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Article

Modeling Height—Diameter Relationship Using Artificial Neural Networks for Durango Pine Species in Mexico

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Abstract: The total tree height (*h*) and diameter at breast height (*dbh*) relationship is an essential tool in forest management and planning. The height—diameter (*h-dbh*) relationship had been studied with several approaches and for several species worldwide. The nonlinear mixed effect modeling (*NLMEM*) has been extensively used and lately the resilient backpropagation artificial neural network (*RBPANN*) approach has been a trend topic for modeling this relationship. The artificial neural network (*ANN*) is a computing system based in artificial intelligence and inspired in biological neural network for supervised learning. In this study the NLMEN and *RBPANN* approaches were used for modeling the *h—dbh* relationship for Durango pine species (*Pinus durangensis* Martínez) in mixed-species forest from Mexico. The total dataset considered 1,000 (11,472 measured trees) randomly selected from 14,390 temporary forest inventory plots and the dataset was randomly divided into two parts; 50% for training and 50% for testing. An unsupervised clustering analysis was used to grouped the dataset into 10 clusters based on k-means clustering method and plot-variables like density, basal area, mean *dbh*, mean *h*, quadratic mean diameter, altitude and aspect. The *RBPANN* was performed for tangent hyperbolicus (*RBPANN*-tanh), softplus (*RBPANN*-softplus), and logistic (*RBPANN*-logistic) activation functions for functions in cross product of the covariate or neurons and the weights for the *ANN* analysis. For both training and testing, 10 classical statistics (e.g., RMSE, R^2, AIC, BIC, logLik) were computed for the residual values and assess the approaches for *h—dbh* relationship. For training and testing, the *ANNs* approach outperformed the *NLMEM* approach, and the *RBPANN*-tanh has the best performance in both training and testing phases.

Keywords: artificial intelligence; artificial neural network; height-diameter relationship; nonlinear mixed effect modeling

1. Introduction

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines, wherein they are programmed to think and learn in a manner similar to humans. The AI has been used in forest modelling for different purposes and objectives. The machine learning (ML) is a subset of AI that focuses on the development of algorithms and models that enable computer to learns from a specific dataset and make predictions or take actions without being explicitly programmed [1,2]. One of the most ML techniques is the artificial neural network (*ANN*) and the resilient backpropagation artificial neural network (*RBPANN*) perform supervised ML in multi-layer perceptron, and the main principle is to eliminate the harmful influence of the size of the partial derivative on the weight step [3-5]. The *ANNs* are computational models inspired in the natural neurons and they represent a

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generalization of mathematical models of human cognition or neural biology [1,6,7]. In *ANNs*, the training and testing datasets are used to train and evaluate the performance of the network for a specific randomly selected dataset. The training dataset is used to train the neural network. It consists of a set of input data points and their corresponding target output values, while, the testing dataset is a separate dataset that is used to evaluate the performance of the trained neural network [1,8,9].

One of the most important relationships in forest modeling is the total tree height and diameter at breast height (*h-dbh*) relationship, and this relationship is usually applied in forest inventory or for height estimation in forest management and planning [10]. The knowledge of *h-dbh* relationship is a fundamental both developing and applying many growth and yield models [11,12]. This relationship has mainly studied with nonlinear mixed effect modeling (*NLMEM*) with fix and random parameters for several species and grouping level or ecological conditions [10,11,13-16]. Lately, this relationship has been studied with AI, and the ML thought *ANN* has been used [7,17,18]. Also, other variables as basal area [19], crown width [20], biomass [21], volume [22], forest fire [23], and annual radial growth with competition indices [24] have been studied with different ML algorithms. Occasionally, the clustering analysis based in unsupervised ML has been included in to group similar data point together based on their inherent characteristics or similarities [1,25-27]. The unsupervised clustering analysis could identify patterns or structures in dataset to improve the fitted models in forest modeling.

Specifically, in the Mexican Forestry the *h-dbh* relationship has been extensively studied with *NLMEM* for local and generalized models and occasionally the unsupervised cluster analysis was included in modelling [12,28,29]. The *NLMEM* are better than fitted models by ordinary least squares method and those use random parameter to explain the variability between groups, sites, or ecological regions. Lately, the ML algorithms are taken attention in forestry research and the results outperform the *NLMEM* approach for the *h-dbh* relationship. In *ANN* analysis is convenient to separate the dataset in two parts, one for training and other one for testing or validation [7,17]. The main used model for *NLMEM* has been th Chapman-Richards model [30], which is base in a sigmoid relationship growth based on age [31].

Considering the above schemes and the context of AI in forestry research, this study aim the *h-dbh* relationship for Durango Pine species (*Pinus durangensis* Martínez) by *NLMEM* and *ANN* for unsupervised clustered dataset for training and testing sets. The algorithms were compared in both training and testing phases and some conventional statistics like root mean square error, coefficient of determination, Akaike's information criterion, Bayesian information criterion, and loglikelihood were uses to perform the approaches. The resilience backpropagation of *ANN* (*RBPANN*) was employed, and three activation functions were computed and evaluated. The activation functions were tangent hyperbolicus (*RBPANN*-tanh), softplus (*RBPANN*-softplus), and logistic (*RBPANN*-logistic), and those were trained by resilience backpropagation and maximum likelihood was used.

2. Materials and Methods

2.1. Study area

The study was developed in a forest community in Norther Mexico, specifically in Durango state. The forest community is called San Diego de Tezains, and the total area is around 61,098 ha, which 30,000 ha are used for forest management and timber harvesting. The main applied silvicultural treatments are based on continuous cover forestry (CCF) and rotation forest management (RFM) [32]. The silvicultural treatments for CCF area base on selection, while three thinning and shelterwood cutting treatments for RFM with 15-years of forest cycle cutting [33]. The location of study area is showed in Figure 1. The mean annual temperature ranges from 5 to 18 °C, and the lowest temperature occurs in January (− 6 °C) and the hottest in May (28 °C). The altitude varies from 1,500 to 3,033 m. The mixed-species stands are represented by seven genera: *Pinus*, *Quercus*, *Juniperus*, *Cupressus*, *Pseudotsuga*, *Arbutus*, and *Alnus*. The main species are *Pinus durangensis* Martínez and *Quercus sideroxyla* Bonpl. Lately, the Improve forest management combine the forest

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management and credit carbon offsets according to the Mexican Protocol developed by The Climate Action Reserve [34].

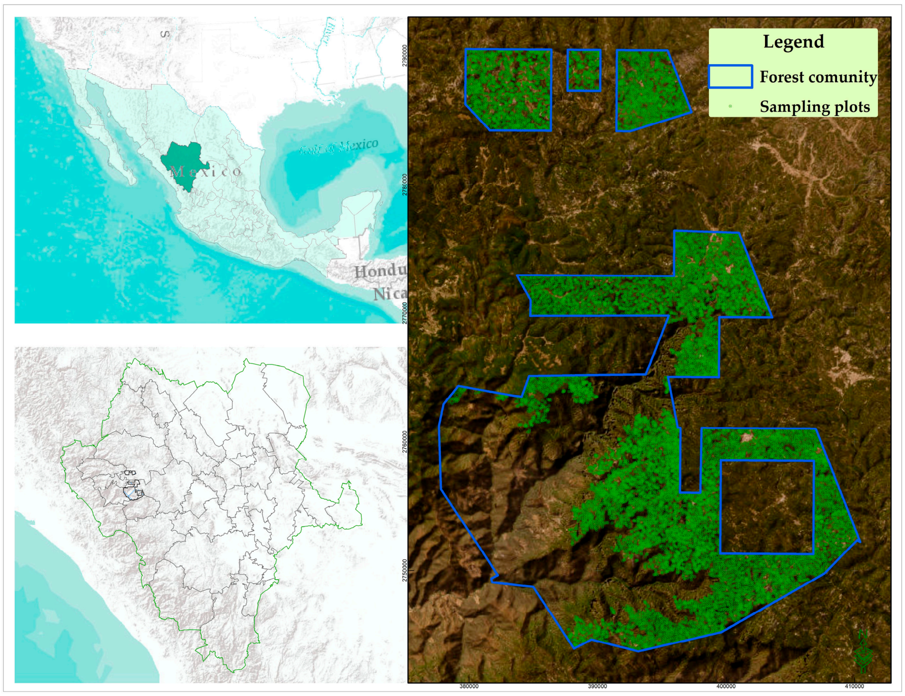

Figure 1. Study area location in Northern Mexico.

2.2. Dataset description

The dataset came from temporary forest inventory plots with a random sampling design for framework of 30,000 ha. A total of 14,390 temporary forest inventory plots were considered and Durango pine species was selected. A random sample of 1,000 plots was selected in *sampling* R package [35], and 11,472 measured trees were considered. Firstly, the unsupervised clustering analysis was used for grouping the dataset [1,25] according to the k-Means Clustering of *kmeans* R package [35]. Ten clusters were generated according with density (N, trees per hectare), basal area (BA, m^2), mean diameter (Dm, cm), mean total tree (Hm, m), quadratic mean diameter (QMD, cm), altitudes (A, m), slope (S, %), and aspect (As, categorical variable). All variables were standardized, which perform values bounded 0.0 and 1.0 [21,36,37]. The standardization was performed according to Milligan and Cooper [38] and the Equation 1.

$$Z = (x - Min(x))/(Max(x) - Min(x)) \quad (1)$$

where Z is the standardized variable, x is the variable, Min and Max are the minimum and maximum values of x.

In the Clustering analysis, the cluster (k = 10) were generated, and the explained variance was 61.8812%. The data set is shown in Figure 2 for the total dataset and the clusters.

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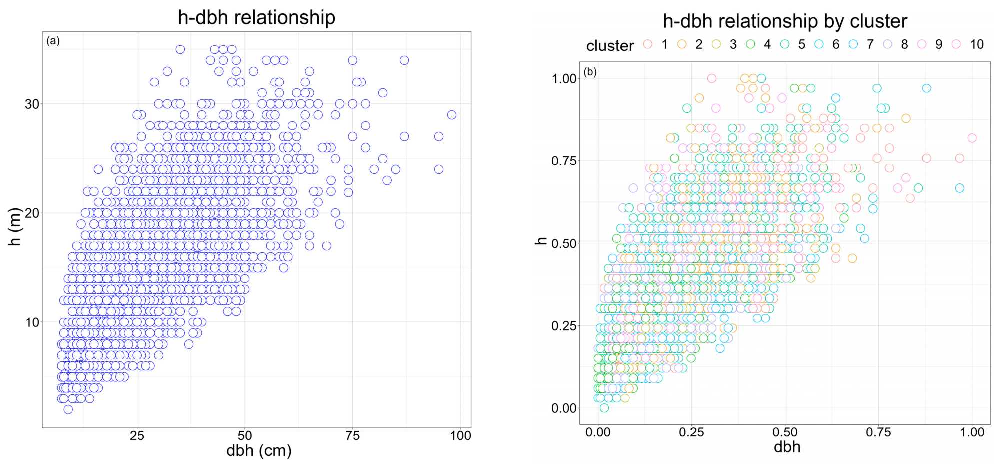

Figure 2. Scatter plot for *h-dbh* relationship for full dataset (a) and grouping dataset by cluster (b).

The site-specific variables for clustering analysis are recorded as a descriptive statistic in Table 1. All variables were standardized with Equation 1 to improve the clustering analysis [38].

Table 1. Descriptive statistics for plot-specific variables used in clustering analysis.

	Statistic				
Variable	**n**	**Minimum**	**Mean**	**Maximum**	**SD**
N	1000	1.0000	11.4720	57.0000	8.7717
BA	1000	0.0007	0.0193	0.0924	0.0137
Dm	1000	8.5000	22.9636	75.0000	7.6788
Hm	1000	4.0000	12.8062	35.0000	3.9813
QMD	1000	8.5147	24.7478	75.0000	8.0708
A	1000	2032.0000	2588.2170	2978.0000	137.3215
S	1000	0.0000	43.0499	96.0000	20.0551
As		1	5	9	2

N = density (trees per hectare); BA = basal area (m^2); Dm = mean diameter (cm); Hm = mean total tree (m); QMD = quadratic mean diameter (cm); A = altitudes (m); S = slope (%); and As = aspect (categorical variable; 1 = Plain, 2 = N, 3 = S, 4 = E, 5 = W, 6 = NE, 7 = SE, 8 = NW, 9 = SW); n = observations; SD = standard deviation.

The total dataset (11,472 pairs of *h-dbh* relationship) was randomly divided in two sets; 50% for training and 50% for testing or validation. The main statistics for both training and testing dataset are shown in Table 2 for the total tree height and diameter at breast height (*h-dbh*).

Table 2. This is a table. Tables should be placed in the main text near to the first time they are cited.

Dataset	Statistic					
	Variable	**n**	**Minimum**	**Mean**	**Maximum**	**SD**
Training	*h*	5736	7.5000	21.5362	95.0000	11.4394
	dbh	5736	3.0000	12.3900	35.0000	5.3217
Testing	*h*	5736	7.5000	21.3846	98.0000	11.5267
	dbh	5736	2.0000	12.1742	35.0000	5.2871

h = total tree height (m); *dbh* = diameter at breast height (cm); n = observations; SD = standard deviation.

2.3. Nonlinear mixed effect modeling (NLMEM)

The base growth model developed by Richards [30] was used to model the nonlinear *h-dbh* relationship. This model is based on a sigmoid curve, and it is represented by Equation 2. This model had been extensively used in this kind of relationship [7,11,17,28].

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$$h_{ij} = A_0 + \alpha_0\left(1 - e^{-\alpha_1 dbh_{ij}}\right)^{\alpha_2} + e_{ij} \quad (2)$$

where h_{ij} = total tree height *j* in the plot *i*; A_0 = lower asymptote parameter; α_0, α_1 and α_1 = upper asymptote, growth rate, and slope of growth parameters; e = exponential function; dbh_{ij}= diameter at breast height *j* in the plot *i*; e_{ij} = residual *j* in the plot *i*. In this case for A_0 parameter, the value 1.3 was fixed. This warranted the total tree height equal to 1.3 m when diameter at breast height is equal to 0 mentioned by Fang and Bailey [39].

For *NLMEM*, the parameter vector of nonlinear model was defined according to Pinheiro, *et al.* [40] and summarize as follows [7,11,13] (Equation 3):

$$\boldsymbol{\Phi_k} = \boldsymbol{A_k}\lambda + \boldsymbol{B_k}\boldsymbol{b_k} \quad (3)$$

where λ is the $p \times 1$ vector of fixed parameters (p is the number of fixed parameters in the model), $\boldsymbol{b_k}$ is the $q \times 1$ vector of random effect associated with lth cluster (q is the number of random parameters in the model), and $\boldsymbol{A_k}$ and $\boldsymbol{B_k}$ are the design matrices of size $r \times p$ and $r \times q$ (r is the total number of parameters in the model) for the fixed and random effects specific to each cluster. The residual vector ($\boldsymbol{e_{ij}}$), and the random effect vector ($\boldsymbol{b_k}$) are frequently assumed uncorrelated and normally distributed with mean zero and variance-covariance matrices $\boldsymbol{R_k}$ and $\boldsymbol{D}$, respectively.

The upper asymptote parameter (α_o) was treated as a random parameter in the analysis for each cluster (α_{ol} $l = 1, 2, \ldots, 10$), which explain about the maximum relationship between *h* and *dbh*. The random effect vector represent the variability between clusters for the asymptote parameter.

2.4. Artificial neural network (ANN)

The *ANN* are inspired by the early models of sensory processing by the brain. An *ANN* can easy be created by simulating a network of model neurons in a computer or specific programming language. Also, by applying mathematical algorithms that mimic the process of real neurons, we can make the network "learn" to solve many types of problems [41]. The *ANNs* can learn by themselves. Because of they have similarities with the information processing features of the human brain (nonlinearity, high parallelism, capability to generalize), this modeling technique has the potential ability to solve problems that are difficult to formalize, such as problems of biological nature [7,41]. The resilient backpropagation artificial neural network (*RBPANN*) is a logical adaptative learning scheme, which perform supervised batch learning in multi-layer perceptron. The basic principle of *RBPANN* is to eliminate the harmful influence of the size of the partial derivative on the weight steps [3,4,19].

According to Barbosa, Costa, Schons, Finger, Liesenberg and Bispo [19], and Anastasiadis, *et al.* [42], the RBP for *ANN* employs a sign-based scheme to update the weights in order to eliminate harmful influences of the derivatives´ magnitude on the weight updates. The size of the update step along a weight direction is exclusively determined by a weight-specific "update-value" as follows:

$$\Delta w_{ij}^k = \begin{cases} -\Delta_{ij}^k \; if \; \dfrac{\partial E(w^k)}{\partial w_{ij}} > 0 \\ +\Delta_{ij}^k \; if \; \dfrac{\partial E(w^k)}{\partial w_{ij}} < 0 \\ 0 \; otherwise \end{cases} \quad (4)$$

where $\partial E(w^k)$ denotes the partial derivative of bathc error with respect to weight w_{ij} at the *k*th iteration.

The second step of RBP learning is to determine the new update values [19], as follows:

$$\Delta_{ij}^k = \begin{cases} \eta^+\Delta_{ij}^k \; if \; \dfrac{\partial E(w^{k-1})}{\partial w_{ij}}\dfrac{\partial E(w^{k-1})}{\partial w_{ij}} > 0 \\ \eta^-\Delta_{ij}^k \; if \; \dfrac{\partial E(w^{k-1})}{\partial w_{ij}}\dfrac{\partial E(w^{k-1})}{\partial w_{ij}} < 0 \\ \Delta_{ij}^{k-1} \; otherwise \end{cases} \quad (5)$$

where $0 < \eta^- < 1 < \eta^+$.

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The total number of parameters in *RBPANN* is five; (i) the increase factor isa set to $\eta^+ = 1.2$; (ii) the decrease facto is set to $\eta^- = 0.5$; (iii) the initial updates-value is set to $\Delta_o = 0.1$: (iv) the maximum step; (v) the minimum steps.

According to Cartwright [43], the first step in using *ANNs* is to determine a suitable topology, optimal if possible (number of inputs and outputs, number of hidden layers, and neurons in each layer) and optimal (weights, biases, and activation functions). The process of *ANNs* begins by setting up the weights as small random variables. Then, each input pattern undergoes a feedforward phase, where the input signal is received and transmitted to all nodes in the hidden layer. In *ANNs*, every hidden node calculates the sum of its weighted input signals, applies an activation function to determine its output signal, and transmits this signal to the output node. At the output node, the final output signal is computed using the received signals from the hidden nodes [7]. Within the context of *RBPANN*, the associated error (δ_k) is computed, and this error is utilized to adjust the weights. The weights correction term is determined based on the error, and it is subsequently employed to update the corresponding weights. Additionally, the δ_k is transmitted to each hidden node. Each hidden node then calculates its error information term by summing the inputs received from the output node, multiplied by the derivative of its activation function [7,43,44]. According to Fausett [45] and Cartwright [43], the general formulation for *RBPANN* could be as follows (Equation 6):

$$\Delta w_{ij}(t+1) = \alpha \delta_k Z_j + \mu \Delta w_{ij} \tag{6}$$

where w_{ij} is the bias on output unit k, α is the learning rate, δ_k is the ratio of error correction weight fitted for w_{ij} that is due to an error at output O_k, also the information about the error at unit O_k that is propagated back to the hidden units that feed into unit O_k, Z_j is the output activation of the hidden unit j and μ is the momentum parameter (refers to the contribution of the gradient calculated at the previous time step to the correction of the weights) [43].

The used activation functions for smoothing the *h-dbh* relationship through *RBPANN* were tangent hyperbolicus (*RBPANN*-tanh), softplus (*RBPANN*-softplus), and logistic (*RBPANN*-logistic) functions [4,42], these activation functions occur between the hidden layers or between the input layer and hidden layer [17]. These functions were defined for *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic in Equations 7, 8, and 9, respectively. Also, the derivatives are in Equations 10, 11 and 12, respectively.

$$f(x) = \frac{e^x - e^{-s}}{e^x + e^{-s}} \tag{7}$$

$$f(x) = \frac{1}{1 + e^{-s}} \tag{8}$$

$$f(x) = \log\left(1 + e^s\right) \tag{9}$$

$$f'^{(x)} = 1 - \left(\frac{e^s - e^{-s}}{e^s + e^{-s}}\right)^2 \tag{10}$$

$$f'(x) = \frac{e^{-s}}{(1 + e^{-s})^2} \tag{11}$$

$$f'(x) = \frac{e^s}{1 + e^s} \tag{12}$$

where $s = \sum w_i x_i$ is the information of the node transmits, in which w_i are the weights and x_i are the input values with $s \in [-1, 1]$, $s \in [0, \infty]$, and $s \in [0, 1]$ for *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic, respectively.

In the *ANN* learning process, a different vector from 1 to 10 for each hidden layer was performed in a preliminary analysis, and the best results were obtained when the vector was 10 nodes for each hidden layer c(10, 10, 10). In Figure 3, the *ANNs* plot are presented for vectors c(3, 3, 3), c(5, 5, 5), and c(10, 10, 10) in the hidden layer.

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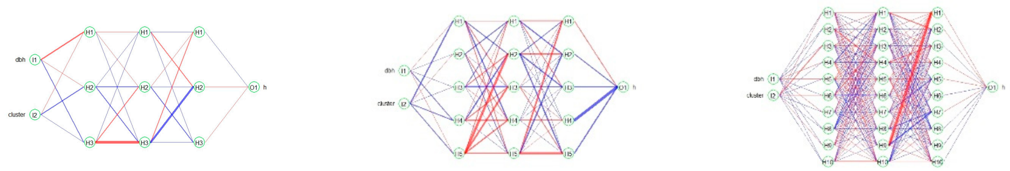

Figure 3. Plots of *ANNs* for vectors of c(3, 3, 3) on the left, c(5, 5, 5) on the center, and c(10, 10, 10) on the right, in the hidden layer.

For both *RBPANN*-tanh and *RBPANN*-logistic functions, the topology was as follows: (i) two inputs (*dbh* and *cluster*); (ii) one output (*h*); (iii) a vector c(10, 10, 10) hidden layers; and (iv) two nodes for the first layer, 11 nodes for the second, third and fourth layer layers (Bias node is included) and two nodes for the fifth layer. The *ANNs* for *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic activation functions are presented in Figure 4. Input variables are represented by "I" in nodes, hidden nodes are represented by "H", input variable is represented by "O", and Bias nodes are represented by "B".

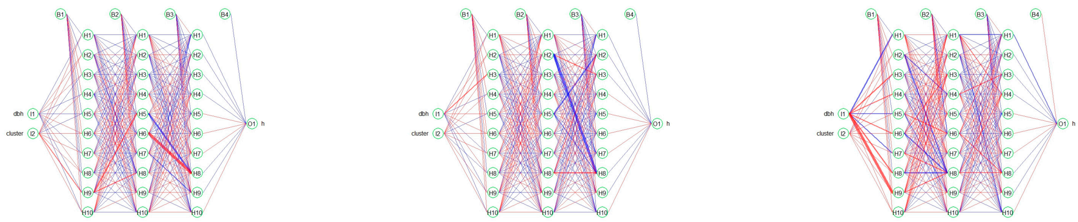

Figure 4. Plots of *RBPANN*-tanh (left), *RBPANN*-softplus (center), and *RBPANN*-logistic (right) for *h-dbh* relationship with unsupervised clustering analysis. Bias is included in nodes "B". Positive weight values in the visual representation are denoted by blue lines, while negative weight values are represented by red lines.

For *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic activation functions. The number of repetitions was 10, the maximum steps for training of the NN was 10^7 , and the threshold was 0.1, which is similar that arguments used by Özçelik, Diamantopoulou, Crecente-Campo and Eler [7] and Shen, Hu, Sharma, Wang, Meng, Wang, Wang and Fu [17]. Also, the training algorithm for *ANNs* was the resilient backpropagation with weight backtracking [4,42,43]

2.5. Fitting modeling

For *NLME*, the total tree height and diameter at breast height (*h-dbh*) relationship was fitted in "*nlme*" R package [35] and used maximum likelihood estimation method [40] for fixed and random parameters withing cluster groups. While for *ANN* models, the "*neuralnet*" R package [35] was used. For *ANN*, the resilient backpropagation (RPROP) for tangent hyperbolicus (*tanh*), softplus (*softplus*), and logistic (logistic) functions were programed for smoothing the result of the cross product of the covariate or neurons and the weights [3,4,45]. All functions about fitting statistics for both training and testing were programmed in R environment [35].

2.6. Models performance criteria

For both training and testing steps, the fitting statistics were obtained in two levels, first one for the entire dataset and second one for each cluster. The statistics were the root mean square error (*RMSE*), standard error of estimate (*SEE*), relative SEE (*RSEE*), fitting index (*FI*), mean error (*E*),

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relative E (RE), Akaike information criterion (*AIC*), Bayesian information criterion (*BIC*) and the log-likelihood (*logLik*). The statistics were computed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \quad (13)$$

$$SEE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n-p}} \quad (14)$$

$$RSEE = \frac{SEE}{\bar{O}} \quad (15)$$

$$FI = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (16)$$

$$E = \frac{\sum_{i=1}^{n}(O_i - P_i)}{n} \quad (17)$$

$$RE = \frac{E}{\bar{O}} \quad (18)$$

$$AIC = nlog\left(\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}\right) + 2p \quad (19)$$

$$BIC = n\,log\left(\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}\right) + p\,log\,n \quad (20)$$

$$logLik = -n\,log\left(\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}\right) \quad (21)$$

where O_i, P_i and $\bar{O}$ are observed, predicted and average values of *h* variable; n = observations; p = number of parameters estimated; and log = logarithm function.

In all cases, the residual values were obtained with the implementation of *NLMEM* or *RBPANN* models and the statistics were programmed in R environment [35]. Lately, the *NLMEM* and *ANNs* models were ranked based on the overall dataset and cluster-group for all fitting statistics. A ranking system of Kozak and Smith [46] was used. All fitted statistics were equally weighted and Rank 1 was used for the best model and 4 for the poorest.

3. Results

3.1. Training phase

3.1.1. NLMEM

The fitted growth equation for *h-dbh* relationship by *NLMEM* performed well and all parameters were significantly different to zero at 5% of significance level. The relationship between total tree height and diameter at breast height can be explained with fixed and random parameters. In Table 3, the estimated parameters and their statistical properties can be found for the entire training dataset. Furthermore, the confidence interval for each parameter is recorded at a 95% confidence level.

Table 3. Estimated parameter for *h-dbh* relationship in Durango pine by *NLMEM*.

Parameter	Estimate	SE	DF	t-value	p-value	lower	upper
α_0	26.409060	1.100113	5724	24.005770	<0.00001	24.252985	28.565134
α_1	0.029786	0.002534	5724	11.754320	<0.00001	0.024820	0.034752
α_2	1.083133	0.040518	5724	26.732200	<0.00001	1.003723	1.162543
$sd(\alpha_0)$	1.928939	0.583997	5724	3.302992	0.000962	1.210579	3.073574
σ	3.110839	0.029338	5724	106.033502	<0.00001	3.054379	3.168342
$\alpha_{0,1}$	-3.371745	0.106547	407	-31.645570	<0.00001	-3.580578	-3.162913
$\alpha_{0,2}$	-2.840826	0.089770	320	-31.645570	<0.00001	-3.016775	-2.664877
$\alpha_{0,3}$	-0.601879	0.019019	631	-31.645570	<0.00001	-0.639157	-0.564601
$\alpha_{0,4}$	3.572580	0.112894	133	31.645570	<0.00001	3.351309	3.793851
$\alpha_{0,5}$	0.773802	0.024452	925	31.645570	<0.00001	0.725876	0.821729
$\alpha_{0,6}$	0.478565	0.015123	1109	31.645570	<0.00001	0.448925	0.508206

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$\alpha_{0,7}$	0.945549	0.029879	364	31.645570	<0.00001	0.886985	1.004113
$\alpha_{0,8}$	-0.308794	0.009758	876	-31.645570	<0.00001	-0.327919	-0.289668
$\alpha_{0,9}$	0.012327	0.000390	654	31.645570	<0.00001	0.011564	0.013091
$\alpha_{0,10}$	1.340420	0.042357	317	31.645570	<0.00001	1.257400	1.423440

SE = asymptotic standard error; *DF* = freedom degrees; sd = standard deviation for random effect between cluster groups; σ = standard error within-cluster-group.

The training phase's fitting statistics are presented in Table 4, which includes the overall training dataset as well as the cluster-groups individually. For both overall training dataset, and cluster-groups, the fitting statistics were accurate and showed the potential to offer the *NLMEM* approach for the *h-dbh* relationship. The RMSE value for the overall training dataset was 3.1085 m, the best value was 2.4735 for cluster-group 1 (*C1*) and the worst value for cluster-group 4 (*C4*). Additionally, the overall training dataset exhibited an *E* value of -0.0005. The highest value was observed in *C3*, indicating the poorer performance, while the lowest value was found in *C4*, indicating the best performance. In terms of AIC, the C4 demonstrated the best performance, whereas C6 exhibited relatively poorer performance.

Table 4. Fitting statistics for *h-dbh* relationship in Durango pine by *NLMEM*.

Dataset	n	RMSE	SEE	RSEE	FI	E	RE	AIC	BIC	logLik
All-dataset	5736	3.1085	3.1123	25.1193	0.6588	-0.0005	-0.0042	13039.75	13139.57	-13009.75
C1	631	2.4735	2.4889	6.4322	0.6182	-0.0324	-0.3161	8834.14	772.23	-736.18
C2	407	2.5289	2.5489	6.1485	0.5378	0.0050	0.0515	7113.33	627.39	-592.78
C3	925	2.9631	2.9749	8.4267	0.6525	-0.1111	-0.9526	16437.91	1408.51	-1369.83
C4	1109	3.8688	3.9442	2.9876	0.5610	0.3416	1.7378	4306.53	388.22	-358.88
C5	320	3.1341	3.1426	10.6971	0.6312	-0.0072	-0.0610	25348.12	2153.32	-2112.34
C6	654	2.8727	2.8792	10.3014	0.6134	0.0555	0.4528	28074.42	2381.60	-2339.53
C7	364	3.4345	3.4584	6.5911	0.6329	-0.0640	-0.4879	10767.05	932.64	-897.25
C8	876	3.3842	3.3939	10.2592	0.6015	0.0210	0.1632	25618.61	2175.54	-2134.88
C9	133	3.2098	3.2221	8.8088	0.6138	-0.0229	-0.1862	18292.63	1563.28	-1524.39
C10	317	3.6168	3.6458	5.1452	0.6196	-0.0058	-0.0353	9768.73	848.61	-814.06

RMSE = root mean square error (m); *SEE* = standard error of estimate (m); *RSEE* = relative SEE (%); *FI* = fitting index; *E* = mean error (m); *RE* = relative (%); *AIC* = Akaike information criterion; *BIC* = Bayesian information criterion; *logLik* = log-likelihood value; C = cluster-group.

3.1.1. RBPANN

The results about performed *ANNs* for *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic activation functions are shown in Table 5. The statistics are in standardized variables and observed in 10 repetitions in the learning process. In this scenario, all three activation functions exhibit favorable outcomes. Specifically, both *RBPANN*-tanh and *RBPANN*-softplus deliver comparable performance. In contrast, *RBPANN*-logistic exhibited the lowest performance among the three activation functions. Additionally, the *RBPANN*-logistic achieved the minimum number of steps (88) required for convergence.

Table 5. Main fitting statistics for *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic activation functions tested for *h-dbh* relationship.

ANN	Error	Reached Threshold	Steps	AIC	BIC
RBPANN-tanh	27.8455	0.0775	301	577.69	2314.52
RBPANN-softplus	27.3939	0.0838	1885	576.79	2313.62
RBPANN-logistic	28.4113	0.0994	88	578.82	2315.65

AIC = Akaike information criterion; *BIC* = Bayesian information criterion.

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The fitting statistics for three *ANNs* applied to examine the h-dbh relationship in Durango pine are presented for both the overall dataset and each cluster-group in Table 6 for training phase. The nine fitting statistics illustrate the accuracy of *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic activation functions in the *ANNs* models. The topology of each *ANN*, as depicted in Figure 4, exhibited satisfactory results in predicting *h* based on *dbh* and an unsupervised clustering analysis for ten groups. Overall, the estimations demonstrate similar characteristics across the three activation models. However, *RBPANN*-tanh exhibits certain advantages that are comparable to the other activation functions in the training phase. All *ANNs* were trained using the resilience backpropagation learning algorithm, and the likelihood function was employed.

Table 6. Fitting statistics for *h-dbh* relationship in Durango pine by *ANNs and different backpropagations activation functions.*

Dataset	RMSE	SEE	RSEE	FI	E	RE	AIC	BIC	logLik
RBPANN-tanh									
All-dataset	2.8122	2.8134	22.7071	0.7208	0.0001	-0.0003	11872.59	11912.52	-11860.59
C1	2.6322	2.6427	8.0184	0.7258	0.0002	0.0018	14644.89	1259.09	-1220.41
C2	2.2127	2.2264	6.1634	0.6945	0.0073	0.0717	7745.69	681.53	-645.47
C3	2.8170	2.8246	10.2988	0.7020	-0.0087	-0.0741	22979.70	1955.95	-1914.98
C4	2.5795	2.5853	9.9082	0.6883	0.0636	0.5191	25209.16	2142.83	-2100.76
C5	2.4178	2.4370	6.2966	0.5776	-0.6268	-6.4583	6768.31	598.64	-564.03
C6	2.8907	2.9019	8.4977	0.6867	0.2559	2.0805	16649.44	1426.35	-1387.45
C7	3.1340	3.1558	6.4423	0.6943	0.3677	2.8037	9967.09	865.97	-830.59
C8	3.0652	3.0740	9.9535	0.6731	-0.3691	-2.8636	23537.45	2002.11	-1961.45
C9	3.7470	3.8200	3.0995	0.5882	1.5107	7.6864	4204.43	379.71	-350.37
C10	3.2490	3.2751	4.9509	0.6930	-0.1391	-0.8426	8952.96	780.63	-746.08
RBPANN-softplus									
All-dataset	2.8431	2.8443	22.9565	0.7143	0.7146	-0.0013	-0.0107	11997.88	12037.81
C1	2.6516	2.6621	8.0772	0.7218	0.0489	0.4190	14755.60	1268.32	-1229.63
C2	2.4591	2.4744	6.8498	0.6226	-0.9459	-9.2408	8777.19	767.49	-731.43
C3	2.8529	2.8606	10.4301	0.6944	0.4200	3.5697	23260.85	1979.38	-1938.40
C4	2.6003	2.6062	9.9882	0.6833	0.3109	2.5351	25423.15	2160.66	-2118.60
C5	2.4956	2.5154	6.4993	0.5499	-0.9140	-9.4178	7011.62	618.91	-584.30
C6	2.8841	2.8952	8.4781	0.6882	-0.1042	-0.8472	16613.23	1423.33	-1384.44
C7	3.1030	3.1246	6.3787	0.7003	0.1339	1.0213	9880.37	858.75	-823.36
C8	3.0748	3.0837	9.9847	0.6711	-0.3712	-2.8799	23603.31	2007.59	-1966.94
C9	3.8187	3.8931	3.1588	0.5723	1.6461	8.3754	4264.92	384.75	-355.41
C10	3.2550	3.2811	4.9600	0.6919	0.0992	0.6009	8966.90	781.80	-747.24
RBPANN-logistic									
All-dataset	2.8486	2.8498	23.0012	0.7135	-0.0052	-0.0420	12020.19	12060.12	-12008.19
C1	2.6570	2.6676	8.0938	0.7206	0.0785	0.6729	14786.65	1270.90	-1232.22
C2	2.4675	2.4828	6.8732	0.6201	-0.9254	-9.0403	8810.45	770.26	-734.20
C3	2.8586	2.8664	10.4510	0.6932	0.4146	3.5237	23305.34	1983.09	-1942.11
C4	2.6024	2.6083	9.9962	0.6827	0.2868	2.3386	25444.48	2162.44	-2120.37
C5	2.5183	2.5382	6.5583	0.5417	-0.9468	-9.7561	7081.01	624.69	-590.08
C6	2.9055	2.9167	8.5411	0.6835	-0.1415	-1.1503	16729.32	1433.01	-1394.11
C7	3.0957	3.1172	6.3636	0.7017	0.1066	0.8129	9859.77	857.03	-821.65
C8	3.0740	3.0828	9.9818	0.6712	-0.3751	-2.9095	23597.18	2007.08	-1966.43
C9	3.8192	3.8936	3.1592	0.5721	1.6756	8.5253	4265.34	384.79	-355.45
C10	3.2584	3.2845	4.9652	0.6912	0.1835	1.1115	8974.85	782.46	-747.90

RMSE = root mean square error (m); *SEE* = standard error of estimate (m); *RSEE* = relative SEE (%); *FI* = fitting index; *E* = mean error (m); *RE* = relative (%); AIC = Akaike information criterion; *BIC* = Bayesian information criterion; *logLik* = log-likelihood value; C = cluster-group.

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The residual and predicted values are presented in Figure 5 for each cluster-group by *RBPANN*-tanh, which was the best approach in training phase to model the *h-dbh* relationship. In general, the residuals ranged between -6 m and 6 m. Enhancing the training phase could involve increasing the number of repetitions or epochs, however, the computational process ought to be significantly time-consuming.

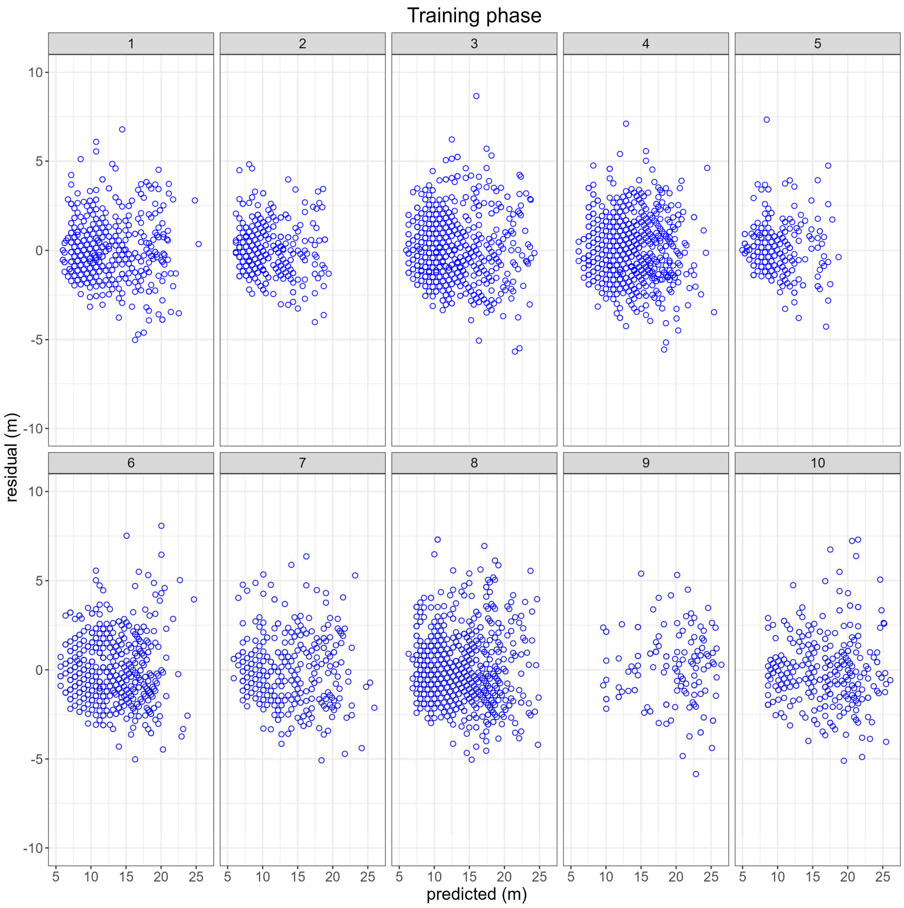

Figure 5. Residual versus predicted values for *RBPANN*-tanh model in training phase and each cluster-group.

Finally, The ranks and sums of ranks for hierarchy of *NLMEN* and *ANNs* are presented in Table 7. The statistics for both the overall dataset and the cluster-group were ranked from 1 to 4. In terms of the overall dataset, the *RBPANN*-softplus exhibited the best performance during the training phase, which was comparable to the *NLMEN* model and other *ANNs*. The *RBPANN*-tanh activation function ranked second, while the *RBPANN*-logistic ranked third. On the other hand, the *NLMEN* approach had the lowest rank sum, indicating poorer performance compared to the other models. A similar pattern was observed within the cluster-groups, and the sum of ranks resulted in the following rankings: 176, 241, 269, and 304 for *RBPANN*-tanh, *RBPANN*-softplus, NLMEN, and *RBPANN*-logistic, respectively. It is worth noting that only the *RBPANN*-logistic demonstrated lower performance compared to the NLMEN approach. The number in parenthesis indicate the ranking for models in the overall dataset.

Table 7. Ranks and sum of ranks based on the fitting statistics for fitted models in training phase.

Model	Dataset	RMSE	SEE	RSEE	FI	E	RE	AIC	BIC	logLik	Rank
NLMEM	Overall	4	4	4	4	3	2	4	4	4	33 (4)
RBPANN-tanh	Overall	1	1	1	1	4	4	2	1	2	17 (2)
RBPANN-softplus	Overall	2	2	2	2	1	3	1	2	1	16 (1)

RBPANN-logistic	Overall	3	3	3	3	2	1	3	3	3	24 (3)
NLMEM	*C1*	1	1	1	4	2	2	1	1	1	14
RBPANN-tanh	*C1*	2	2	2	1	1	1	2	2	2	15
RBPANN-softplus	*C1*	3	3	3	2	3	3	3	3	3	26
RBPANN-logistic	*C1*	4	4	4	3	4	4	4	4	4	35
NLMEM	*C2*	4	4	1	4	1	1	1	1	1	18
RBPANN-tanh	*C2*	1	1	2	1	2	2	2	2	2	15
RBPANN-softplus	*C2*	2	2	3	2	4	4	3	3	3	26
RBPANN-logistic	*C2*	3	3	4	3	3	3	4	4	4	31
NLMEM	*C3*	4	4	1	4	2	2	1	1	1	20
RBPANN-tanh	*C3*	1	1	2	1	1	1	2	2	2	13
RBPANN-softplus	*C3*	2	2	3	2	4	4	3	3	3	26
RBPANN-logistic	*C3*	3	3	4	3	3	3	4	4	4	31
NLMEM	*C4*	4	4	1	4	4	2	1	1	1	22
RBPANN-tanh	*C4*	1	1	2	1	1	1	2	2	2	13
RBPANN-softplus	*C4*	2	2	3	2	3	4	3	3	3	25
RBPANN-logistic	*C4*	3	3	4	3	2	3	4	4	4	30
NLMEM	*C5*	4	4	4	1	1	1	4	4	4	27
RBPANN-tanh	*C5*	1	1	1	2	2	2	1	1	1	12
RBPANN-softplus	*C5*	2	2	2	3	3	3	2	2	2	21
RBPANN-logistic	*C5*	3	3	3	4	4	4	3	3	3	30
NLMEM	*C6*	1	1	4	4	1	1	4	4	4	24
RBPANN-tanh	*C6*	3	3	2	2	4	4	2	2	2	24
RBPANN-softplus	*C6*	2	2	1	1	2	2	1	1	1	13
RBPANN-logistic	*C6*	4	4	3	3	3	3	3	3	3	29
NLMEM	*C7*	4	4	4	4	1	1	4	4	4	30
RBPANN-tanh	*C7*	3	3	3	3	4	4	3	3	3	29
RBPANN-softplus	*C7*	2	2	2	2	3	3	2	2	2	20
RBPANN-logistic	*C7*	1	1	1	1	2	2	1	1	1	11
NLMEM	*C8*	4	4	4	4	1	1	4	4	4	30
RBPANN-tanh	*C8*	1	1	1	1	2	2	1	1	1	11
RBPANN-softplus	*C8*	3	3	3	3	3	3	3	3	3	27
RBPANN-logistic	*C8*	2	2	2	2	4	4	2	2	2	22
NLMEM	*C9*	1	1	4	1	1	1	4	4	4	21
RBPANN-tanh	*C9*	2	2	1	2	2	2	1	1	1	14
RBPANN-softplus	*C9*	3	3	2	3	3	3	2	2	2	23
RBPANN-logistic	*C9*	4	4	3	4	4	4	3	3	3	32
NLMEM	*C10*	4	4	4	4	1	1	4	4	4	30
RBPANN-tanh	*C10*	1	1	1	1	3	3	1	1	1	13
RBPANN-softplus	*C10*	2	2	2	2	2	2	2	2	2	18
RBPANN-logistic	*C10*	3	3	3	3	4	4	3	3	3	29

RMSE = root mean square error; *SEE* = standard error of estimate; *RSEE* = relative SEE; *FI* = fitting index; *E* = mean error; *RE* = relative *E*; AIC = Akaike information criterion; *BIC* = Bayesian information criterion; *logLik* = log-likelihood value; C = cluster-group.

3.1. Testing or Validation phase

3.1.1. NLMEM

During the testing phase, 5,736 pairs of heights and diameters from 50% of the dataset were utilized. Height estimations were performed using fixed and random parameters for each cluster-group provided by *NLMEM* approach. The nine testing statistics were computed at two levels: for the overall dataset and for each cluster-group. The Table 8 presents the statistics for testing the

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advantages of NLMEN for overall dataset and for each cluster-group. All the statistics displayed satisfactory performance, which depended on the number of observations. Additionally, the cluster-groups with limited information exhibited the lowest values. Among the cluster-groups, *C4* had the maximum number of observations, whereas *C9* had the minimum number of observations.

Table 8. Testing statistics for *h-dbh* relationship in Durango pine by *NLMEM* in testing phase.

Dataset	n	RMSE	SEE	RSEE	FI	E	RE	AIC	BIC	logLik
All-dataset	5736	3.1438	3.1476	25.8549	0.6464	-0.1611	-1.3229	13169.29	13269.10	-13139.29
C1	631	2.7037	2.7141	24.1931	0.6893	-0.0987	-0.8795	15671.32	1344.87	-1305.94
C2	407	2.9045	2.9228	29.6973	0.4680	1.2223	12.4194	10249.76	890.11	-854.15
C3	925	3.0941	3.1029	27.5443	0.6136	-0.7206	-6.3964	23870.14	2029.86	-1989.18
C4	1109	3.0509	3.0578	25.0690	0.6102	-0.0942	-0.7725	29971.18	2539.72	-2497.60
C5	320	2.7563	2.7797	28.6992	0.5175	0.9194	9.4926	7263.59	639.50	-605.30
C6	654	3.1718	3.1834	25.4080	0.6085	0.1428	1.1398	19047.71	1626.51	-1587.31
C7	364	3.4512	3.4752	26.2781	0.6545	-0.7996	-6.0462	10839.28	938.67	-903.27
C8	876	3.0615	3.0704	24.6303	0.6290	-0.1456	-1.1680	23216.40	1975.28	-1934.70
C9	133	5.0061	5.1138	25.4219	0.2128	-2.4332	-12.0959	4665.31	417.55	-388.78
C10	317	3.8668	3.8957	24.6024	0.5555	-0.7956	-5.0245	10991.37	950.90	-915.95

RMSE = root mean square error (m); *SEE* = standard error of estimate (m); *RSEE* = relative *SEE* (m); *FI* = fitting index; *E* = mean error (m); *RE* = relative *E* (%); AIC = Akaike information criterion; *BIC* = Bayesian information criterion; *logLik* = log-likelihood value; C = cluster-group.

3.1.1. RBPANN

During the testing phase, the results for the *ANNs* were similar to the training phase. The *ANN* utilizing the tangent hyperbolicus activation function (*RBPANN*-tanh) exhibited the highest performance, followed by *RBPANN*-logistic, and finally *RBPANN*-softplus. The Table 9 records the statistics for the testing dataset, both in the overall dataset and within each cluster-group. The *FIs* values for the overall dataset were higher than 0.7029, when *RBPANN*-tanh demonstrating the best performance and *RBPANN*-logistic exhibiting the poorest performance. A similar pattern was observed for other statistics such as AIC BIC and logLik. Furthermore, in this instance, the *ANN*s demonstrate superior performance compared to the *NLMEM* approach.

Table 9. Testing statistics for both overall dataset and each cluster-group in testing phase with *ANNs* approaches.

Dataset	RMSE	SEE	RSEE	FI	E	RE	AIC	BIC	logLik
RBPANN-tanh									
All-dataset	2.8693	2.8706	23.5793	0.7055	0.6603	5.4241	12103.39	12143.32	-12091.39
C1	2.5090	2.5186	8.1057	0.7324	0.6015	5.3617	14492.43	1246.63	-1207.70
C2	2.4793	2.4949	7.1292	0.6124	0.8309	8.4421	8726.27	763.15	-727.19
C3	2.7294	2.7372	10.1704	0.6994	0.4046	3.5917	21218.12	1808.86	-1768.18
C4	2.8842	2.8907	11.1931	0.6516	0.8969	7.3531	28460.68	2413.85	-2371.72
C5	2.3880	2.4083	6.0227	0.6378	0.0825	0.8517	6234.38	553.73	-519.53
C6	3.0888	3.1001	9.1436	0.6287	1.2080	9.6415	18609.70	1590.01	-1550.81
C7	3.1665	3.1885	6.4643	0.7091	0.8613	6.5128	10085.03	875.82	-840.42
C8	2.7710	2.7790	9.2458	0.6961	0.1519	1.2183	21146.63	1802.80	-1762.22
C9	4.2322	4.3232	3.2613	0.4374	1.8156	9.0259	4177.60	376.91	-348.13
C10	3.4732	3.4992	5.7063	0.6414	0.5225	3.2997	10118.01	878.12	-843.17
RBPANN-softplus									
All-dataset	2.8764	2.8776	23.6371	0.7040	0.6578	5.4029	12131.48	12171.41	-12119.48
C1	2.5181	2.5278	8.1353	0.7305	0.6756	6.0219	14550.00	1251.43	-1212.50
C2	2.3388	2.3536	6.7253	0.6551	-0.0814	-0.8266	8164.99	716.38	-680.42

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C3	2.8312	2.8393	10.5500	0.6765	0.8131	7.2176	21992.85	1873.42	-1832.74
C4	2.9657	2.9724	11.5095	0.6317	1.1148	9.1400	29209.97	2476.29	-2434.16
C5	2.4000	2.4204	6.0529	0.6342	-0.2679	-2.7660	6270.23	556.72	-522.52
C6	2.9772	2.9881	8.8135	0.6550	0.7866	6.2785	18002.41	1539.40	-1500.20
C7	3.1029	3.1244	6.3344	0.7207	0.6147	4.6485	9907.23	861.00	-825.60
C8	2.7748	2.7828	9.2584	0.6952	0.1450	1.1632	21174.89	1805.15	-1764.57
C9	4.3045	4.3971	3.3171	0.4180	2.0025	9.9547	4226.81	381.01	-352.23
C10	3.5266	3.5530	5.7940	0.6303	0.8555	5.4026	10242.05	888.46	-853.50
RBPANN-logistic									
All-dataset	2.8820	2.8832	23.6832	0.7029	0.6484	5.3263	12153.85	12193.77	-12141.85
C1	2.5071	2.5168	8.0998	0.7328	0.6480	5.7760	14481.07	1245.68	-1206.76
C2	2.3476	2.3624	6.7505	0.6525	-0.0800	-0.8123	8200.94	719.38	-683.41
C3	2.8287	2.8368	10.5405	0.6771	0.8418	7.4726	21973.90	1871.84	-1831.16
C4	2.9718	2.9785	11.5331	0.6302	1.1385	9.3342	29264.97	2480.87	-2438.75
C5	2.3833	2.4035	6.0108	0.6392	-0.2199	-2.2702	6220.20	552.55	-518.35
C6	2.9674	2.9783	8.7844	0.6573	0.8301	6.6255	17947.97	1534.87	-1495.66
C7	3.1024	3.1240	6.3335	0.7208	0.6342	4.7956	9905.96	860.90	-825.50
C8	2.7763	2.7843	9.2634	0.6949	0.1438	1.1539	21186.18	1806.09	-1765.51
C9	4.2538	4.3453	3.2780	0.4316	1.9452	9.6698	4192.42	378.14	-349.37
C10	3.4913	3.5174	5.7360	0.6377	0.7841	4.9519	10160.28	881.65	-846.69

RMSE = root mean square error (m); *SEE* = standard error of estimate (m); *RSEE* = relative *SEE* (%); *FI* = fitting index; *E* = mean error (m); *RE* = relative *E* (%); AIC = Akaike information criterion; *BIC* = Bayesian information criterion; *logLik* = log-likelihood value; C = cluster-group.

The Figure 6 displays the representation of residual and predicted values for each cluster-group obtained through *RBPANN*-tanh. In this scenario, the residual dispersion appears to be larger compared to the training phase. However, this can be attributed to the utilization of a new dataset, where the predictions are made under different training conditions. Cluster-groups 4 and 10 exhibited higher levels of dispersion compared to the remaining cluster-groups.

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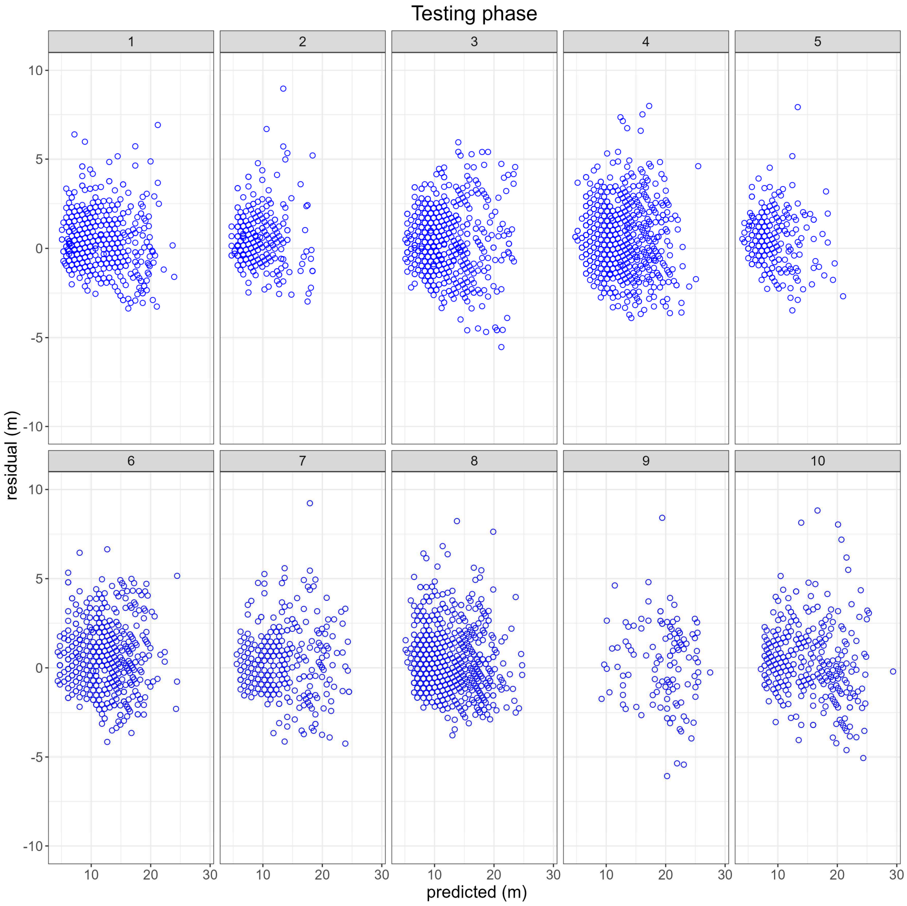

Figure 6. Residual versus predicted values for *RBPANN*-tanh model in testing phase for each cluster-group.

Finally, the ranks and sums of ranks for hierarchy of *NLMEN* and *ANNs* are presented in Table 10. During the testing phase, the *RBPANN*-tanh achieved the highest rank of 1 with a sum of ranks of 9, while the *NLMEM* approach performed the poorest, ranking 4 with sum of ranks of 36. The *RBPANN*-softplus and *RBPANN*-logistic exhibited relatively similar performance conditions. Among the proven models of *ANNs*, the *RBPANN*-logistic exhibited the poorest performance. In terms of the sum of ranks for the combined overall dataset and cluster-groups, the *RBPANN*-tanh demonstrated the best performance with a sum of ranks of 181. Following that, the *RBPANN*-logistic, *RBPANN*-softplus, and *NLMEM* were ranked 2nd, 3rd, and 4th, with sum of ranks of 201, 240, and 368, respectively.

Table 10. Ranks and sum of ranks based on the fitting statistics for fitted models in testing phase.

Model	Dataset	RMSE	SEE	RSEE	FI	E	RE	AIC	BIC	logLik	Rank
NLMEM	Overall	4	4	4	4	4	4	4	4	4	36 (4)
RBPANN-tanh	Overall	1	1	1	1	1	1	1	1	1	9 (1)
RBPANN-softplus	Overall	2	2	2	2	2	2	2	2	2	18 (2)
RBPANN-logistic	Overall	3	3	3	3	3	3	3	3	3	27 (3)
NLMEM	*C1*	4	4	4	4	1	1	4	4	4	30
RBPANN-tanh	*C1*	2	2	2	2	2	2	2	2	2	18
RBPANN-softplus	*C1*	3	3	3	3	4	4	3	3	3	29
RBPANN-logistic	*C1*	1	1	1	1	3	3	1	1	1	13
NLMEM	*C2*	4	4	4	4	4	4	4	4	4	36
RBPANN-tanh	*C2*	3	3	3	3	3	3	3	3	3	27
RBPANN-softplus	*C2*	1	1	1	1	2	2	1	1	1	11

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RBPANN-logistic	*C2*	2	2	2	2	1	1	2	2	2	16
NLMEM	*C3*	4	4	4	4	2	2	4	4	4	32
RBPANN-tanh	*C3*	1	1	1	1	1	1	1	1	1	9
RBPANN-softplus	*C3*	3	3	3	3	3	3	3	3	3	27
RBPANN-logistic	*C3*	2	2	2	2	4	4	2	2	2	22
NLMEM	*C4*	4	4	4	4	1	1	4	4	4	30
RBPANN-tanh	*C4*	1	1	1	1	2	2	1	1	1	11
RBPANN-softplus	*C4*	2	2	2	2	3	3	2	2	2	20
RBPANN-logistic	*C4*	3	3	3	3	4	4	3	3	3	29
NLMEM	*C5*	4	4	4	4	4	4	4	4	4	36
RBPANN-tanh	*C5*	2	2	2	2	1	1	2	2	2	16
RBPANN-softplus	*C5*	3	3	3	3	3	3	3	3	3	27
RBPANN-logistic	*C5*	1	1	1	1	2	2	1	1	1	11
NLMEM	*C6*	4	4	4	4	1	1	4	4	4	30
RBPANN-tanh	*C6*	3	3	3	3	4	4	3	3	3	29
RBPANN-softplus	*C6*	2	2	2	2	2	2	2	2	2	18
RBPANN-logistic	*C6*	1	1	1	1	3	3	1	1	1	13
NLMEM	*C7*	4	4	4	4	3	3	4	4	4	34
RBPANN-tanh	*C7*	3	3	3	3	4	4	3	3	3	29
RBPANN-softplus	*C7*	2	2	2	2	1	1	2	2	2	16
RBPANN-logistic	*C7*	1	1	1	1	2	2	1	1	1	11
NLMEM	*C8*	4	4	4	4	3	3	4	4	4	34
RBPANN-tanh	*C8*	1	1	1	1	4	4	1	1	1	15
RBPANN-softplus	*C8*	2	2	2	2	2	2	2	2	2	18
RBPANN-logistic	*C8*	3	3	3	3	1	1	3	3	3	23
NLMEM	*C9*	4	4	4	4	4	4	4	4	4	36
RBPANN-tanh	*C9*	1	1	1	1	1	1	1	1	1	9
RBPANN-softplus	*C9*	3	3	3	3	3	3	3	3	3	27
RBPANN-logistic	*C9*	2	2	2	2	2	2	2	2	2	18
NLMEM	*C10*	4	4	4	4	3	3	4	4	4	34
RBPANN-tanh	*C10*	1	1	1	1	1	1	1	1	1	9
RBPANN-softplus	*C10*	3	3	3	3	4	4	3	3	3	29
RBPANN-logistic	*C10*	3	3	3	3	4	4	3	3	3	29

RMSE = root mean square error (m); *SEE* = standard error of estimate; *RSEE* = relative SEE; *FI* = fitting index; *E* = mean error; *RE* = relative *E*; AIC = Akaike information criterion; *BIC* = Bayesian information criterion; *logLik* = log-likelihood value; C = cluster-group.

4. Discussion

Having knowledge about the total tree height and diameter at breast height is essential for both the development and application of many growth and yield models. Models focusing on the *h-dbh* relationship serve as valuable tools for accurately predicting tree height based on *dbh* measurements. Because of the *dbh* can be conducted quickly, easily, and accurately, but the measurement of total tree height is comparatively complex, time consuming, and expensive [11]. The *NLME* had been a capable approach to generate models in *h-dbh* relationship for different species and assumed fixed and random parameters for specific-groups or covariables to study the variability inter-and intra-plots, ecological regions or cluster-groups [10,16,39]. Also, these models have been studied for local and generalized formulations with *NLMEM* approach [12,13,16,28]. In this case of study the *NLMEM* performance was accurately strong to model the *h-dbh* relationship for Durango pine and the inclusion of unsupervised clustering analysis improve the estimated parameters and its statistics properties [36,47], which involve fixed parameter for the overall dataset in training phase and random parameter for each cluster-group, also parameter to give information about general variability and variability within cluster-group.

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The *NLMEM* demonstrated outstanding performance during the training phase, with the fitting process converging quickly and effortlessly. Additionally, the maximum likelihood approach yielded favorable and suitable results particularly when expressing the asymptote parameter with mixed effects (Table 3 and Table 4). All parameters in fitting process were significantly different to zero at 5% of significance level and the random parameters allow suitable estimations in training phase and those were used for cluster-groups in testing phase. The application of the *NLMEM* approach on the testing dataset resulted in successful outcomes that aligned with the expected results (as shown in Table 8), accompanied by the utilization of appropriate statistical measures. As an illustration, the root mean square error (RMSE) for the overall dataset during the testing phase was determined to be 3.1438 m, with an average value of 3.3773 m observed within the cluster-groups (refer to Table 8). By employing a mixed-effect model and incorporating cluster-group inclusion, the Chapman-Richards growth equation [30] (Equation 2) proves to be a highly effective model for predicting the height of Durango pine trees. Similar results have been conducted for several species an different conditions [11,16,28]. Even though the *NLMEM* method is accurate for height prediction based on diameter measurements, it is worth considering that *ANNs* could be a suitable alternative for modeling the *h-dbh* relationship under several dataset conditions and the incorporation of grouped strategies [7,14,48]. In recent times, there has been a growing application of AI and ML techniques in the fields of biology and forestry. These advanced approaches have proven valuable in addressing challenges that require substantial computational resources and unsupervised learning methods [1,41], Several of these approaches have been employed in studying the height-diameter at breast height (h-dbh) relationship, leading to notable outcomes and reported successes for various species and under diverse forest management conditions, demonstrating their versatility and effectiveness [7,14,15,17,48]. In this context the *ANNs* model outperformed the *NLMEM* approach.

In this study, the *ANNs* were evaluated and compared with the traditional *NLMEM* method. The *ANNs* utilized the RBP learning algorithm along with three activation functions. In most cases, the *ANNs* employing *RBPANN*-tanh, *RBPANN*, and *RBPANN*-logistic (Equations 7, 8, an 9, respectively) exhibited superior performance compared to the results obtained by *NLMEM*, both during the training and testing phases. The training statistics for three *ANNs*, as presented in Table 6, exhibited enhanced fitting performance compared to the statistics obtained by *NLMEM* (see Table 4). This improvement was observed in both the overall dataset and cluster-group analyses. These findings provide evidence that the clustering analysis using the k-means algorithm effectively grouped the dataset utilized in this study [36,47]. The *RBPANN*-tanh model, employing a tangent hyperbolic activation function, demonstrated the highest performance in predicting height measurements during both the training and testing phases (it can see in Table 6 and 9). Furthermore, the ranks and sum of ranks, based on the ranking system proposed by Kozak and Smith [46], provided evidence of the advantages of the *ANNs* models over the *NLMEM* approach. Models such as *RBPANN*-logistic were reported by Özçelik, Diamantopoulou, Crecente-Campo and Eler [7] revealed that models such as *RBPANN*-logistic exhibited advantages over *NLMEM* models when predicting the growth of Crimean juniper in the southern and southwestern regions of Turkey. Conversely Shen, Hu, Sharma, Wang, Meng, Wang, Wang and Fu [17] developed *ANNs* models utilizing *RBPANN*-logistic and *RBPANN*-tanh transfer or activation functions for *Populus spp*. L. in China, where the *RBPANN*-logistic model outperformed both the NLMEN and the *RBPANN*-tanh model. In our case, the best *ANN* was the *RBPANN*-tanh and this outperformed other tested *ANNs* and *NLMEM* approach. Similar results have been reported the advantages of *ANNs* or deep learning algorithms over the ordinary least square and *NLMEM* models in both training and testing or validation phases [14,15,48,49]. In all cases, the implementation of *ANNs* exhibited significant advantages over traditional approaches when modeling the *h-dbh* relationship.

In this study, based on the implemented ranking system, the *RBPANN*-tanh model emerged as the top performer (residual and predicted values are showed in Figures 5 and 6). It achieved a sum of ranks of 176 for the training phase and 81 for the testing phase. These sums of ranks account for both the overall dataset and cluster-groups, as illustrated in Tables 7 and 10, respectively. In terms of training, the *RBPANN*-softplus model ranked second, whereas during the testing phase, the

RBPANN-logistic model exhibited the second-best performance. On the other hand, the *RBPANN*-logistic model performed least effectively in the training phase, while the *NLMEM* model demonstrated comparatively lower performance during the testing phase. The *ANNs* developed in this study, as depicted in Figure 4, were trained using the RBP algorithm. The *ANNs* were then evaluated using three different activation functions: *RBPANN*-tanh, *RBPANN*-softplus, and *RBPANN*-logistic. These models comprised a total of five layers, including three hidden layers. The training process involved ten repetitions to ensure robustness and accuracy. Even though the *RBPANN*-logistic converging in 88 steps, it exhibited relatively poorer performance compared to the *RBPANN*-tanh, which achieved better results within 301 steps. Interestingly, the *RBPANN*-logistic required a longer convergence time of 1885 steps, indicating its comparatively poorer performance in this aspect. As a result, the developed *ANNs* model showcased a high capability for predicting total tree height measurements. This highlights the potential application of AI in modeling the *h-dbh* relationship, not only for Durango pine but also for general forest modeling purposes or other variables [6,19,21,50]. The *ANNs* could be used to improve the estimations in forest inventory and forest management and planning in mixed-species forest in Durango, Mexico.

5. Conclusions

The nonlinear mixed effect modeling (*NLMEM*) and Artificial Neural Networks (*ANN*) with resilience backpropagation (RBP) were employed to model the height-diameter at breast height (*h-dbh*) relationship for Durango pine species. Unsupervised clustering analysis was conducted to enhance the capability of the trained and tested models.. Three activation functions, namely tangent hyperbolicus (*RBPANN*-tanh), softplus (*RBPANN*-softplus), and logistic (*RBPANN*-logistic), were utilized in *RBPANN*. Those activation functions were trained and tested on both overall dataset and each cluster group. In general, the *ANNs* outperformed the *NLMEM* for predictions of heights in training and testing phases. The best model in both training and testing phases was the *RBPANN*-tanh, which assumed five layers in the *ANN* and three of them were hidden. The use of *ANNs* proves to be a suitable and effective approach for estimating the total tree height of Durango pine species. Additionally, incorporating unsupervised clustering analysis enhances the estimation accuracy in *ANN* models, highlighting the capabilities of artificial intelligence (AI) in this context. In conclusion, AI techniques such as *ANNs* prove to be suitable and modern statistical tools for forest modeling.

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References

1. Wodecki, A. Artificial Intelligence Methods and Techniques. In *Artificial Intelligence in Value Creation*, Wodecki, A., Ed. Springer International Publishing: Cham, 2019; https://doi.org/10.1007/978-3-319-91596-8_2pp. 71-132.
2. Holzinger, A.; Keiblinger, K.; Holub, P.; Zatloukal, K.; Müller, H. AI for life: Trends in artificial intelligence for biotechnology. *New Biotechnology* **2023**, *74*, 16-24, doi:https://doi.org/10.1016/j.nbt.2023.02.001.
3. Riedmiller, M.; Braun, H. *A direct adaptive method for faster backpropagation learning: The RPROP algorithm*; 0780309995; IEEE: 1993; pp 586-591.
4. Riedmiller, M.; Braun, H. *Rprop-description and implementation details*; Technical Report. Univer: 1994.
5. Hecht-Nielsen, R. III.3 - Theory of the Backpropagation Neural Network**Based on "nonindent" by Robert Hecht-Nielsen, which appeared in Proceedings of the International Joint Conference on Neural Networks

1, 593–611, June 1989. © 1989 IEEE. In *Neural Networks for Perception*, Wechsler, H., Ed. Academic Press: 1992; https://doi.org/10.1016/B978-0-12-741252-8.50010-8pp. 65-93.
6. Chen, W.; Shirzadi, A.; Shahabi, H.; Ahmad, B.B.; Zhang, S.; Hong, H.; Zhang, N. A novel hybrid artificial intelligence approach based on the rotation forest ensemble and naïve Bayes tree classifiers for a landslide susceptibility assessment in Langao County, China. *Geomatics, Natural Hazards and Risk* **2017**, *8*, 1955-1977, doi:https://doi.org/10.1080/19475705.2017.1401560.
7. Özçelik, R.; Diamantopoulou, M.J.; Crecente-Campo, F.; Eler, U. Estimating Crimean juniper tree height using nonlinear regression and artificial neural network models. *Forest Ecology and Management* **2013**, *306*, 52-60, doi:https://doi.org/10.1016/j.foreco.2013.06.009.
8. Russell, S.J. *Artificial intelligence a modern approach*; Pearson Education, Inc.: 2010.
9. Gui, Y.; Li, D.; Fang, R. A fast adaptive algorithm for training deep neural networks. *Applied Intelligence* **2023**, *53*, 4099-4108, doi:https://doi.org/10.1007/s10489-022-03629-7.
10. Mehtätalo, L.; de-Miguel, S.; Gregoire, T.G. Modeling height-diameter curves for prediction. *Canadian Journal of Forest Research* **2015**, *45*, 826-837, doi:https://doi.org/10.1139/cjfr-2015-0054.
11. Sharma, M.; Parton, J. Height–diameter equations for boreal tree species in Ontario using a mixed-effects modeling approach. *Forest Ecology and Management* **2007**, *249*, 187-198, doi:https://doi.org/10.1016/j.foreco.2007.05.006.
12. Santiago-García, W.; Jacinto-Salinas, A.H.; Rodríguez-Ortiz, G.; Nava-Nava, A.; Santiago-García, E.; Ángeles-Pérez, G.; Enríquez-del Valle, J.R. Generalized height-diameter models for five pine species at Southern Mexico. *Forest Science and Technology* **2020**, *16*, 49-55, doi:https://doi.org/10.1080/21580103.2020.1746696.
13. Szurszewski, J.H. Mechanism of action of pentagastrin and acetylcholine on the longitudinal muscle of the canine antrum. *J Physiol* **1975**, *252*, 335-361, doi:https://doi.org/10.1113/jphysiol.1975.sp011147.
14. Elliott, R.J.; Gardner, D.L. Proline determination with isatin, in the presence of amino acids. *Anal Biochem* **1976**, *70*, 268-273, doi:https://doi.org/10.1016/S0003-2697(76)80068-1.
15. Ogana, F.N.; Ercanli, I. Modelling height-diameter relationships in complex tropical rain forest ecosystems using deep learning algorithm. *Journal of Forestry Research* **2021**, *33*, 883-898, doi:https://doi.org/10.1007/s11676-021-01373-1.
16. Raptis, D.I.; Kazana, V.; Kazaklis, A.; Stamatiou, C. Mixed-effects height–diameter models for black pine (Pinus nigra Arn.) forest management. *Trees* **2021**, *35*, 1167-1183, doi:https://doi.org/10.1007/s00468-021-02106-x.
17. Shen, J.; Hu, Z.; Sharma, R.P.; Wang, G.; Meng, X.; Wang, M.; Wang, Q.; Fu, L. Modeling height–diameter relationship for poplar plantations using combined-optimization multiple hidden layer back propagation neural network. *Forests* **2020**, *11*, 442, doi:https://doi.org/10.3390/f11040442.
18. Diamantopoulou, M.J. Predicting fir trees stem diameters using Artificial Neural Network models. *The Southern African Forestry Journal* **2005**, *205*, 39-44, doi:https://doi.org/10.2989/10295920509505236.
19. Barbosa, L.O.; Costa, E.A.; Schons, C.T.; Finger, C.A.G.; Liesenberg, V.; Bispo, P.d.C. Individual Tree Basal Area Increment Models for Brazilian Pine (Araucaria angustifolia) Using Artificial Neural Networks. *Forests* **2022**, *13*, 1108, doi:https://doi.org/10.3390/f13071108.
20. Qin, Y.; Wu, B.; Lei, X.; Feng, L. Prediction of tree crown width in natural mixed forests using deep learning algorithm. *Forest Ecosystems* **2023**, *10*, 100109, doi:https://doi.org/10.1016/j.fecs.2023.100109.
21. Vahedi, A.A. Artificial neural network application in comparison with modeling allometric equations for predicting above-ground biomass in the Hyrcanian mixed-beech forests of Iran. *Biomass and Bioenergy* **2016**, *88*, 66-76, doi:https://doi.org/10.1016/j.biombioe.2016.03.020.
22. Diamantopoulou, M.J.; Milios, E. Modelling total volume of dominant pine trees in reforestations via multivariate analysis and artificial neural network models. *Biosystems Engineering* **2010**, *105*, 306-315, doi:https://doi.org/10.1016/j.biosystemseng.2009.11.010.
23. Wu, Z.; Wang, B.; Li, M.; Tian, Y.; Quan, Y.; Liu, J. Simulation of forest fire spread based on artificial intelligence. *Ecological Indicators* **2022**, *136*, 108653, doi:https://doi.org/10.1016/j.ecolind.2022.108653.
24. Richards, M.; McDonald, A.J.S.; Aitkenhead, M.J. Optimisation of competition indices using simulated annealing and artificial neural networks. *Ecological Modelling* **2008**, *214*, 375-384, doi:https://doi.org/10.1016/j.ecolmodel.2008.03.008.
25. Öhman, K.; Lämås, T. Clustering of harvest activities in multi-objective long-term forest planning. *Forest Ecology and Management* **2003**, *176*, 161-171, doi:https://doi.org/10.1016/S0378-1127(02)00293-1.
26. Akay, A.O.; AKGÜL, M.; Esin, A.I.; Demir, M.; ŞENTÜRK, N.; ÖZTÜRK, T. Evaluation of occupational accidents in forestry in Europe and Turkey by k-means clustering analysis. *Turkish Journal of Agriculture and Forestry* **2021**, *45*, 495-509, doi:https://doi.org/10.3906/tar-2010-55.
27. Phillips, P.D.; Yasman, I.; Brash, T.E.; van Gardingen, P.R. Grouping tree species for analysis of forest data in Kalimantan (Indonesian Borneo). *Forest Ecology and Management* **2002**, *157*, 205-216, doi:https://doi.org/10.1016/S0378-1127(00)00666-6.

28. Corral-Rivas, S.; Álvarez-González, J.; Crecente-Campo, F.; Corral-Rivas, J. Local and generalized height-diameter models with random parameters for mixed, uneven-aged forests in Northwestern Durango, Mexico. *Forest Ecosystems* **2014**, *1*, 6, doi:https://doi.org/10.1186/2197-5620-1-6.
29. Castillo-Gallegos, E.; Jarillo-Rodríguez, J.; Escobar-Hernández, R. Diameter-height relationships in three species grown together in a commercial forest plantation in eastern tropical Mexico. *Revista Chapingo serie ciencias forestales y del ambiente* **2018**, *24*, 33-48, doi:https://doi.org/10.5154/r.rchscfa.2017.05.033
30. Richards, F.J. A Flexible Growth Function for Empirical Use. *Journal of Experimental Botany* **1959**, *10*, 290-300, doi:https://doi.org/10.1093/jxb/10.2.290.
31. Burkhart, H.E.; Tomé, M. *Modeling forest trees and stands*; Springer Science & Business Media: 2012.
32. Von Gadow, K.; Nagel, J.; Saborowski, J. *Continuous cover forestry: assessment, analysis, scenarios*; Springer Science & Business Media: 2002; Vol. 4.
33. Quiñonez-Barraza, G.; Zhao, D.; De Los Santos Posadas, H.M.; Corral-Rivas, J.J. Considering neighborhood effects improves individual dbh growth models for natural mixed-species forests in Mexico. *Annals of forest science* **2018**, *75*, 1-11, doi:https://doi.org/10.1007/s13595-018-0762-2.
34. Climate Action Reserve [CAR]. Protocolo Forestal para México. Versión 3.0. CA, USA. Climate Action Reserve: 2022; Vol. Versión 3.0, p 2080 p.
35. R Core Team. A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing; 2012. *https://www.r-project.org/* **2023**.
36. Ghoshal, S.; Nohria, N.; Wong, M. A K-means clustering algorithm. Algorithm AS 136. *Applied Statistics* **1979**, *28*, 100-108.
37. Forgy, E.W. Cluster analysis of multivariate data: Efficiency vs. interpretability of classifications. *biometrics* **1965**, *21*, 768-769.
38. Milligan, G.W.; Cooper, M.C. A study of standardization of variables in cluster analysis. *Journal of Classification* **1988**, *5*, 181-204, doi:https://doi.org/10.1007/BF01897163.
39. Fang, Z.; Bailey, R.L. Height–diameter models for tropical forests on Hainan Island in southern China. *Forest Ecology and Management* **1998**, *110*, 315-327, doi:https://doi.org/10.1016/S0378-1127(98)00297-7.
40. Pinheiro, J.C.; Bates, D.M.; Lindstrom, M.J. *Model building for nonlinear mixed effects models*; University of Wisconsin, Department of Biostatistics Madison, WI: 1995.
41. Krogh, A. What are artificial neural networks? *Nat Biotechnol* **2008**, *26*, 195-197, doi:https://doi.org/10.1038/nbt1386.
42. Anastasiadis, A.D.; Magoulas, G.D.; Vrahatis, M.N. New globally convergent training scheme based on the resilient propagation algorithm. *Neurocomputing* **2005**, *64*, 253-270, doi:https://doi.org/10.1016/j.neucom.2004.11.016.
43. Cartwright, H. *Artificial neural networks: Methods in Molecular Biology*, Third Edition. New Yor, NY USA ed.; Springer Human Press: New Yor, NY USA, 2021; Vol. 2190. 368 p.
44. Han, W.; Nan, L.; Su, M.; Chen, Y.; Li, R.; Zhang, X. Research on the prediction method of centrifugal pump performance based on a double hidden layer BP neural network. *Energies* **2019**, *12*, 2709, doi:https://doi.org/10.3390/en12142709.
45. Fausett, L.V. *Fundamentals of neural networks: architectures, algorithms and applications*; Pearson Education India: 2006.
46. Kozak, A.; Smith, J.H.G. Standards for evaluating taper estimating systems. *The Forestry Chronicle* **1993**, *69*, 438-444, doi:https://doi.org/10.5558/tfc69438-4.
47. Bicego, M. K-Random Forests: a K-means style algorithm for Random Forest clustering. In Proceedings of 2019 International Joint Conference on Neural Networks (IJCNN), 14-19 July 2019; pp. 1-8.
48. Ercanlı, İ. Innovative deep learning artificial intelligence applications for predicting relationships between individual tree height and diameter at breast height. *Forest Ecosystems* **2020**, *7*, 12, doi:https://doi.org/10.1186/s40663-020-00226-3.
49. Skudnik, M.; Jevšenak, J. Artificial neural networks as an alternative method to nonlinear mixed-effects models for tree height predictions. *Forest Ecology and Management* **2022**, *507*, 120017, doi:https://doi.org/10.1016/j.foreco.2022.120017.
50. Thanh, T.N.; Tien, T.D.; Shen, H.L. Height-diameter relationship for Pinus koraiensis in Mengjiagang Forest Farm of Northeast China using nonlinear regressions and artificial neural network models. *Journal of Forest Science* **2019**, *65*, 134-143, doi:https://doi.org/10.17221/5/2019-JFS.