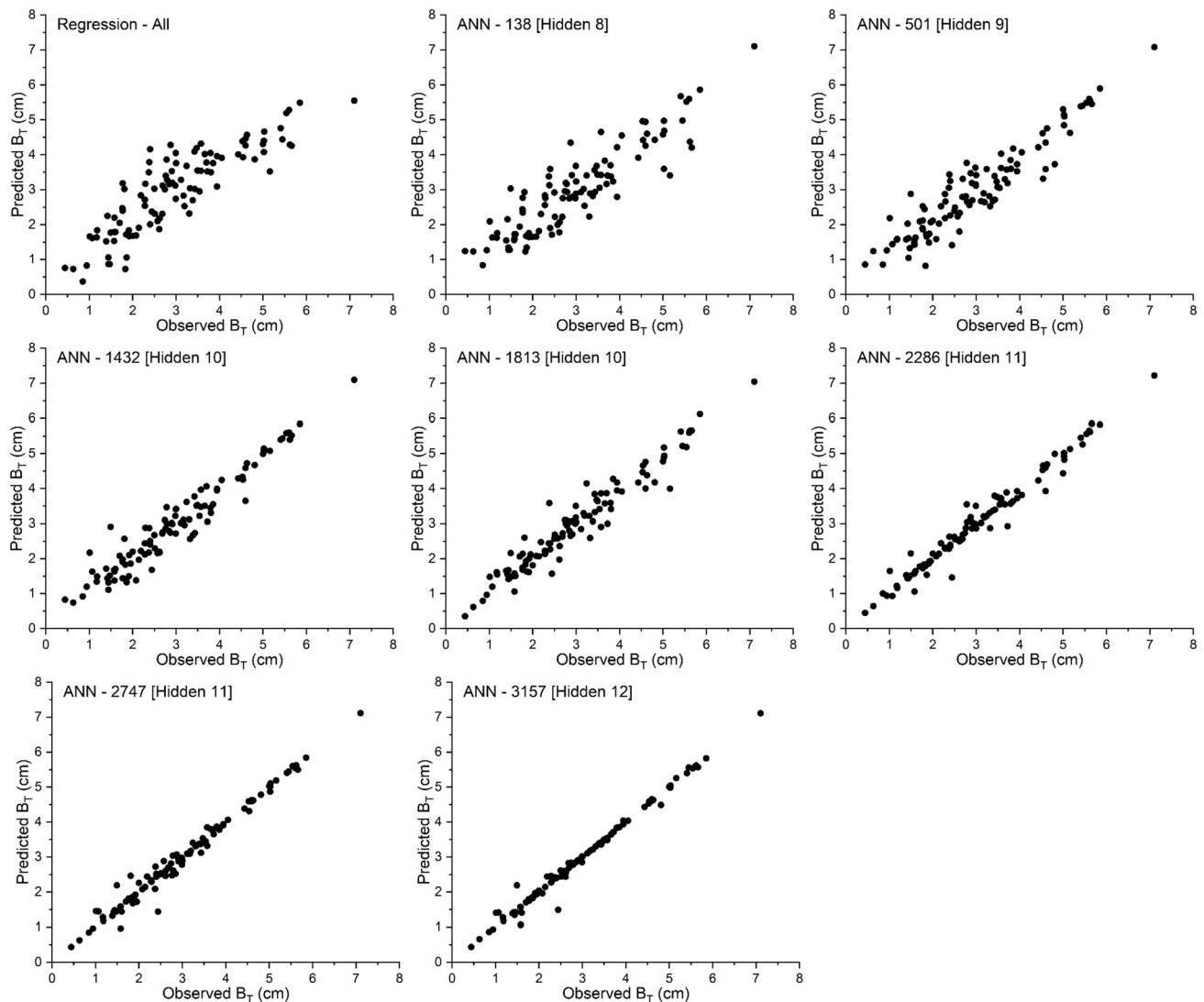
Fig. 4 Relationship between predicted bark thickness (B_T) *vs.* observed values for the best-trained networks for each variable inclusion

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