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SHORT COMMUNICATION – Forest Management

Estimation height level of *Copaifera* sp. (Leguminosae) by Artificial Neural Networks

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Abstract

The knowledge of tree attributes of the genus *Copaifera* sp. (copaiba), such as the height of the trunks, helps to estimate the productive potential of oleoresin and to propose more suitable ways of handling, aiming at optimizing production. This research aimed to test hypsometric equations and deterministic methods of Artificial Neural Networks (ANN) to estimate the total heights levels of the trunks of 31 copaiba trees of the Western Brazilian Amazon, at unknown ages. However, the ANN correlation coefficients obtained were greater than 0,99, demonstrating that they are appropriate for the estimation of height level (*h100%*). Among the ANN architectures, ANN 3 with 2 neurons in the hidden layer stood out. The application of ANN to estimate the total height of the trunk of *Copaifera* sp. native trees is a viable tool that can contribute to optimize modeling of the different important aspects to determine the productive potential of oleoresin.

Keywords: Artificial intelligence, Forest inventory, Forest measurement, Forest technology, Hypsometry, Non-timber forest products.

Trees of *Copaifera* L. (Leguminosae) genus secrete an oleoresinous substance (LPWG, 2017) with properties of interest to the pharmaceutical and chemical industries (Araújo et al., 2018; Medeiros et al., 2018; Heck et al., 2012). Angelo et al. (2018) analyzed the market for non-timber forest products in the Brazilian Amazon, between 1973 and 2011, indicated copaiba as one of the relevant products, and pointed out the need to modernize the extractive industry. One of the main problems of oleoresin exploitation is unpredictable productivity per individual, without an average reference value (Newton et al., 2011; Veiga Junior & Pinto, 2002). Using tree size as a parameter to estimate the amount of oleoresin to be obtained from a given population is the objective of many researchers and forest managers. Individual tree models are composed of submodels that generally estimate competition, mortality and growth in height and diameter of each tree (Vieira et al., 2018). Variables that are difficult to obtain can be estimated by regression models, enabling the establishment of the functional relationship between two variables, using linear and non-linear models (Scolforo, 2005). Also, Artificial Neural Networks (ANN) are used to estimate the height and volume of trees and can be used to obtain the potential of extractive production (Diamantopoulou, 2012). ANNs are computational systems with parallel layers, consisting of several simple processing units (artificial neurons) connected to each other in order to perform a certain task (Fleck et al., 2016). These "neurons" are mathematical models inspired by the functioning of biological neurons, which process the information received, weight it by synaptic weights and provide one or more responses (Haykin, 2001; Silva, Spatti & Flauzino, 2010). The measurement of the total height of the stem impacts the costs of the forest inventory, demonstrating the relevance of studies that correlate hypsometric characteristics using modern statistical techniques for the quantification of oleoresin productivity. This research tested hypsometric models and Artificial Neural Networks as estimators of the total height of the stem of *Copaifera* sp. of the Brazilian Western Amazon, at unknown ages. Thirty-one trees were analyzed from two sites in the state of Acre (10°28' S; 67°55' O (Remanso) e 7°44' S; 72°32' O (Croa). For each tree, the following variables were obtained: i) height (m), in the sections 0% (diameter at breast height - DBH - 1,30 m from the ground), 25%, 50%, 75% and 100% (1st trunk bifurcation - h100%); and ii) diameter at the respective heights (cm). Among these, 12 trees were measured at the base (20 cm above the soil surface), DBH, at 2-meter intervals and h100%, and the variables corresponding to the other heights were obtained through interpolation. To measure these variables, abseiling equipment and measuring taper segmentation, were used. Four regression models were selected to test the ability to estimate h100% as a function of DBH (Table 1).

Table 1. Hypsometric models used to verify the correlation value between diameter and tree height *Copaifera* sp. Source: Ré *et al.* (2015).

Type	Hypsometric models	Model
Straight line	$h = \beta_0 + \beta_1 * DBH + E$	(1)
Parabolic	$h = \beta_0 + \beta_1 * DBH + \beta_2 * DBH^2 + E$	(2)
Curtis	$\frac{1}{\sqrt{h}} = \beta_0 + \beta_1 * \frac{1}{DBH} + \mathrm{E}$	(3)
Stoffels	$\sqrt{h} = \beta_0 + \beta_1 * \ln DBH + E$	(4)

Note: DBH = Diameter at breast height (cm); h = Total tree height (stem length) (m); = Error (random) associated with each estimate; β_0, β_1 e β_2 = model coefficients.

The hypsometric models were adjusted using the Microsoft Excel 2016 software and evaluated according to the following parameters: Correlation coefficients (r), Determination (R^2) and Adjusted determination (Adjusted R^2), Standard error, Calculated F and tabulated F. Subsequently, Artificial Neural Networks (ANN) of the type *Multilayer Perceptron* (MLP) ANN (Heidari et al., 2019) were tested, with sigmoidal activation in the hidden and outgoing layers. The trained algorithm was the *Resilient Propagation* (RPROP+), with values of the learning rate varying between zero (0) and one (1), using the average error of 0.0001 and the limit of 3000 cycles as a stopping criterion. The general supervised learning architecture was used (Ludwig Jr. & Montgomery, 2007). Five ANN were tested for three different architecture configurations (9x2x1, 9x4x1 and 9x8x1), respectively, two, four and eight artificial neurons in the hidden layer; nine variables in the input layer (*h0%*, *h25%*, *h50%*, h*75%* and respective diameters); and a variable in the output layer (*h100%*). The origin of the trees (sites) was used as a categorical variable. The NeuroDAP program was used for training, a System for Generation and Application of Artificial Neural Networks, version 4.0 (DAP Florestal, 2020; Bonete & Lanssanova, 2020). Due to the size of the studied population, all trees' data were used in training [1]. The selection of the ANN was carried out based on the quality criteria: Correlation (*r e* R^2); *bias* (additive junction or synaptic link); Residual Sum of Squares (RSS) and Variance (Var); Root of the Mean Square of Error (RMSE); Standard Error of Estimate (*Syx*) and Relative Standard Error of Estimate (*Syx*%). Also, a graphic analysis of the residues was realized. In general, trees predominated in classes that DBH varied between 34,70 and 112,39 cm, and *h100%* between 13,27 and 19,13 m. There was no significant correlation between: DBH and *h100%* (p-value = 0,727); *h25%* and diameter 25% (p-value = 0,059); *h50%* and diameter 50% (p-value = 0,445); *h75%* and diameter 75% (p-value = 0,101); *h100%* and diameter 100% (p-value = 0,065); and between DBH and *h0%* (p-value = 0,105). In a natural forest, the correlation between DBH and height is very weak, due to the different ages and environmental conditions (Scolforo, 2005). Besides, studies show that variables such as topsoil and age are not significant for productivity, but the stem height is significant [2] (Roquette, 2014). In the present study, the hypsometric equations tested were not appropriate for estimating the h100% (Table 2).

Table 2. Precision measurements of the regression statistics of hypsometric models, tested for native trees of *Copaifera* sp.

Parameter	Hypsometric equation			
	(1)	(2)	(3)	(4)
r	0,065	0,168	0,066	0,093
R^2	0,004	0,028	0,004	0,009
Adjusted R^2	-0,030	-0,041	-0,030	-0,025
Standard error	3,415	3,433	0,032	3,407
Calculated F	0,12397	0,4081	0,128	0,2547
Tabulated F	4,18	3,42	4,18	4,18

Note: r = Correlation coefficient; R^2 = Determination coefficient.

ANN 1 (9x2x1) provided the highest number of h100% values that reliable to real values (93,87%), followed by ANN 3 (9x2x1), ANN 2 (9x8x1) and ANN 4 (9x4x1) with, respectively, 72,26%, 70,68% and 70,00% (Table 3). However, the effective hit is not the most appropriate criterion for choosing the ANN.

[1] Copaibas are trees of rare occurrence, and, in the forests of Acre, it is expected to find a number of individuals ranging from 0,1 ha^{-1} a 1,5 ha^{-1} (Martins et al., 2016).

[2] These and other variables "most often have complex relationships and often non-linear trends" (Binoti et al., 2014, p.59).

Table 3. Estimates of *h100%,* by ANN training algorithms, with different numbers of neurons in the hidden layer, tested for native trees of *Copaifera* sp.

Tree	*h100%* real	ANN - 2 neurons					ANN - 4 neurons					ANN - 8 neurons				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
*rm*1	7,40	7,93	7,62	7,62	8,15	8,26	8,17	8,14	8,21	7,40	7,78	8,31	7,73	7,82	7,54	8,20
*rm*2	15,05	15,03	15,04	15,01	15,03	15,00	15,03	15,02	15,12	15,09	14,96	15,04	15,06	15,03	15,06	14,97
*rm*3	15,80	15,81	15,78	15,75	15,75	15,72	15,86	15,79	15,83	15,80	15,81	15,79	15,80	15,79	15,83	15,78
*rm*4	19,00	19,00	19,05	18,98	19,01	19,01	19,01	18,98	19,07	19,00	18,99	19,00	19,02	19,07	19,09	19,04
*rm*5	15,50	15,52	15,50	15,43	15,49	15,44	15,48	15,50	15,55	15,51	15,42	15,50	15,49	15,48	15,52	15,50
*rm*6	14,50	14,49	14,51	14,41	14,49	14,48	14,40	14,47	14,51	14,50	14,33	14,50	14,50	14,46	14,50	14,29
*rm*7	16,37	16,33	16,36	16,29	16,34	16,32	16,39	16,36	16,39	16,42	16,25	16,36	16,35	16,37	16,41	16,37
*rm*8	14,15	14,13	14,16	14,07	14,14	14,11	14,06	13,97	14,20	14,16	14,00	14,15	14,14	14,16	14,15	14,12
*rm*9	12,30	12,28	12,31	12,21	12,19	12,24	12,24	12,27	12,34	12,29	12,22	12,30	12,30	12,25	12,26	12,24
*rm*10	15,38	15,33	15,38	15,32	15,37	15,34	15,40	15,38	15,41	15,43	15,37	15,37	15,38	15,37	15,40	15,33
*rm*11	17,00	16,98	17,00	16,93	16,99	16,99	17,05	16,98	17,07	17,02	16,93	16,99	17,01	17,06	17,02	17,02
*rm*12	15,00	15,00	14,99	14,91	14,90	14,97	14,97	14,95	15,04	15,01	14,94	15,00	15,00	14,97	15,01	14,98
*rm*13	20,20	20,21	20,25	20,17	20,22	20,20	20,20	20,20	20,26	20,20	20,18	20,21	20,21	20,32	20,19	20,24
*rm*14	17,30	17,29	17,30	17,28	17,25	17,29	17,32	17,31	17,38	17,34	17,24	17,29	17,31	17,34	17,30	17,32
*rm*15	14,50	14,48	14,48	14,44	14,50	14,47	14,43	14,48	14,57	14,50	14,29	14,50	14,50	14,46	14,50	14,48
*rm*16	15,00	14,97	15,02	14,95	14,98	14,98	14,97	14,99	15,01	15,00	14,89	15,00	15,00	14,97	15,01	14,93
*rm*17	11,38	11,35	11,34	11,30	11,19	11,35	11,06	11,36	11,44	11,38	11,25	11,38	11,58	11,27	11,36	11,31
*rm*18	10,55	10,48	10,56	10,51	10,40	10,46	10,57	10,52	10,56	10,85	10,37	10,55	11,58	10,43	10,53	10,45
*rm*19	20,50	20,51	20,54	20,50	20,53	20,51	20,50	20,49	20,56	20,50	20,49	20,50	20,50	20,62	20,60	20,54
*rm*20	14,00	13,94	13,97	13,93	13,96	13,96	13,96	13,97	14,00	13,99	13,94	14,00	13,99	13,99	14,00	13,94
*rm*21	16,00	16,01	16,01	15,97	15,97	15,93	16,01	15,98	16,06	16,04	15,97	16,00	15,96	16,00	16,03	16,01
*rm*22	16,50	16,51	16,51	16,44	16,41	16,46	16,54	16,49	16,56	16,50	16,45	16,49	16,50	16,51	16,52	16,51
*rm*23	18,00	18,02	18,04	17,98	18,01	18,00	18,01	17,99	18,08	18,00	17,99	18,00	18,01	18,02	18,06	18,00
*rm*24	18,00	18,01	18,03	17,99	18,01	18,00	18,04	18,00	18,07	18,16	17,95	18,00	18,01	18,12	17,99	17,99
*rm*25	16,00	16,00	16,04	15,93	15,97	15,99	16,00	15,97	16,02	16,00	15,98	15,99	16,00	16,00	16,02	16,00
*rm*26	18,00	18.01	18.01	17,97	18,02	17,99	18.03	17,99	18,07	18,00	17,96	18,00	17,99	18,04	18,03	18,02
*rm*27	18,40	18,40	18,45	18,37	18,37	18,39	18,43	18,39	18,48	18,40	18,38	18,40	18,42	18,46	18,41	18,44
*cr*28	19,00	18,99	19,00	18,93	19,06	18,99	19,00	18,99	19,05	19,00	19,00	19,00	19,01	19,12	19,08	19,00
*cr*29	22,70	22,70	22,84	22,88	22,79	22,72	22,70	22,70	22,73	22,44	23,03	22,70	22,18	22,77	22,90	22,73
*cr*30	18,68	18,69	18,75	18,63	18,69	18,68	18,69	18,67	18,76	18,68	18,65	18,68	18,68	18,70	18,77	18,68
*cr*31	23,73	23,01	22,95	22,88	23,63	23,62	23,59	23,26	23,36	22,44	23,03	23,69	22,18	23,16	22,90	23,47

Note: *h100%* = total tree height level (trunk length); *rm* = site Remanso; *cr* = site Croa.

Correlations between input (real *h100%*) and *output* (estimated *h100%*) generated considered very good adjustments ($r \geq 0{,}99$). However, ANN 2 (9x8x1) and ANN 3 (9x2x1) reached, in addition to an excellent correlation, the lowest Var associated with lower values RMSE and *bias*. Although ANN 1 (9x2x1) presented the best distribution of errors around the midline of the regression (Figure 1), it was found that this generated high RMSE, *Syx* and *Syx* (%), while ANN 3 (9x2x1) and ANN 2 (9x8x1) generated reduced RMSE, *Syx* e *Syx* (%) (Table 4).

The numbers of neurons and hidden layer do not guarantee that the ANN will carry out an appropriate generalization, and *overfitting* and *underfitting* failures may occur, in both cases, the RMSE level is the parameter to be considered, in addition, the ANN selection must prioritize the lowest number of neurons in the hidden layer (Silva et al., 2010). Training is the stage that teaches ANN, and learning occurs from the trained network, its architecture, and its topology (Furtado, 2019). However, ANN validation should not be ignored, as it allows verifying the performance of the network when applying it to new data (Silva et al., 2010). ANN 3 (9x2x1) was selected as the best network for estimating the *h100%* of *Copaifera* sp. The lack of significant linear correlation between the dendrometric variables and the specificities of the sites did not prevent the predictive capacity of the ANN.

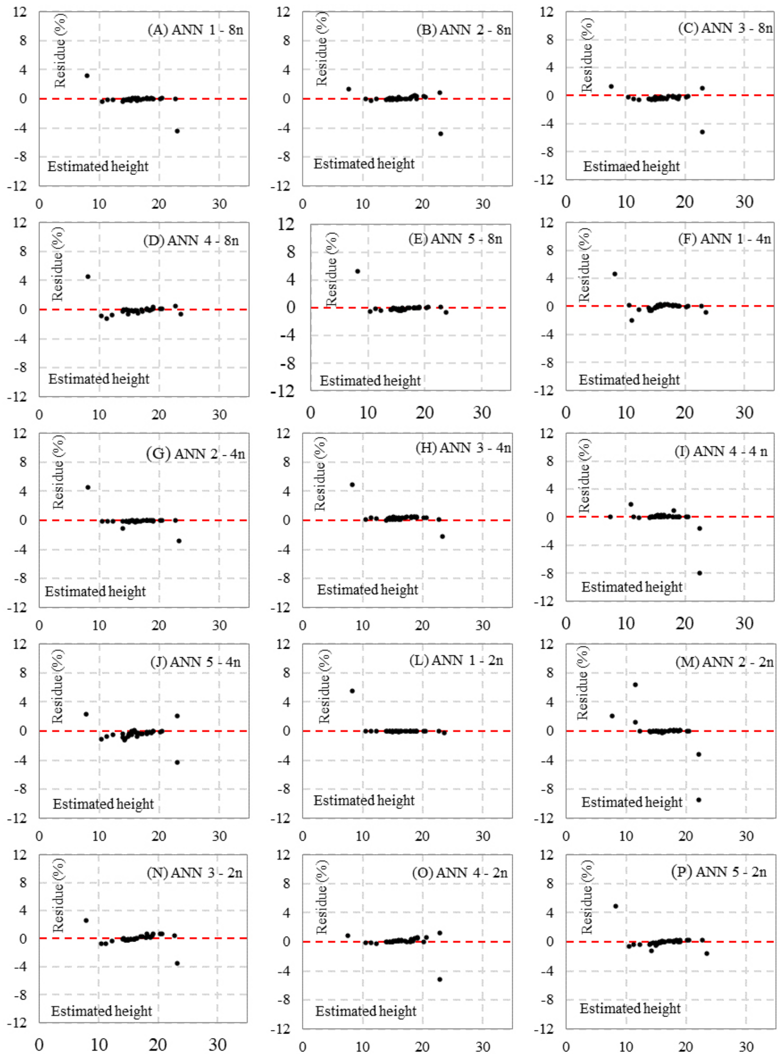

Figure 1. Dispersion of percentage errors (y), as a function of estimated total trunk heights (x) for *Copaifera* sp. trees, native to Western Amazonia, Brazil, for Artificial Neural Networks with 9x2x1, 9x4x1 and 9x8x1 architectures.

Table 4. Adjustment quality criteria of ANN models with 9x2x1, 9x4x1 and 9x8x1 architectures, used to estimate the total stem length of *Copaifera* sp. trees, native to Western Amazonia, Brazil.

N	ANN	*r*	*bias*	RSS	Var	RMSE	*Syx*	*Syx* (%)
2	ANN 1	0,999068	0,0270	0,8207	0,0266	0,1627	0,1603	0,9822
	ANN 2	0,996403	0,0340	1,4941	0,0486	0,2195	0,3487	2,1369
	ANN 3*	0,999144	0,0257	0,2934	0,0091	0,0973	0,0799	0,4896
	ANN 4	0,998893	0,0301	0,1036	0,0025	0,0578	0,1579	0,9674
	ANN 5	0,998953	0,0091	0,7323	0,0243	0,1537	0,1583	0,9699
4	ANN 1	0,998977	0,0119	0,7347	0,0243	0,1540	0,1537	0,9416
	ANN 2	0,999128	0,0052	0,5880	0,0196	0,1377	0,1592	0,9754
	ANN 3	0,999198	0,0723	0,7389	0,0192	0,1544	0,1652	1,0126
	ANN 4	0,997840	0,0148	0,1970	0,0063	0,0797	0,2417	1,4813
	ANN 5	0,998774	-0,0367	0,4740	0,0144	0,1237	0,1733	1,0620
8	ANN 1	0,999116	0,0084	0,2966	0,0098	0,0978	0,1592	0,9754
	ANN 2*	0,999093	0,0218	0,0903	0,0025	0,0540	0,1470	0,9008
	ANN 3	0,998966	-0,0351	0,1774	0,0046	0,0756	0,1678	1,0282
	ANN 4	0,999035	0,0009	0,6763	0,0225	0,1477	0,1465	0,8978
	ANN 5	0,998998	0,0025	0,7794	0,0260	0,1586	0,1572	0,9633

Caption: N = number of neurons in the hidden layer; ANN = artificial neural network; * = ANN that showed the most promising results; *r* = correlation coefficient; *bias* = threshold, additive junction or synaptic link; RSS = Residual Sum of Squares; Var = Variance; RMSE = Root-Mean-Square Error; *Syx* = Standard Error of Estimate; *Syx* (%) = Relative Standard Error of Estimate.

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Daniel Henrique Breda Binoti: methodology-supporting, software, supervision-supporting, writing – original draft-supporting.

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