TITLE

Estimation of Tree Heights in Mixed Forest Plantation Using Artificial Intelligent Models

ABSTRACT

The diameters and heights of the trees are two of the most important measurements in a forest inventory for biomass estimation and sustainable management. Measuring tree height in a forest stand is time consuming and costly, it is necessary to develop models that accurately estimate tree heights from easily measured variables (tree diameter). This study aims to develop models for estimating tree height in a forest plantation located in North-central, Nigeria. The systematic sampling method was used to allocate 21 0.09 ha sample plots in study area. Data on tree height and diameter were collected using relaskop. Artificial neural network (ANN) model, support vector regression (SVR) model, and four empirical nonlinear models were tested for estimating tree height. The models were evaluated using the Coefficient of Determination, Residual standard Error, Mean Bias and Akaike's Information Criterion. The results showed that the SVR model best predicted tree heights in the study area than the ANN and empirical nonlinear models. The SVR model explain about 94% variance associating with the dependent variable, while only 92% variance was explained by ANN model in this study. R-square of 0.94, RMSE (1.017), and Bias (-0.005) were some of the performance metrics that support the superiority of the SVR model over other models. The SVR models can be conveniently used for predicting the height of trees in the study area. The complex nature of trees, data collecting restrictions, simplifying assumptions, fluctuation in environmental variables, and problems in forecasting future conditions all contribute to the scientific uncertainty of the SVR tree height model. However, there should be caution when using the model outside this region.

Keywords: Artificial neural network, Height–diameter models, Non-linear, Tree height

INTRODUCTION

Tree height and diameter at breast height (DBH) are the two key factors in tree growth models. Tree height, however, is more difficult to measure in the field than DBH. Both observer error and visual obstacles frequently have an impact on tree height measurement (Colbert *et al.,* 2002; Lei *et al.,* 2009). An allometric relationship exists between tree height and DBH, which is useful and widely employed in stand-level planning for effective monitoring and alternative silviculture strategies (Rojo *et al.,* 2005; Cutini *et al.,* 2013). As a result, DBH may be used to accurately measure tree height. For yield modeling, measuring above-ground biomass and carbon, and compiling forest inventories, accurate tree height prediction is crucial (Peng et al., 2004; Leduc *et al.,* 2009; Stankova *et al.,* 2013). Accurate tree height estimation is crucial for biomass estimation and sustainable forest management. It enables precise carbon stock estimation, aids in reducing climate change, and encourages the formation of well-informed judgments regarding techniques for managing forests, such as logging and regeneration.

The lack of data on tree height in tropical forests is caused by the challenge of measuring it in closed-canopy forests, including the associated time and cost requirements of the measurement (Larjavaara and Muller-Landau 2013). In carbon-accounting programmes, tree height is frequently overlooked due to the challenges in data acquisition (Hunter *et al.,* 2013), which could lead to increased bias. This tree height data acquisition problem can be solved by using height-diameter models (Chave *et al.,* 2014; Feldpausch *et al.,* 2012).

A nonlinear function is widely used to model the relationship between the height and diameter of trees.Different researchers have fitted height-diameter models using the least squares regression method (Chenge, 2021), Neural networks (Zçelik*et al.,* 2013; Thanh *et al.,* 2019), mixed-effect regression (Kalbi *et al.,* 2018; Corral Rivas *et al*., 2019; Vanderschaaf, 2020), quantile regression (Zhang, *et al.,* 2020), and reduced major axis regression (Chen, 2018). Ogana (2019) worked on Tree height prediction models for two forest reserves in Nigeria using mixed-effects approach. Ogana (2021) also modeled height-diameter relationships in complex tropical rain forest ecosystems using deep learning algorithm. However, there is not any published work that has been done on modeling H-D of trees in Tar-ukpe forest plantation in north-central Nigeria, using artificial intelligence models. Limited studies have carried out to facilitate the management of the forest for optimum growth and yield. This study aims to development a model for estimating the height of trees in the plantation. This holds great significance in environmental conservation and climate change mitigation by providing accurate estimations of forest structure and biomass. It enables efficient forest inventories, aids in sustainable forest management, and contributes to ecological studies and disaster risk management. Furthermore, this research advances artificial intelligence techniques and promotes the understanding and valuation of ecosystem services provided by forests.

MATERIALS AND METHODS

Study Area

The Tar-Ukpe forest plantation (between 7°21′25.2″ N, 7°21′50.4″ N and 9°2′30.8″ E, 9°3′7.2″ E, Fig. 1) is located in Yandev, Gboko Local Government Area of Benue State, North-Central Nigeria. The forest covers approximately about 35.3 hectares. The plantation is a mixed species stand of predominantly *Gmelina arborea*, *Daniellia oliverii*, and *Tectona grandis*, tree species. There are two distinct seasons in the study area's climate: the rainy season and the dry season. The rainy season lasts from April to October, and the dry season is from November to March. The Tar-Ukpe Forest plantation falls within the Guinea savannah ecological zone of Nigeria, which is characterized by mainly woodland with shrubs and grasses.

Data Collection

The systematic sampling method (Avery and Burkhart, 2002) was used to locate 21 sample plots of 0.09 ha in study area. A GIS software was used to overlay a systematic grid with 21 plot points spaced at regular intervals of 133.8 meters on the map of the forest plantation (Japheth *et al*., 2022). The plots' coordinates were taken out and entered into a global positioning system (Garmin GPSMAP 78) (Japheth and Meer, 2023). Using the GPS, the plots were then located in the forest, and each plot coordinates were retaken at the plot center and recorded. Measurements of DBH and tree height for all live trees in the sample plots, that had a stem diameter at breast height (DBH) equal to or greater than 10 cm, were taken; the Spiegel relaskop was used for measuring the tree heights.

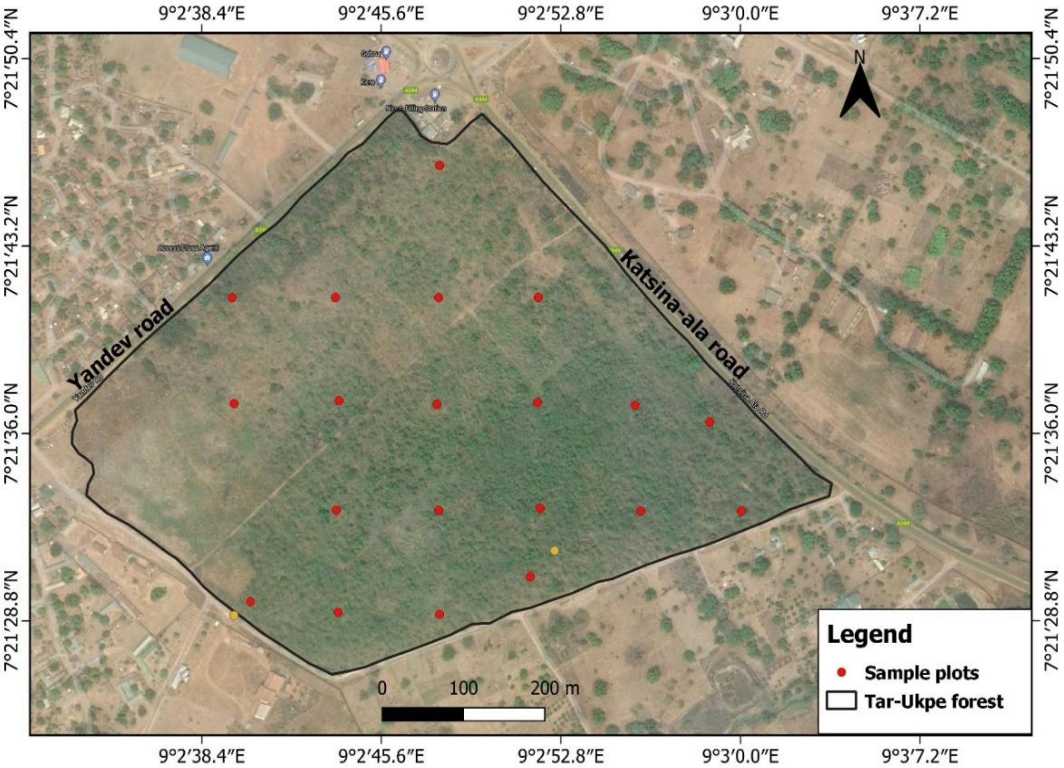


Figure 1: A map of Tar-Ukpe forest plantation Gboko LGA

Data Analysis

The data collected were partitioned into model fitting (80%) and model validation (20%) data sets. The nature of the relationship between the tree height and DBH variables was assessed using a scatter plot. The R program software (version 4.1.1) was used to analyze all the data. Four common nonlinear models (Table 1) including Power (Arabatzis and Burkhart, 1992), Chapman-Richards (Richards, 1959 and Chapman, 1961), Logistics (Zeide, 1993), and Weibull

(Zeide, 1993) models were fitted to the fitting data. The "nls function" in the R software was used tofit the models. The starting values for the model was determined using the “startHDpower, startHDrichards, startHDlogistic and startHDweibull” function of the “lmfor” package in R (Mehtatalo, 2020).

The machine learning algorithms Support Vector Regression (Samadianfard*et al.*, 2019) and Artificial Neural Network (Bayat*et al.*, 2020) were fitted to the fitting data using the "svm function" for SVM in the "e1071 package" (Meyer, 2021) and "neuralnet function" for ANN in the "neuralnet package" (Fritsch, 2019).

Table 1: A list of candidate height-diameter models

Model	Input	Equation	References
M. 1 (SVR)	*D*	$f(x) = \sum_{i=1}^{N}(\alpha_i^* - \alpha_i)K(x, x_i) + B$	Samadianfard*et al.*, 2019.
M. 2 (ANN)	*D*	$f(x) = \frac{w}{w + e^{-x}}$	Bayat*et al.*, 2020.
M. 3 (Power)	*D*	$H = 1.3 + aD^b$	Arabatzis and Burkhart, 1992.
M. 4 (Chapman-Richards)	*D*	$H = 1.3 + a(1 - \exp(-bD))^c$	Richards, 1959 and Chapman, 1961.
M. 5 (Logistics)	*D*	$H = 1.3 + \frac{a}{1 + b\exp(-cD))}$	Zeide, 1993.
M. 6 (Weibull)	*D*	$H = 1.3 + a(1 - \exp(-bD^c))$	Yang *et al.*, 1978 and Zeide, 1993.

SVR = Support Vector Regression, ANN = Artificial Neural Network, H = Height, D = Diameter at Breast Height (DBH), $f(x)$= activation function,$K(x, x_i)$= Kernel function for SVR,B = gamma, *exp* = Exponential, K = Cost,α = epsilon, w = start-weight, x = input information of neuron for ANN,$\alpha_i^*, \alpha_i \geq 0$ are Lagrange multipliers for SVR.

The models were evaluated using the Adjusted coefficient of determination (R^2_{adj}), Akaike information criterion (AIC), residual standard error (RSE) and mean bias (e).

$$R^2_{adj} = 1 - (1 - R^2) * (n - 1)/(n - K - 1) \qquad (1)$$

$$AIC = n\ln(\sum_{i=1}^{n}(y_i - \hat{y}_i)^2/n) + 2K \qquad (2)$$

$$RSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (3)$$

$$e = \sum_{i=1}^{n}(y_i - \hat{y}_i)/n \qquad (4)$$

Where R^2_{adj} *= Adjusted coefficient of determination, n = number of observations, K = number of parameters in the model, ln = the natural logarithm of a number,*y_i*= observed height, and* $\hat{y}_i$*= predicted height*

RESULTS

A total of 590 individual trees were sampled, which belong to 14 different tree species and 6 families (Table 2). *Gmelina arborea* (390), *Daniellia oliverii* (58), and *Tectona grandis* were the most abundant tree species in the forest plantation. A stand density of 312 trees per hectare was estimated. The DBH of all trees in the plantation ranged from 10.2 to 54.7 cm, and the height of all trees ranged from 4.0 to 20.5 m. The mean DBH and height values were 22.9 cm (± 6.6) and 11.2 m (± 4.2), respectively. DBH and height ranges of the fitting and validation data are presented in Table 3. The nature of the relationship between the sampled trees as visually examined using scatter plots is shown in Figure 2. A nonlinear relationship was observed, thus fitting non-linear models to the data was appropriate. The results of the parameter estimate of all the models are presented in Table 4, and the model evaluation statistics are presented in Table 5.

All parameter estimates for nonlinear functions were significant (p 0.05). $R^2_{adj}$and *RSE* values for the nonlinear models ranged from 0.821 to 0.923 and 1.149 to 1.78, respectively. The SVR and ANN models hadR^2_{adj} values of 0.94 and 0.924, and *RSE* values of 1.017 and 1.142 respectively. The Power (Model 3) showed the poorest fit with the lowest R^2_{adj} (0.821), highest *RSE* (1.78), and highest *AIC* (1889.557). The SVR (Model 1), ANN (Model 2), Chapman-Richards (Model 4), Logistics (Model 5), and Weibull (Model 6) had higher R^2_{adj} values and lower *RSE* as shown in Table 5. The nonlinear empirical model with the best fit statistics was the logistics (Model 5), while the machine learning model with the best fit statistics was the SVR model. Overall, the SVR model produced the best fitted statistics, followed by the ANN model. The curve fit for all tested models is displayed in Figure 3. The validation of all the models using the independent validation data also showed that SVR model produced the best prediction results.

The residual plots for the best nonlinear empirical model (Logistics) and the best machine learning model (SVR) were examined for outliers, lack of fit, and unequal variance. The two graphs (residuals scatter plots and quantiles of standard normal plot), as illustrated in Figure 4, depict approximately homogeneous variances of the residuals over the full range of predicted values, with zero mean, indicating that the assumptions of the regression analysis were met and that the height was well predicted across diameter. The normal probability plots also indicate no departures from the assumption of normality for errors within the models.

Table 2:Tree species Occurrence in the study area

Species	Family	Occurrence	Relative Frequency
Afzeliaafricana	Fabaceae	8	1.4
Anthocleistadjalonensis	Gentianaceae	17	2.9
Daniellaolivera	Fabaceae	58	9.8
Ficussur	Moraceae	1	0.2
Gmelinaarborea	Lamiaceae	390	66.1
Khayasenegalensis	Fabaceae	19	3.2
Lanneaschimperi	Anacardiaceae	9	1.5
Mangiferaindica	Anacardiaceae	1	0.2
Parkiabiglobosa	Fabaceae	2	0.3
Pterocarpuserinaceus	Fabaceae	9	1.5
Sarcocephaluslatifolius	Rubiaceae	2	0.3
Sennasiamea	Fabaceae	18	3.1
Tectonagrandis	Lamiaceae	46	7.8
Vitexdoniana	Fabaceae	10	1.7
Total		**590**	**100.0**

Table 3: Summary Statistics of Growth Variables in the Study Area

Descriptive Statistics	Diameter at Breast Height (cm)			Height (m)		
	Fitting	Validation	Total	Fitting	Validation	Total
Mean	22.81	23.46	22.94	11.1	11.4	11.16
Minimum	10.2	12.1	10.2	4	4	4
Maximum	55	50.9	54.7	20.5	19.3	20.5
Standard Deviation	6.53	7.09	6.64	4.15	4.29	6.64
Sample Size	472	118	590	472	118	590

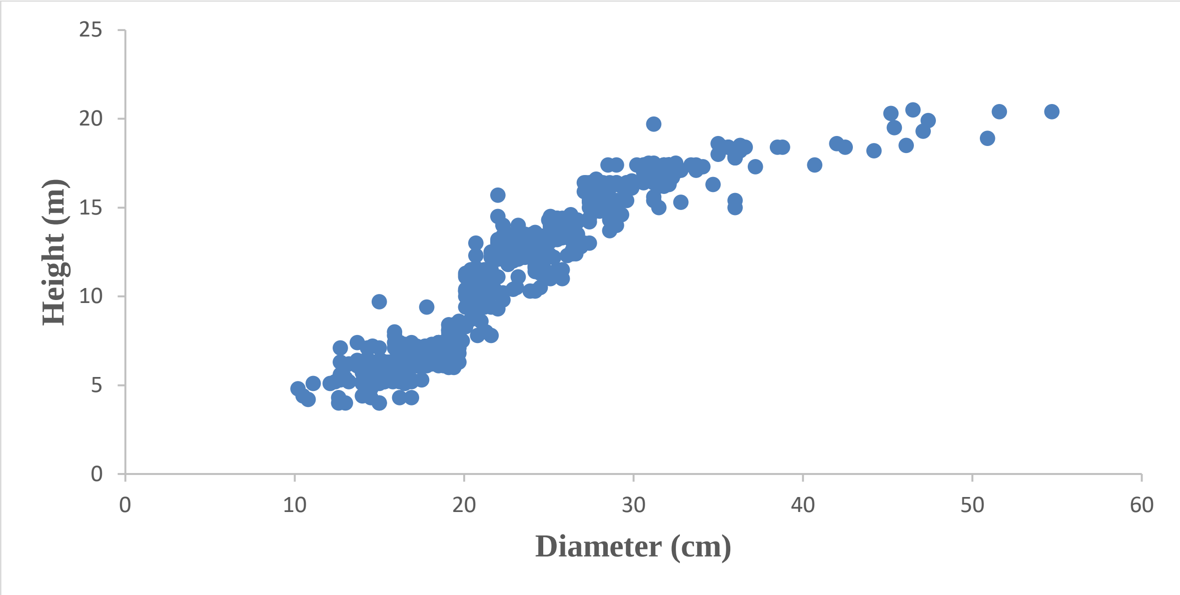


Figure 2: Scatter plot showing the relationship between Tree Height and Diameter

Table 4:Parameter estimates of Models developed in the Study Area

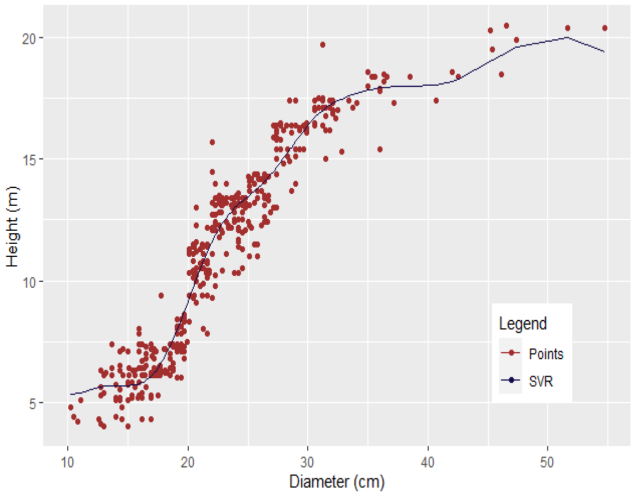
Model	**Parameters of Models**			
	w	**K**	**B**	$\boldsymbol{\alpha}$
Model 1 (SVR)	-	1	1	0.1
Model 2 (ANN)	1	-	-	-
	a	**b**	**c**	-
Model 3 (Power)	0.06	1.61	-	-
Model 4 (Chapman-Richards)	38.2	0.04	0.11	-
Model 5 (Logistics)	24.96	18.69	0.11	-
Model 6 (Weibull)	24.96	0	2.08	-

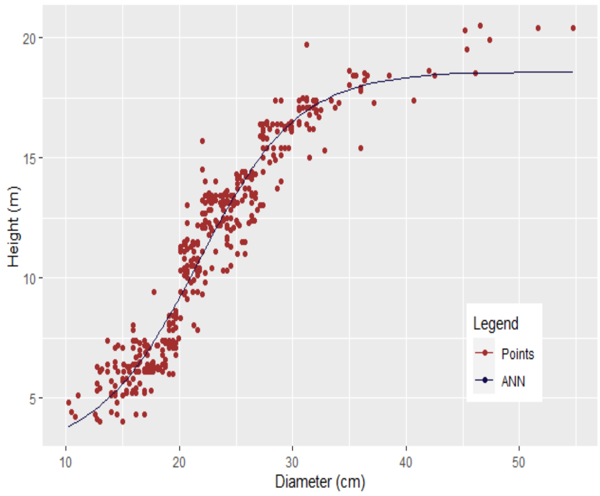
SVR = Support Vector Regression, ANN = Artificial Neural Network,B = gamma, K = Cost,α = epsilon, w = start-weight, a, b and c = Parameters.

Table 5: Statistics Evaluation for Models developed in the Study Area

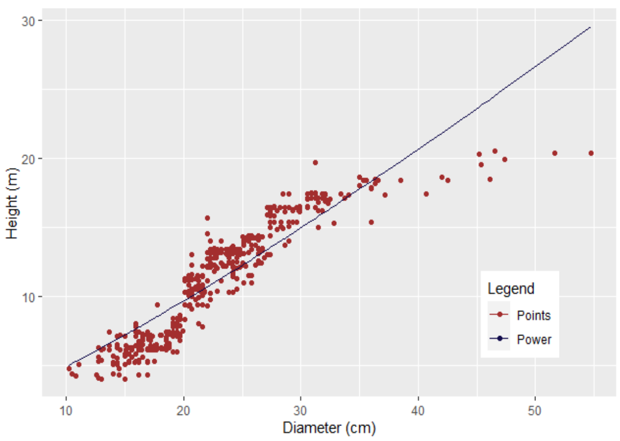
Model	**Fitting (80%)**				**Validation (20%)**	
	R^2_{adj}	***RSE***	***Bias***	***AIC***	***RSE***	***Bias***
M. 1 (SVR)	0.94	1.017	-0.005	-	0.979	-0.057
M. 2 (ANN)	0.924	1.142	0.000002	-	1.082	-0.065
M. 3 (Power)	0.821	1.780	-0.098	1889.557	1.896	-0.151
M. 4 (Chapman-Richards)	0.918	1.191	0.027	1512.424	1.219	-0.022
M. 5 (Logistics)	0.923	1.149	0.009	1478.6	1.118	-0.053
M. 6 (Weibull)	0.821	1.168	0.014	1494.326	1.153	-0.049

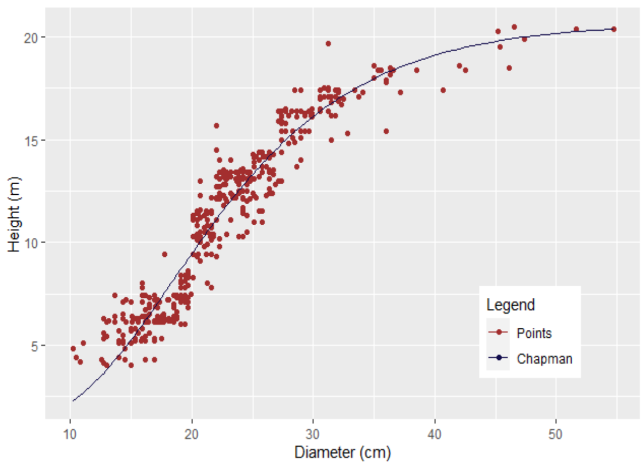
SVR = Support Vector Regression,ANN = Artificial Neural Network, R^2 = Coefficient of Determination,$RMSE$ = Root Mean Squared Error,AIC = Akaike's Information Criterion.



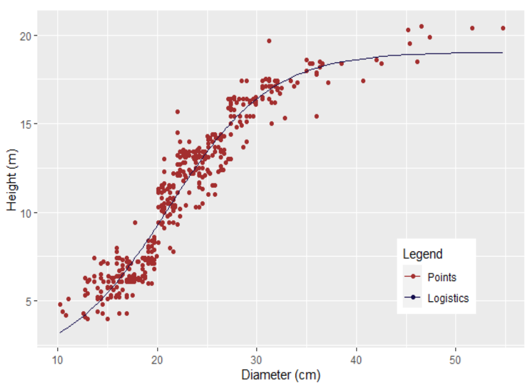


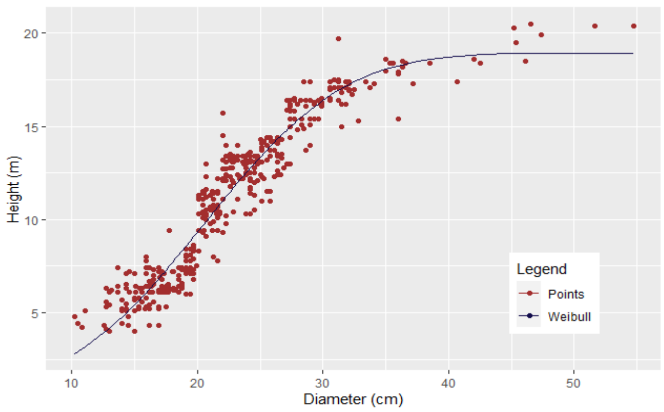
Model 1 (SVR) **Model 2 (ANN)**





Model 3 (Power) **Model 4 (Chapman-Richards)**





Model 5 (Logistics) **Model 6 (Weibull)**

Figure 3: Curve Fit for all the Tested Models in the Study Area

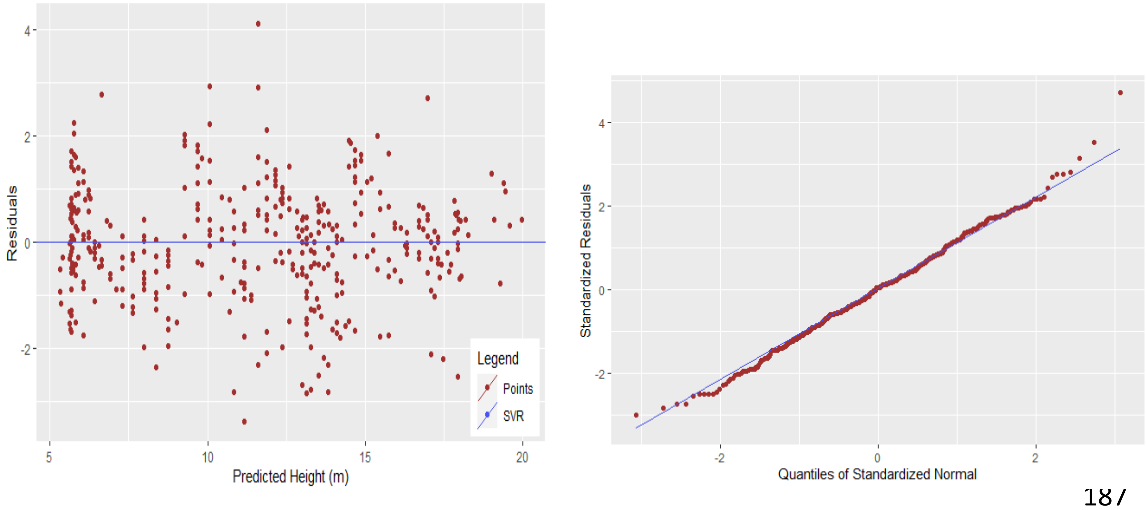


Figure 4: Residuals Scatter plots and Quantiles of Standard Normal Plot

DISCUSSION

Accurate tree height prediction is essential for the development of forest inventories, yield models, management decisions, and the carbon budget (Peng *et al.*, 2004; Leduc *et al.*, 2009; Stankova *et al.*, 2013). The three top-performing candidate models for height prediction, were model 1 (SVR), model 2 (ANN), and model 5 (Logistics) out of the six tested. The power model which have been shown to produce good results in some previous studies (Imani et al., 2017; Mensah et al., 2018; Chenge, 2021) produced the least results in this study.

Overall, the SVR model outperformed all other models tested for predicting the height of trees in the study area. The machine learning models (SVR and ANN) tested in this study outperformed all the other empirical nonlinear models. This indicates the potential of machine learning models for tree height-diameter modeling as also shown in several other studies (e.g. Diamantopoulou and Ozcelik, 2012; Bourque et al.,2019; Bayat *et al*., 2020; Diamantopoulou et al., 2023). Bayat *et al*. (2020) evaluated ten nonlinear functions and the machine learning algorithms ANN and ANFIS (Adaptive Neuro-Fuzzy Inference System) to fit height-diameter models in a mixed unevenly aged forest in Northern Iran, and found that the machine learning models produced the best results.Diamantopoulou and Ozçelik (2012) evaluated six nonlinear regression models and the generalized regression neural network (GRNN) technique to estimate tree heights in the western Mediterranean Region Forests of Turkey. The validation data of their models revealed that the GRNN model had both greater and lower error rates than all the tested nonlinear regression models. Diamantopoulou et al. (2023), also found the SVR model outperformed the GRNN model, nonlinear fixed and mixed effects model, and quantile regression model evaluated in their study. Lee *et al.* (2018) predicted the tree heights of forest stands in South Korea using three new machine learning techniques, including support vector regression (SVR), modified regression trees (RT), and a random forest (RF), and found that these three models were effective.

Each artificial intelligence and regression model used to forecast forest performance has advantages and disadvantages of its own. The vast range of statistical assumptions, such as the independence of the variables and the data's normal distribution, are just two of the many shortcomings of conventional regression models (Bayat *et al.,* 2020). The fact that artificial intelligence modeling techniques typically do not have the same limitations as empirical models is one advantage of adopting them (Lombardi *et al.,* 2017). For instance, some assumptions (such as data normality and others) may influence the quality of empirical models (Vieira *et al.*, 2013). Other advantages of artificial intelligence systems that are often widely recognized in predicting tree heights include the capacity to work with qualitative qualities as well as relative accuracy and precision (Vieira *et al.,* 2018). All of these are consistent with this research in demonstrating the superiority of neural network and artificial intelligence methods over regression models, despite variations in the types of neural network and vector power models utilized in our investigations or in the quantities and types of model inputs.

CONCLUSION

Accurate models that can predict crucial aspects of the forest, like tree diameters and heights, are necessary for forest management. The study concludes that in forest modelling, machine learning models have the potential to both supplement and replace empirical models (nonlinear functions). For the cases modelled here, the SVR model outperformed all empirical models (nonlinear functions) in estimating the tree height for the study area, supporting previous research on the topic and demonstrating that machine learning techniques can take the place of empirical models in projects requiring the estimation of forest conditions. The results in this study show the SVR model is more precise, flexible, and better able to model complex and nonlinear interfaces. However, a given diameter-height model may not always be suitable for all types of settings where a particular tree species may be found because site factors might influence the diameter-height connection.

Declaration of Competing Interest

The authors guarantee that none of their financial or close personal relationships that are known to them appear to have impacted the research provided in this paper.

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