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Testing artificial neural networks for estimating relationships between diameter at breast height and stump diameter in *Quercus cerris*

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FOREST MANAGEMENT

ABSTRACT

Background: Accurate prediction of diameter at breast height (DBH) from stump diameter measurements is essential for sustainable forest management, particularly in post-harvest assessments, illegal logging investigations, and carbon accounting protocols in Quercus cerris stands. Traditional allometric models often fail to capture the complex nonlinear relationships inherent in tree growth patterns, necessitating advanced computational approaches. This study aims to develop and validate artificial neural network (ANN) models for predicting DBH from stump diameter in Q. cerris stands across diverse ecological conditions in Turkish forests.

Results: We conducted an extensive field survey across 103 systematically distributed sample plots encompassing 1,077 individual Q. cerris trees within the Bursa Regional Directorate of Forestry, Türkiye. The study area represented diverse site conditions including five site quality classes, stand age, and varying stand densities. Fourteen traditional regression models were compared against five distinct ANN architectures with varying activation functions. The ANN model employing hyperbolic tangent sigmoid activation function between input and hidden layers coupled with pure-linear function between hidden and output layers (ANN-2) with 8 neurons demonstrated superior predictive performance (SSE = 567.07, RMSE = 2.290, MSE = 4.797, R^2adj = 0.9484). Among conventional models, quadratic regression (Model 4) exhibited competitive performance but showed evidence of heteroscedasticity and model assumption violations.

Conclusions: This research demonstrates the superior capability of artificial neural networks in modeling complex DBH-stump diameter relationships in Q. cerris compared to traditional statistical approaches. The developed ANN models provide forest managers with robust, accurate tools for retrospective forest assessments, illegal logging quantification, and sustainable management planning.

Keywords: Allometric relationships; forest biometrics; machine learning; stump modeling; Turkish oak.

HIGHLIGHTS

ANN models outperformed traditional regression in DBH prediction accuracy (R^2adj = 0.948)
Optimal network architecture achieved with 8 neurons using tan-sig/pure-lin functions
Comprehensive field survey included 1,077 trees across 103 plots in Turkish forests
Developed tools enable illegal logging assessment and carbon accounting applications

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INTRODUCTION

Oak species—referred to as Quercus—are of great ecological and economic importance in the Turkish forestry. The species diversity of oak in Türkiye plays an important role in its forest industry, as these trees generate a diverse set of forest products (Kavgacı et al., 2021).According to the General Directorate of Forestry's 2020 inventory, Quercus species are vital components of the Turkish forestry, occupying 6.74 million hectares (29.42%) of Türkiye's total forest area of 22.93 million hectares (GDF, 2020). Turkey oak, scientifically known as *Quercus cerris*, is an oak species of significant economic value. The wood of this tree is high density and is durable, making it useful in the manufacture of furniture, flooring, and barrels. Moreover, Turkey oak can be efficiently grown in various ecological conditions, which enables it to form homogeneous forest communities in cases where other tree species cannot survive. Apart from its use in structures, wood of *Q. cerris* is favored for making barrels to store wine or spirits (Sönmez and Gencal, 2023).

Quercus cerris-related research has been common in exploring certain growth dynamics or its response to silvicultural treatments important in managing its productivity. These can range from ecology, which includes seedling survival and growth rates, to forest management practices such as pruning or spacing (Sönmez and Gencal, 2023).

Among a range of forestry management purposes, the diameter at breast height (DBH) is known because of a close correlation with the main forest metrics, including tree volume, tree biomass, and carbon sequestration in the trees (Corral-Rivas *et al.*, 2007; Bueno-López and Bevilacqua, 2013; Diamantopoulou *et al.*, 2024). DBH, as one of the basic external measurements taken at the height of 1.3 meters from the ground, helps estimate physical and ecological characteristics of a tree and is, therefore, also crucial for forests utilization (Burkhart *et al.*, 2018). DBH plays a crucial role in forest inventory systems by setting the ground for multiple approaches regarding forest structure assessment, estimation of ecological status and development of appropriate management decisions.

Forest management in Türkiye is typically characterized by the application of volume tables designed exclusively on the DBH basis to ensure a precise investigation of the tree volume. Although double-entry volume tables that account for height as well as the diameter at the breast height are more accurate in volume calculation, it is common to use single-entry tables considering DBH measurements only as they provide more convenience and simplicity in the field. However, the challenge arises when trees are cut down at a lower height for quick removal, often in illegal cutting, making it difficult to measure DBH at the standard height. In this case, the link between DBH and stump diameter is used to determine tree volume, which helps forest management to determine the effect of removal and take its conservation and restoration into account (Özçelik *et al.*, 2010; Koren *et al.*, 2024; Rodríguez-León *et al.*, 2025).

In practical forestry applications, predicting DBH from stump measurements is crucial when direct measurements are not possible due to harvesting or illegal logging activities. Most of the time due to illegal logging or after natural disturbances victims have been removed and used elsewhere. Therefore, the necessity of using stump diameter at 0.3 m height as a proxy is justified: it enables assessment of tree size and, subsequently, makes it possible to determine the estimates of volume and biomass to ensure effective management of the forest (Corral-Rivas *et al.*, 2007).

The methodology of DBH estimation based on stump measurements serves several essential needs of forestry. These include performing volume calculations post-harvest, surveying illegal forestry by acquired information required for legislation issues and restoration, and measuring damage after environmental disturbance. This approach will ensure not only continuance of the disturbed forest ecosystem management practices but also will contribute to providing a high degree of certainty to assess the previous stand structure and composition accurately which is entirely in line with sustainable management of the forest.

Also, when it comes to Türkiye and other such countries with a developed forestry sector, the knowledge of the connection between DBH and stump diameter is vital for the creation and improvement of prediction models. Such models are the basis of data used for forest inventories. Due to the massive amount of logging in the countries under analysis, it is impossible to measure each tree. In conclusion, it is important to note that the models associated with relationships between stand diameter and stump diameter or DBH are critical for forest managers to improve the precision of estimate forests stand volume and biomass, as well as the basis for the assessment of forests' condition and productivity (Özçelik *et al.*, 2010).

The study of the relationships between stump diameter and DBH is considered important in the field of forestry both in Türkiye and globally. It was previously shown that it is possible to determine trees' volume, DBH, and stump diameter with a high degree of accuracy, regardless of the species and environments (Bylin, 1982; Corral-Rivas *et al.*, 2007; Milios *et al.*, 2016; Chukwu and Osho, 2017; DI Cosmo and Gasparini, 2020; Chukwu and Ezenwenyi, 2020; Horvath and Popa, 2021; Popa *et al.*, 2021;Ige, 2022; Guzman-Santiago *et al.*, 2023; Koren *et al.*, 2024).

Turkish researchers have also contributed extensively to this body of knowledge, examining the predictive relationships among different native species such as Scots pine (*Pinus sylvestris*), Turkish pine (*Pinus brutia*), Anatolian black pine (*Pinus nigra*), Eastern spruce (*Picea orientalis*) and Oak (*Quercus petraea*) highlighting the versatility and adaptability of these models across diverse ecological settings (Durkaya and Durkaya, 2011; Şenyurt, 2012; Ercanlı *et al.*, 2015; Sağlam *et al.*, 2016; Sakıcı and Yavuz, 2016; Sakıcı and Özdemir, 2018; Şahin *et al.*, 2019; Durkaya and Dağlı, 2021; Özdemir *et al.*, 2020; Özçankaya and Batur, 2022).

Artificial Neural Networks (ANNs) are a successful type of computational model inspired by the behavior of the human brain. They are widely used in solving complex and technically challenging problems in a broad range of disciplines characterized by multiple interconnected nodes or neurons. It makes ANNs extremely efficient for pattern recognition and predictive modeling since these networks can be trained on data by adjusting their structure. A foundational reference on this topic explains that ANNs involve layers of nodes connected by weights, where learning occurs through adjustments in these weights based on input data, allowing the network to make predictions or classifications based on learned patterns (Fine and Hassaun, 1996).

Similarly, in forestry, recent developments in deep learning have greatly increased ANN applicability in forestry, particularly the use of convolutional neural networks for forest assessment. Recent advances in machine learning have also significantly increased ANN applicability in terms of deep learning approach to tree parameters modelling. For example, Diamantopoulou *et al.* (2024) proved the efficacy of machine learning methods for the prediction of the biomass and weight of carbon in Lebanon cedar trees, whereas Ercanli (2020) achieved positive outcomes when applying deep learning algorithms to modeling the relationship between tree height and diameter at breast height. Thus, as of the current date, research demonstrated that modern, advanced neural network architectures could dramatically increase the level of accuracy in predicting the characteristics of forest inventories, especially in problematic cases when traditional statistical methods are useless due to challenges of precision (Güner *et al.*, 2022). It has been shown that ANNs were able to develop strong models for complex relationships, e.g., between DBH and stump diameter, which could be applied for predicting and assessment purposes. Studies have demonstrated that ANNs could predict DBH from stump diameter and estimate various tree attributes (volume, taper, height, bark volume biomass, basal area) from DBH, offering versatile tools for forest management and planning. This application underscores the versatility and precision of ANNs in handling nonlinear relationships and large datasets in ecological research (Diamantopoulou, 2005a; Diamantopoulou, 2005b; Özçelik *et al.*, 2010; Leite *et al.*, 2011; Soares *et al.*, 2011; Özçelik *et al.*, 2013; Ashraf *et al.*, 2013; Nunes and Görgens, 2016; Diamantopoulou *et al.*, 2015; Özçelik *et al.*, 2017; Tavares Júnior et al., 2019; Bayat et al., 2019; Mi and Chen 2020; Yuan et al. 2020, Şenyurt et al., 2020; Guner et al., 2022; Sandoval and Acuna, 2022; Şahin, 2024; Diamantopoulou et al., 2024).

Our study aims to develop and evaluate ANN models specifically for predicting DBH from stump diameter measurements in *Quercus cerris*. This effort includes comparing the effectiveness of ANNs with traditional linear and nonlinear regression models to capture the complex dynamics of tree growth within this species. By incorporating these advanced modeling techniques, we hope to enhance the predictive accuracy and reliability of DBH estimations, thereby contributing to more informed and effective forest management strategies for *Quercus cerris*, a species of considerable ecological and economic importance in Türkiye's forests. This comprehensive modeling approach is designed to not only refine our understanding of *Quercus cerris* but also to advance sustainable forest management practices that support both conservation and economic objectives. This comprehensive modeling approach builds on recent machine learning advances (Chen and Guestrin, 2016; Breiman, 2001; Yun et al., 2024) in forestry to enhance sustainable forest management practices supporting both conservation and economic objectives.

MATERIAL AND METHODS

Study Area

The study area is located within the broader boundaries of the Bursa, Bilecik, Bozuyuk, İnegöl, Keles, Mustafakemalpaşa, Orhaneli, and Yalova Forest Management Enterprises, spanning an expansive terrain rich in both biodiversity and forestry resources. Covering approximately 1.555 million hectares, with 749,000 hectares dedicated to forested land, the region encompasses both forested and non-forested areas, reflecting a variety of ecosystems and management challenges.

In this paper, sample plots were selected and arranged proportionally to the surface area of *Quercus cerris* stands in Umurbey, Keles, Meyran, Çaltılıbük, and Yeniköy Forest Enterprise Directorates. Figure 1 displays the number of sample plots within each Forest Enterprise Directorate (FED) and the total *Quercus cerris* area of the Bursa Regional Directorate of Forestry (Bursa RDO). The sample plots range in age class and site index to create a comprehensive representation of the forest structure in the Bursa region. The selected sample areas encompass 793.5 hectares in Umurbey, 402 hectares in Keles, 80.7 hectares in Meyran, 1799.5 hectares in Çaltılıbük, and 1931.9 hectares in Yeniköy. This selection ensures a comprehensive analysis of the *Quercus cerris* stands within the Bursa RDO.

Data Collection and Sampling Design

In the preliminary study determining the locations of the sample plots, auxiliary materials such as the forest management plans and stand maps which belong to the relevant planning units of Bursa RDO have been used.Sample plot locations were selected using a stratified sampling approach to ensure representative coverage of Turkish oak (*Quercus cerris*) stands across different site conditions. Plot selection criteria included: (1) pure or predominantly Turkish oak stands (>80% basal area), (2) representation across five site quality classes (I, II, III, IV and V), (3) coverage of different age classes (young, middle-aged, and mature stands), (4) varying stand densities (sparse, medium, and dense), and (5) accessibility for field measurements. Within each stratum defined by these criteria, plots were randomly selected from available stands identified in forest management plans to avoid subjective bias in plot placement.

For the *Quercus cerris* stands, 103 sampling plots were identified by the Bursa RDF in FED and representatives executed in varying stand conditions, including site quality, age classes, and stand densities. The selected sample included 1077 trees from the plots. DBH and stump diameter were measured to the nearest 0.1 cm using standard forestry calipers. Two perpendicular diameter measurements were

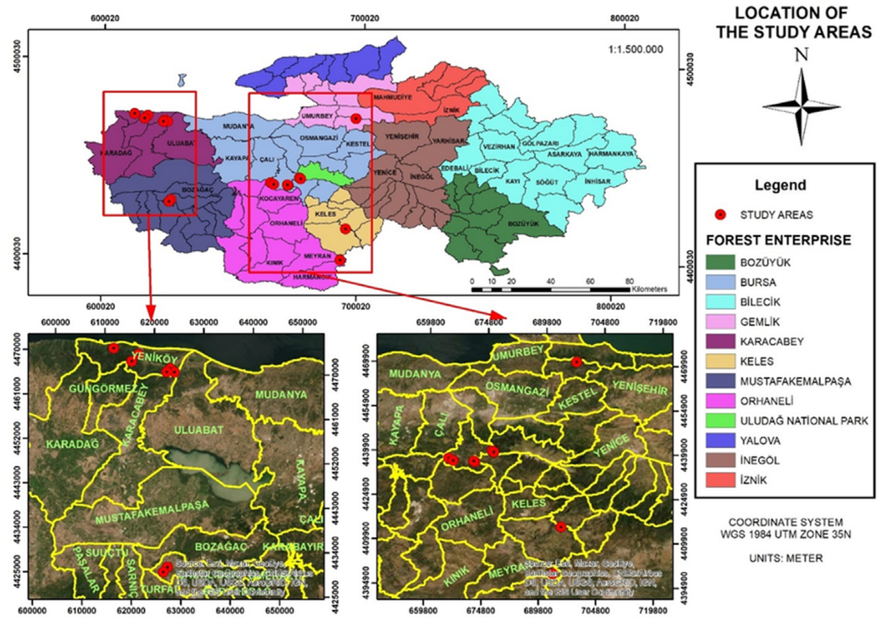

Figure 1: Study Area.

taken at each height and averaged to account for potential stem irregularities. For each sample plot, all living trees with the DBH ≥ 4.0 cm were measured excluding only those with forked stems below breast height or severely damaged/broken tops that would compromise accurate diameter measurements. This selection criterion ensured reliable data for developing stump-to-DBH conversion models.

This sampling approach is consistent with commonly used practices in forest biometric studies (Sakici and Ozdemir, 2018; Sağlam, 2025) and provides adequate representation across diameter classes. To develop the statistical models, the dataset was randomly split into two subsets at the tree level: approximately 85% (916 trees) for model training and 15% (161 trees) for independent validation. The random splitting was performed while maintaining proportional representation of different diameter classes and plot characteristics in both subsets to ensure unbiased model evaluation (Table 1; Figure 2)

Statistical Models

Traditional Regression Models

To determine the relationship between DBH and stump diameters for *Quercus cerris*, 14 linear and nonlinear models were selected based on the following criteria: (1) previous successful application in stump-to-DBH conversion studies for oak species or similar hardwood species, (2) biological plausibility of the mathematical form for representing tree taper relationships, (3) computational feasibility and convergence properties during preliminary testing, and (4) inclusion of commonly used model forms in forestry biometrics (linear, logarithmic, power, exponential functions).

The selected models represent the most employed functional forms in allometric forestry research, ranging from simple linear relationships to more complex nonlinear functions that can capture potential asymptotic behavior in diameter relationships:

Model 1 (Linear): $\mathrm{DBH} = \beta_0 + \beta_1 d_{0.3}^{1}$

Model 2 (Logarithmic): $\mathrm{DBH} = \beta_0 + \beta_1 \ln \ln(d_{0.3})$

Model 3 (Inverse): $\mathrm{DBH} = \beta_0 + \frac{\beta_1}{d_{0.3}}$

Model 4 (Quadratic): $\mathrm{DBH} = \beta_0 + \beta_1 d_{0.3} + \beta_2 d_{0.3}^{2}$

Model 5 (Compound): $\mathrm{DBH} = \beta_0 {\beta_1}^{d_{0.3}}$

Model 6 (Power): $\mathrm{DBH} = \beta_0 d_{0.3}^{\beta_1}$

Model 7 (S-Curve): $\mathrm{DBH} = e^{\beta_0 + \frac{\beta_1}{d_{0.3}}}$

Table 1: Descriptive statistics for train and validation data.

Data Type	Variable	Minimum (cm)	Maximum (cm)	Mean (cm)	Median (cm)	Standart Deviation (cm)	Skewness	Kurtosis
Training Data	Diameter of Breast Height (DBH)	5.1	53.5	22.98	22.23	10.54	0.40	-0.59
	Stump Diameter ($d_{0.30}$)	6.6	62.4	28.32	27.60	11.39	0.41	-0.48
Validation Data	Diameter of Breast Height (DBH)	5.5	49.6	22.16	20.59	10.92	0.58	-0.41
	Stump Diameter ($d_{0.30}$)	7.3	57.2	27.18	24.75	11.98	0.56	-0.46

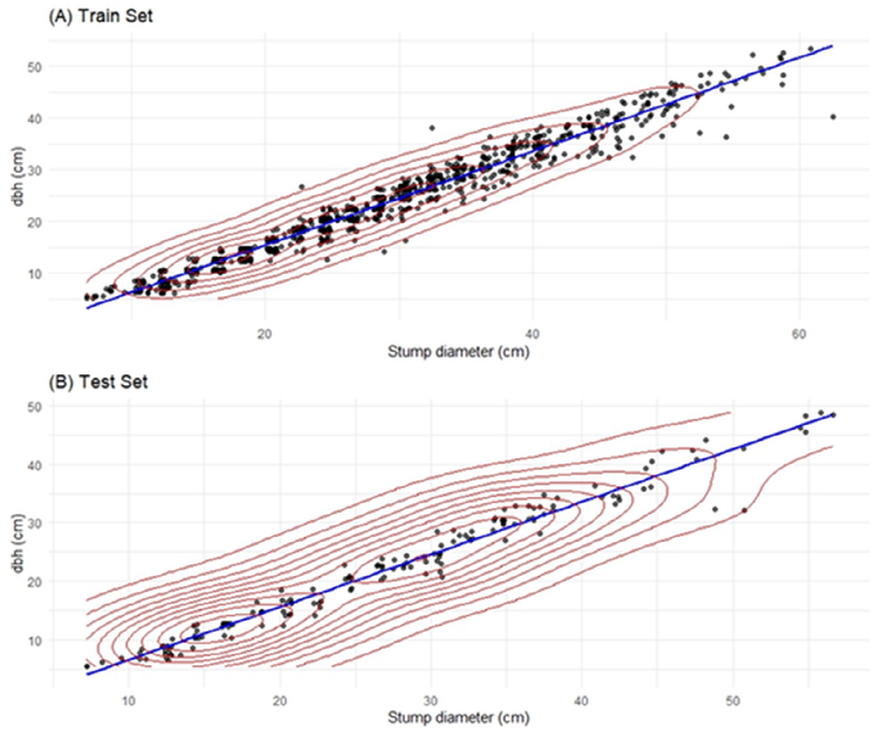

Figure 2: Diameter at breast height and stump diameter for train (A) and validation (B) data

Model 8 (Growth): $\mathrm{DBH} = e^{\beta_0+\beta_1 d_{0.3}}$

Model 9 (Exponential): $\mathrm{DBH} = \beta_0 e^{\beta_1 d_{0.3}}$

Model 10: $\mathrm{DBH} = \beta_0 + \beta_1 d_{0.3} + \beta_2\left(\frac{1}{d_{0.3}}\right)$

Model 11: $\mathrm{DBH} = \beta_0 + \beta_1 d_{0.3} + \beta_2 \ln\ln d_{0.3}$

Model 12: $\mathrm{DBH} = \beta_0 + \beta_1 d_{0.3} + \beta_2 \ln\ln {d^2}_{0.3}$

Model 13: $\mathrm{DBH} = \beta_0 + \beta_1 d_{0.3} + \beta_2\left(\frac{1}{d_{0.3}^2}\right)$

Model 14: $\mathrm{DBH} = \beta_0 + \beta_1 \ln\ln d_{0.3} + \beta_2\left(\frac{1}{\ln\ln d_{0.3}}\right)$

where DBH is the diameter at breast height (measured at 1.30 m above ground level, cm), d0.30 is the stump diameter (measured at 0.30 m above ground level, cm), β_0 is the intercept parameter, β_1 and β_2 are the regression coefficients, and ln denotes the natural logarithm.

The selected regression equations were then fit to pairs of DBH/stump diameter using packages in RStudio. This allowed us to fit the DBH and stump diameter relationship and obtain parameter estimates of the functions. To construct predictive models, it was required that each parameter estimate of any variable in these regression models had to be statistically significant at the 95% probability level.

Artificial Neural Network Models

In this study, Artificial Neural Networks (ANNs) were utilized as an alternative predictive technique to traditional regression methods. Specifically, a feedforward multilayer perceptron (MLP) neural network was employed to model the relationship between stump diameter (d0.30) and DBH. The network was trained using the backpropagation algorithm with the neuralnet package in R (Fritsch *et al.*, 2019). For the ANNs training process, tree stump diameters served as the input variable, and DBH measurements from the sample trees were the target variable.

To determine the optimal network configuration, 100 different ANN models were systematically trained and evaluated, comprising all combinations of 20 different neuron counts (1 to 20 neurons in the hidden layer) and five activation function combinations between the hidden and output layers:

ANN-1: tan-sig/tan-sig (hyperbolic tangent sigmoid for both hidden and output layers)

ANN-2: tan-sig/pure-lin (hyperbolic tangent sigmoid for hidden layer, pure-linear for output layer)

ANN-3: log-sig/log-sig (logistic sigmoid for both layers)

ANN-4: log-sig/pure-lin (logistic sigmoid for hidden layer, pure-linear for output layer)

ANN-5: pure-lin/pure-lin (pure-linear for both layers)

The selection of ANN methodology was supported by recent evidence demonstrating the effectiveness of machine learning approaches in forestry applications, particularly for complex biometric relationships (Diamantopoulou et al., 2024; Ercanlı, 2020a; Güner et al., 2022; Sağlam, 2025).

Model Selection and Evaluation

Model selection is one of the most important stages within predictive analytics; in our study, it was performed with the help of a extended set of performance metrics. The model selection criteria incorporated the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which evaluate the trade-off between the complexity of the model and the fit of the model to the data. Additionally, mean squared error (MSE), sum of squared errors (SSE), root mean square error (RMSE), and the adjusted coefficient of determination (R_{adj}^2) were utilized.

$$R_{adj}^2 = 1 - \frac{\sum_{i=1}^{n}\left(d_i - \hat{d}_i\right)^2 / (n-1)}{\sum_{i=1}^{n}\left(d_i - \bar{d}\right)^2 / (n-p)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(d_i - \hat{d}_i\right)^2}{n-p}}$$

$$MSE = \frac{1}{n-p}\sum_{i=1}^{n}\left(d_i - \hat{d}_i\right)^2$$

$$SSE = \sum_{i=1}^{n}\left(d_i - \hat{d}_i\right)^2$$

$$AIC = -2\log\log(L) + 2p$$

$$BIC = -2\log\log(L) + p\log\log(n)$$

In the equations specified previously: (d_i) represents the observed DBH (measured in the field); ($\hat{d}_i$) denotes the predicted DBH (estimated by the model); ($\bar{d}$) is the mean observed DBH; (n) signifies the total number of data points; (L) refers to the maximum value of the log-likelihood function; and (p) indicates the number of parameters incorporated within the model.

RESULTS

Descriptive statistics, such as minimum, maximum, mean, and standard deviations, were calculated for both the training and validation datasets to provide a comprehensive understanding of their distributions.

As presented in the sampling design section 2.2, both training and validation datasets exhibited similar distributional patterns with low skewness and kurtosis values, indicating approximately normal distributions. The comparable statistics between subsets confirmed the appropriateness of the random data partitioning for unbiased model development and evaluation.

Model Performance Comparison

In this study, the efficacy of fourteen regression models and five ANN configurations for predicting DBH from stump diameter was evaluated using multiple goodness-of-fit statistics including Sum of Squares Error (SSE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Adjusted R^2 (R^2adj).

Table 2 presents the goodness-of-fit statistics of the ANN model with the highest performance in each group

Table 2: Fit statistics (RMSE, MSE, SSE, R2 Adj, AIC, BIC and Number of neurons for ANN models) for Regression and ANN Models.

Regression and ANN Models	Number of neuron (for ANN models)	RMSE	MSE	SSE	R^2 Adj	AIC	BIC
Model 1	-	2.301	5.294	571.70	0.9479	189.345	183.981
Model 2	-	3.464	11.998	1295.78	0.8822	277.717	272.352
Model 3	-	5.732	32.858	3548.66	0.6774	386.521	381.157
Model 4	-	2.190	5.251	777.18	0.9484	286.029	335.431
Model 5	-	3.452	11.916	1286.93	0.8830	276.976	271.612
Model 6	-	2.330	5.428	586.25	0.9467	192.059	186.695
Model 7	-	2.705	7.316	790.12	0.9281	224.290	218.926
Model 8	-	3.452	11.916	1286.93	0.8830	276.976	271.611
Model 9	-	3.452	11.916	1286.93	0.8830	276.976	271.611
Model 10	-	2.300	5.288	571.13	0.9475	193.919	185.873
Model 11	-	2.301	5.294	571.76	0.9475	194.038	185.991
Model 12	-	2.300	5.289	571.23	0.9475	193.937	185.891
Model 13	-	2.295	5.267	568.88	0.9477	193.493	185.446
Model 14	-	2.312	5.344	577.14	0.9470	195.050	187.004
ANN-1	18	2.194	4.814	779.97	0.9482	364.609	534.427
ANN-2	8	2.290	4.797	567.07	0.9484	193.149	185.102
ANN-3	5	2.190	4.799	777.45	0.9389	304.086	381.275
ANN-4	16	2.192	4.806	778.69	0.9483	352.343	503.635
ANN-5	15	2.192	4.808	778.93	0.9482	346.394	488.424

of activation functions, compared to fourteen traditional regression equations. The SSE in all prediction approaches varied between 567.07 and 3548.66, and AIC was in the range from 183.98 to 386.52. As for the BIC, the values were within the limits of 185.10 to 534.43, and RMSE and MSE were 2.19-5.73 and 4.80-32.86, respectively. In turn, R^2adj was delivering between 0.6774 and 0.9484

Among all tested models, the ANN-2 configuration (tan-sig/pure-lin activation functions with 8 neurons) demonstrated the best overall performance with the lowest SSE (567.07), AIC (193.15), and BIC (185.10), along with competitive RMSE (2.290) and MSE (4.797), achieving an R^2adj of 0.9484. The linear regression model (Model 1) also showed strong performance with similar R^2adj (0.9479) and RMSE (2.301). Model 4 (quadratic) achieved the same R^2adj (0.9484) as ANN-2 but with higher SSE (777.18). The inverse model (Model 3) performed poorest with the lowest R^2adj (0.6774) and highest RMSE (5.732).

Tables 3 and 4 present mean performance statistics averaged across all 100 ANN configurations. Table 3 shows the mean performance for each activation function combination (averaged across 20 neuron counts), while Table 4 shows the mean performance for each neuron count (averaged across 5 activation functions)

Table 3: Mean values of the fit statistics for ANN Models.

ANN-Models	MSE	RMSE	SSE	R^2 Adj	AIC	BIC
A1	4.8776	2.2085	790.1670	0.9331	321.7094	422.0562
A2	**4.8324**	**2.1983**	**782.8419**	**0.9337**	**320.2020**	**420.5489**
A3	5.0753	2.2522	822.1906	0.9303	327.9709	428.3177
A4	4.8672	2.2062	788.4945	0.9332	321.3674	421.7143
A5	4.8630	2.2052	787.8135	0.9333	321.2271	421.5740

Among activation function combinations, ANN-2 (tan-sig/pure-lin) achieved the best mean performance with MSE (4.83), RMSE (2.198), and R^2adj (0.9337) (Table 3).

Examining mean performance across all activation functions, simpler architectures generally performed better as shown in Table 4. The 2-neuron configuration achieved the highest mean R^2adj of 0.9454 in addition to a relatively low MSE score of 4.86. Furthermore, the 1-neuron configuration demonstrated lowest AIC and BIC scores of 268.50 and 280.85, respectively. As neuron count increased beyond 2, model complexity increased without corresponding improvement in predictive accuracy, with R^2adj gradually decreasing from 0.9454 to 0.9141 for 20 neurons. However, the optimal individual model for prediction purposes remains ANN-2 with 8 neurons as shown in Table 2.

Table 4: Mean values of fit statistics for the number of neurons.

Neurons	MSE	RMSE	SSE	R^2 Adj	BIC	AIC
1	4.9994	2.2352	809.9097	0.9449	280.8544	268.5041
2	4.8600	2.2045	787.3228	0.9454	291.7410	270.1278
3	4.8869	2.2106	791.6836	0.9440	307.8975	277.0216
4	4.8644	2.2055	788.0387	0.9431	322.4124	282.2736
5	4.8465	2.2015	785.1363	0.9421	337.0761	287.6746
6	4.8766	2.2083	790.0100	0.9406	353.3430	294.6786
7	4.9700	2.2289	805.1408	0.9381	371.5444	303.6173
8	4.8820	2.2095	790.8809	0.9379	384.0431	306.8532
9	4.8503	2.2023	785.7407	0.9369	398.2518	311.7991
10	4.8761	2.2082	789.9332	0.9351	414.3779	318.6624
11	4.9919	2.2337	808.6891	0.9320	433.2898	328.3115
12	4.8741	2.2077	789.6072	0.9320	444.8342	330.5931
13	4.8636	2.2053	787.8999	0.9304	459.7435	336.2396
14	4.9713	2.2293	805.3544	0.9271	478.4503	345.6836
15	4.9344	2.2208	799.3709	0.9257	492.4522	350.4228
16	4.8467	2.2015	785.1726	0.9251	504.9681	353.6758
17	4.9609	2.2269	803.6612	0.9212	523.8866	363.3316
18	4.8677	2.2063	788.5736	0.9205	536.1931	366.3753
19	4.8757	2.2081	789.8713	0.9181	551.7280	372.6475
20	4.9632	2.2274	804.0334	0.9141	569.7575	381.4141

Residual Analysis and Model Diagnostics

Residual plots uncover patterns that separate the traditional regression and ANN approaches' performance (Figure 3.). First, the model 4 (left panel) residuals present signs of heteroscedasticity, with the residual variance seemingly increasing with respect to the systematically increasing fitted values most apparent for the larger trees (fitted values > 40 cm). Moreover, Model 4 has some systematic patterns of residuals, which also indicated potential for non-random distribution and regression assumption violations.The residuals range from approximately -15 to +25 cm, with several notable outliers in the upper range.

In contrast, the ANN model residuals (right panel) demonstrate superior distributional characteristics. The residuals are more tightly distributed around zero (ranging from approximately -10 to +8 cm), showing a more random scatter pattern without obvious systematic trends. In this dataset, ANN residuals appear approximately homoscedastic. Furthermore, the ANN residuals show fewer extreme outliers and a more symmetric distribution around zero.

The narrower residual range of the ANN model is likely because it can capture the nonlinear patterns in the stump-DBH relationship that the Model 4 does not carefully present. Interpretation agrees with the cross-validation results in Section 3.4, with the ANN performance inferred from independent data folds (RMSE: 2.21 ± 0.15 cm), which suggests that the enhanced fit is indeed the result of enhanced pattern recognition, as opposed to overfitting.

These residual pattern differences highlight a key advantage of ANN models: their ability to capture complex nonlinear relationships in biological data. The improved residual characteristics of the ANN model suggest better model specification and more reliable predictions across the full range of tree sizes encountered in *Q. cerris* stands.

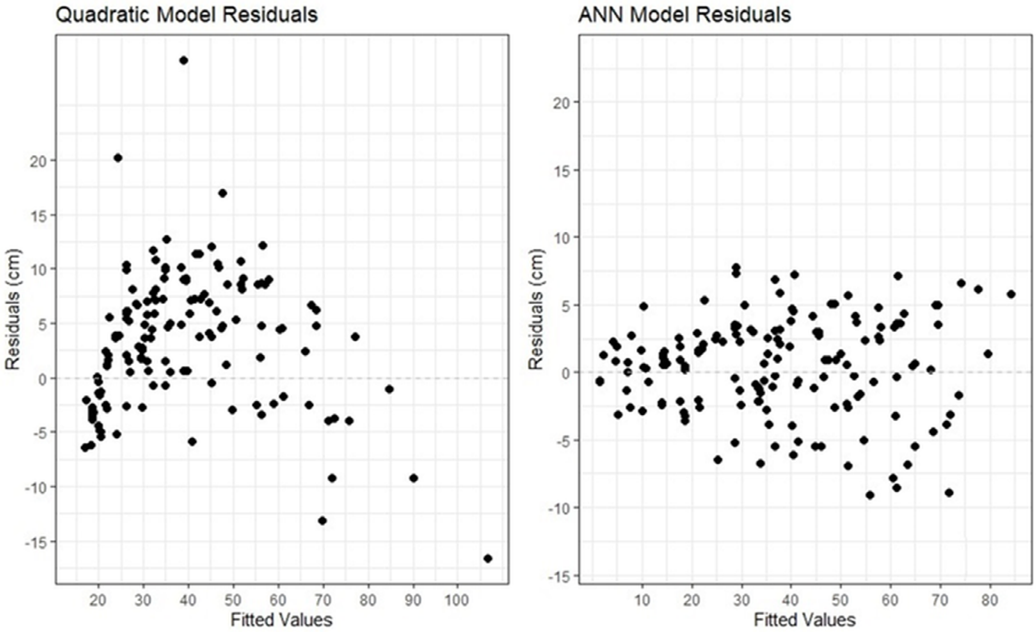

Figure 3: Residuals of plots for best regression model (Quadratic) and ANN Models

Cross-Validation Results

To ensure an adequate level of generalization and avoid overfitting, the 10-fold cross-validation was employed. In this case, the ANN-2 model demonstrated a consistent level of performance in all folds with cross-validation RMSE of 2.21 ± 0.15 cm and $R^2{}_a d_j$ of 0.946 ± 0.008. The latter results in small standard deviations between the folds, which means that the model's performance is stable, well-generalized, and enhanced residuals characteristics observed in Section 3.3 are not overfitting artifacts.

Traditional regression models showed larger variation in cross-validation performance, with Model 4 achieving cross-validation RMSE of 2.28 ± 0.23 cm and $R^2{}_a d_j$ of 0.942 ± 0.015. The larger standard deviations suggest greater sensitivity to training data composition.

DISCUSSION

Model Performance and Comparison

In conclusion, it can be noted that the artificial neural network approach provided a more accurate model than the traditional statistical approaches for DBH estimation from stump diameter in *Quercus cerris*. The ANN-2 configuration with hyperbolic tangent sigmoid activation function appeared to be the best option in parameters of DBH estimation.The achieved performance metrics (R^2adj = 0.9484, RMSE = 2.290) align with the growing body of evidence supporting machine learning applications in forest biometrics. The results are in complete agreement with previous studies, which showed that ANNs are better than traditional regression in taper, volume, diameter, and height equations (Özçelik *et al.*, 2010, 2013; Nunes and Görgens, 2016; Sakıcı & Özdemir, 2018; Ercanlı, 2020a; Ercanlı, 2020b ; Socha *et al.*, 2020; Şenyurt *et al.*, 2020; Diamantopoulou *et al.*, 2024; Güner *et al.*, 2022; Sağlam, 2025).

Neural networks have exhibited a good performance, and it can be explained by the fact that such models are predestined to capture complicated nonlinear relationships because they do not depend on the in-depth mathematical formulation of biological processes (Diamantopoulou *et al.*, 2015; Özçelik *et al.*, 2017). This advantage is especially desirable for tree growth prediction since the relationships between diameters involve complex interactions between physiological and environmental factors that cannot always be accurately represented using traditional parametric models.

Network Architecture Optimization

An important conclusion of this study is the observation that optimal ANN performance was obtained using relatively simple network architectures (1-8 neurons) with performance generally declining beyond 8-10 neurons due to overfitting effects. It is in opposition to the common belief that one applies more sophisticated neural networks to achieve an appropriate level of performance. It is also a demonstration of the bias-variance tradeoff in machine learning applications.

The good results obtained by simple architecture seem to indicate that there is indeed a non-linear relationship between DBH and stump diameter in *Q. cerris*, which does not require very complex modeling approaches. This finding has practical implications, as simpler models are more computationally efficient, interpretable, and easier to implement in operational forest management settings. A similar regularity was also observed by Sağlam (2025), who proved that the XGBoost model of moderate complexity gives the optimal results of the *Pinus brutia* taper modeling.

The effectiveness of the tan-sig/pure-lin activation function combination can be attributed to its ability to provide smooth nonlinear transformation of input variables while maintaining linear scaling for continuous output predictions, allowing unrestricted prediction of DBH values across the full observed range (Diamantopoulou and Georgakis, 2024).

Model Validation and Reliability

To ensure the reliability of the results, this study utilized rigorous methodologies for validation, ten-fold cross-validation, and independent test dataset. The cross-validation results (RMSE = 2.21 ± 0.15 cm, R^2adj = 0.946 ± 0.008) with small standard deviations indicate stable model performance across different data subsets.

The additional inspection of residuals has shown that ANN models provided improved distributional properties than conventional regression methods. The tendency for homogeneity and a lesser number of systematic patterns in ANN residuals demonstrate the efficiency of model specification. This advantage is particularly important for forest inventory applications where prediction reliability across the full range of tree sizes is crucial for accurate volume and biomass estimation (Sakıcı and Özdemir, 2018; Bayat *et al.*, 2019).

Practical Implications and Limitations

The high predictive accuracy attained ensures that these models can be employed in forest management applications such as illegal logging quantification, post-harvest volume verification, and carbon accounting. In the context of Turkish forestry, where Quercus occupies 6.74 million hectares (GDF, 2020), accurate stump-to-DBH conversion models have significant practical value.

Nevertheless, implementation factors need to consider implementation based on computational requirements and the high level of technical knowledge of neural network deployment. Although they result in efficient models, using the extradited models listed above requires some knowledge of ML methods, which hinders the possibility to integrate them immediately into less developed operations, and implies that traditional models still have utility in some cases (Poudel and Cao, 2013). Recent comparative studies have also shown that the relative performance of different modeling approaches can vary among species; Ko *et al.* (2025) reported that traditional models performed better than machine learning approaches for Pinus densiflora, highlighting the importance of species-specific model evaluation.

Future Research Directions

The obtained high performance of the models for *Q. cerris* in the Bursa region is a prerequisite for validation and high accuracy in other geographical regions. For reliable and high-precision applications in different geographic regions, developing multi-regional models including environmental data among predictors should be considered for future research. Furthermore, the use of remote sensing sources and ensemble methods can be applicable to improve predictions. Lastly, the detection of the temporal stability of stump-DBH relations considering the uncertainty of predictions in the context of climate change would be a pertinent issue for further studies.

CONCLUSIONS

This study demonstrates that the ANN-2 configuration employing a hyperbolic tangent sigmoid activation function between input and hidden layers coupled with a pure-linear function between hidden and output layers shows strong potential for DBH estimation from stump diameter in *Quercus cerris*. The ANN-2 model with 8 neurons achieved high performance metrics (SSE = 567.07, RMSE = 2.290, MSE = 4.797, R^2adj = 0.9484), performing better than conventional regression methods in this dataset.

An important finding is that the best performance was achieved using relatively simple network architectures (1-8 neurons) as more complex models can have excessive overfitting due to the bias-variance tradeoff. This has practical implications, as simpler models are more computationally efficient and easier to implement in operational settings.

Consequently, future research is to prioritize multi-spec species approaches, more extensive incorporation of environmental variables, and validation in other areas. Nevertheless, the high accuracy of the developed models already allows their application to forest management tasks, such as quantifying illegal logging, verifying post-harvest volumes, and calculating carbon.

This research, therefore, promotes the use of machine learning approaches within forest biometrics. The high level of performance achieved with easy architecture makes the methods feasible for operational application and useful as powerful techniques in modern forestry that demand accurate quantitative analysis.

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DATA AVAILABILITY:

The datasets analyzed during the current study are available from the corresponding author upon reasonable request.

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