

Modelling crown diameter for *Sal* trees (*Shorea robusta* Gaertn. f.) with an artificial neural network

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Summary

In recent years, Machine Learning algorithms have been frequently used in forest sciences to build Classification and Regression models. Such algorithms are known for their ability to explore complex relationships between the target variable and multiple predictors with minimum tuning and high accuracy. In this article, an Artificial Neural Network (ANN) was used to develop a Crown Diameter (CD) model for *Sal* trees based on four predictors, viz., Diameter, Height, Basal Area (BA) and Height-to-Diameter ratio (HDR). Trees were growing naturally in the Ranibagh forest area located at the foothills of the Kumaun Himalaya. Results indicated a good model fit ($R^2_{adj.} = 0.79$), i.e., the model explained 79% of the variation in crown diameter based on four predictors. The Pearson Correlation coefficient (r) value between actual and predicted CD came out to be 0.89 ($p < 0.001$). The residual plots also indicated homoscedasticity. Mean Absolute Percentage Error (MAPE) for the model came out to be 13.26%. HDR was found to be the most influential predictor for the model, followed by tree height, diameter, and Basal Area. One-way Partial Dependence Plot (PDP) demonstrated that diameter, height and BA had a positive impact on CD. In addition, for HDR, the CD-curve increased up to a certain point with an increase in HDR value and then decreased sharply. Two- way PDP further suggested that HDR in combination with Diameter and BA had a negative influence on crown diameter growth, i.e., HDR had masked the positive effect of diameter and BA on CD. The overall model suggested the competitive nature of *Sal* trees within a forest stand.

JAE 2026, Vol 22

Received: 10 February 2026

Accepted: 15 April 2026

Published: 10 May 2026

<https://doi.org/10.58628/JAE-2622-102>

Associated Editor: Dr. AK Verma

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Keywords: Machine Learning, Artificial Neural Network, Crown diameter model, *Sal* trees

Introduction

With the increasing demand for forest biomass and yield estimation, the importance of individual tree modelling has become increasingly prominent. The tree crown profile, as a key variable reflecting individual tree growth characteristic (Wang et al. 2022), not only represents the vitality and competitiveness of trees but also serves as a crucial indicator for assessing tree health and competitive status. Tree crown plays a vital role in processes such as photosynthesis, energy capture and resource utilization (Plaga et al. 2024; Jucker et al. 2025) and directly influences various aspects such as forest dynamics simulations, stand productivity assessments and biodiversity conservation (Harris et al., 2021). However, due to the time-consuming and labour-intensive nature of manual crown measurements, and the practical limitations of measuring the crown of every tree in field operations, there is an urgent need to develop high-precision crown profile models.

A tree crown diameter is fundamentally linked to and widely used in crown profile models (Deng et al. 2025). Such models often use crown diameter (or crown radius) as a key parameter, either as a predictor

variable or as a target variable being estimated at various heights within the crown. In essence, crown diameter provides a crucial horizontal dimension that, when combined with vertical measurements (like tree height and height to crown base), allows for the mathematical representation and prediction of the entire 3D crown profile. The crown diameter is commonly used to study morphometric characteristics of trees. The variable indicates the species growth stage, vigor, stand density and production efficiency (Sharma et al. 2017). It is also used in growth modelling (Fu et al. 2017), besides being used to predict biomass (Goodman et al. 2014; Lau et al. 2019), and volume (Ozcelik et al. 2014).

The ecological services of trees depend on their ability to capture and utilize sunlight (Savo et al. 2025). The crown shape and the consequential spatial display of leaves directly affect light capture, reproduction, water transport, wind resistance, mechanical support and eventually the competitive advantage of trees (Alves et al. 2002). Tropical forest characteristically displays strong vertical light gradients (Matsuo et al. 2021). As light interception is one of the major factors controlling total carbon assimilation and growth of trees (Tang et al. 2015), differences in light availability along the understory canopy gradient of a tropical forest may originate several strategies in space occupation and resource allocation to photosynthetic

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area among tree species that differ in their maximum size attained (Arguedas et al. 2010; Souza et al. 2021).

Data on trunk allometry are generally used to analyze which crown shape (horizontal and vertical dimensions) would minimize the cost of supporting a given crown size (area, weight, mass) at a given height (Pretzsch et al. 2015). Allometric patterns observed in tropical trees have been related to different light conditions found in the forest, resulting in contrasting growth strategies and allocation patterns to crown and trunk dimensions (Mankou et al. 2021). It has been suggested that within a given stand of a natural forest, there is a dichotomy between species invest in height growth to exploit better conditions in future and those that expand the crown to survive under shaded conditions (Yamakawa et al. 2023). In general, the allometry of trunk diameter and height in larger statured species conforms to elastic similarity or constant stress models (Silva et al. 2015).

In recent years, machine learning (ML) has witnessed increased applications in various sciences, including forestry. Besides the decision-tree learning and sum, the commonly used method is the artificial neural network (Skudnik & Jevsenak 2022). Such algorithms can acquire and maintain information-based knowledge and can be defined as a set of processing units, represented by artificial neurons, interlinked by a multitude of interconnections (artificial synapses) implemented by vectors and matrices of synaptic weights (Taherdoost 2023). The Artificial Neural Network (ANN) models can be applied to various kind of problems, from classification, clustering and optimization to function approximation, and has already been applied in various forestry disciplines, such as forest fire prediction (Safi & Bouroumi 2013; Kantarcioglu et al. 2023; Kumar et al. 2025); prediction of insect outbreaks (Chon et al. 2000; Lee et al. 2016; Anarbekova et al. 2024) and Species distribution models (Scrinzi et al. 2007; Bellin et al. 2022). Apart from these, the ANN regression has been tested to establish Height-Diameter models for *Eucalyptus* trees (Vieira et al., 2018); common beech (Martinez et al. 2013); Crimean Juniper (Ozcelik et al. 2013); Durango Pine (Ou et al. 2023) and Himalayan Pine (Jeelani et al. 2023) etc. Moreover, ANN is also applied to model growth of *Eucalyptus* individuals (Castro et al. 2013); tree survival and mortality (Reis et al. 2018; Bayat et al. 2019); volume of *Cryptomeria japonica* individuals (Sanquetta et al. 2017) and *Pinus patula* - *Pinus pseudostrobus* community forest (Gracia 2025); diameter distribution of oak forest (Long et al. 2021) and stem taper (Sakici et al. 2018; Sandoval & Acuna 2022; Seki 2023). The application of ANNs for tree crown diameter modelling introduces significant novelty to forest science by overcoming the limitations of traditional linear and nonlinear least-squares models. The uniqueness lies in the ability of ANNs to map complex, nonlinear and often heterogeneous relationships between tree characteristic without requiring a predefined functional form.

While Machine Learning has been extensively applied in forestry for biomass estimation, species classification, constructing H-D models and other related aspects, there is a recognized gap in developing of a robust, high- accuracy, ML- based CD- model for *Sal* trees. The present investigation thus focuses on modelling crown diameter for *Sal* trees growing naturally at Ranibagh forest area located in the Bhabhar region of central Kumaun foothills using predictors viz. Tree Diameter, Height, Basal Area and Height-to-Diameter ratio. Crown Diameter model was built for *Sal* trees (a semi- deciduous and ecologically resilient tree species) as it has maximum dominance in this area. Moreover, CD - models has significant practical applications in the field of forestry. It improves the accuracy of biomass estimations, optimizes forest management through better density control and provides key indicators for ecological monitoring and climate change research. Crown diameter is therefore a critical parameter reflecting tree growth, health, light competition and photosynthetic capacity, making it a valuable input for biomass estimation models. Supervised Machine Learning algorithm viz. Artificial Neural Network was applied to train the model for the simple reason that it is a non- parametric approach which do not make any assumptions about the data's underlying distribution, allowing it to fit a wide range of complex patterns. Modelling results are being interpreted and discussed in the present manuscript.

Material and Method

Site Details

Data was collected from the Central- Himalayan sub - tropical *Sal* forest, which lies in Bhabhar belt of District Nainital in the state of Uttarakhand. The site was located in Ranibagh (29°17'10.03" N and 79°32'49.19"E) and was situated at an elevation of 580 m above sea level. The site exhibited dominance of *Sal* and was managed by the Forest Department. It was a relatively mature forest with a stem density ranging between 620 and 810 individuals per hectare, indicating fairly good competition. Other species that co-existed with *Sal* were: *Syzygium cumini*, *Cassia fistula*, *Terminalia chebula*, *Mallotus philippensis*, *Ficus hispida*, *Grewia optiva*, *Holarrhena pubescens*, to name a few.

Pedologically, clay loam or loamy soil texture was reported from the site with slightly acidic to slightly basic soil. Climatically, the study site lies within the sub-tropical zone with pronounced dry summer, cold winter and humid monsoon. The mean minimum temperature ranged between 9°C (January) and 23°C (August) and the mean maximum temperature was between 21°C (January) and 38°C (June). Annual rainfall ranged between 0 mm (October) and 577.6 mm (July).

Data collection and tree measurement

About 180 *Sal* trees were measured to develop the crown diameter model. Tree attributes used to train the model were: Diameter, Height, Basal Area, Height-to-Diameter Ratio and Crown Diameter. All trees of different sizes and ages, having a wide DBH range (Table 1), were measured. Individuals with ≥ 5 cm DBH

were considered as trees and measured (MacDicken 1997). Initially, the circumference at breast height (cbh) was measured at 1.37 m from the ground using a measuring tape. All CBH values were later converted to corresponding DBH values by dividing CBH by π (3.14). Tree Height was measured using a Clinometer. CD was measured using a measuring tape. It was measured in two directions (North- South and East-West) and an average was calculated (Chaturvedi and Khanna, 1982). Basal Area tree⁻¹ was calculated using the formula $BA (m^2) = \pi(D/2)^2$, where D is the tree diameter in meters and π is 3.14 and eventually, tree height was divided by diameter to get the height-to-diameter ratio (dimensionless).

Table 1. Statistical description of tree variables ($\pm$ SD)

Description	Mean	Minimu m	Maximu m
CD (m)	8.98 $\pm$ 2.91	3.33	15.81
Diameter (m)	0.31 $\pm$ 0.14	0.1	0.65
Height (m)	18.31 $\pm$ 6.36	5.21	31.2
BA (m ² tree ⁻¹)	0.09 $\pm$ 0.07	0.01	0.34
HDR (dimensionless)	62.74 $\pm$ 19.88	25.31	130.65

Brief description of Artificial Neural Network (ANN)

ANN is a powerful machine learning (ML) algorithm used to develop Classification and Regression models by mimicking the brain, using layers of interconnected neurons that learn complex patterns through backpropagation to adjust weights, excelling in non-linear tasks like forecasting and image recognition, often outperforming traditional methods for intricate data by learning features directly. ANN models aim to simulate the human nervous system. Their interconnected structure of artificial neurons can receive signals from input data, process them and send an output signal (Zhang 2018). It has been frequently used to model complex, nonlinear interactions in natural real - world systems.

Backpropagation is the fundamental algorithm used to train a neural network by calculating the gradients of the loss function with respect to the network weights (Wright et al. 2022). It is the mechanism by which the network learns from its errors and update its weights accordingly. In addition, hyperparameter tuning is also a critical aspect of a neural network. The weight decay, also known as L2 regularisation, is a regularisation technique used to prevent model overfitting (Laarhoven 2017; Salehin & Kang 2023). In our case, we used the *train ()* function from the caret package in R to train the neural network model. The model simulated a single hidden layer with a wide range of sizes (number of neurons) and weight decay values.

Packages used in R for model training and testing

Statistical analysis and model training was all implemented in R, version 4.4.3 (R Development Core Team, 2025). The *Caret ()* package was used for data splitting, range scaling of target variable (CD) and predictors, hyperparameter tuning and training the neural network model. Package *PerformanceAnalytics ()*, *NeuralNetTools ()* and *pdp ()* were used for model visualization.

Modelling Approach

Data Pre-Processing

The data obtained from the measurement of 180 individuals was used to train (and test) artificial neural network. Entire data was initially reshuffled (resampled) using the *runif ()* function in base R. Next, data was split into training (70%) and testing (30%) sets applying the *createDataPartition ()* function from caret package. This was followed by defining a scaling and inverse scaling function. Next, range scaling was performed on both target and predictor variables using *preprocess ()* function from caret package. Hyperparameter tuning is an essential part of training a neural network which was performed using *trainControl ()* and *tuneGrid ()* functions, *trainControl ()* was set to 10- folds cross-validation and the *tuneGrid ()* was simulated using a wide range of size (number of neurons in a single hidden layer) and weight decay values viz. size = c(1,3,5,7,9,11), decay = c(0.00001,0.0001,0.001,0.01,0.1,0.3). The stopping criteria (Absolute Tolerance) for the model was kept at 0.01. There was no need to set the learning rate while training the model using caret's *train ()* function as caret automatically handles the learning rate for the "nnet" method by setting a default and tuning the decay parameter.

Model training and testing

Eventually, model was trained using *train ()* function from caret package, with maximum number of iterations for backpropagation equals to 1000 and method selected was "nnet". Eventually, applied *predict ()* function to predict crown diameter values from the test set.

Model Evaluation

After training the neural network, model was evaluated using the criteria: R^2_{adj} (Liu et al. 2017), MSE (Huang et al. 2022), RMSE (Huang et al. 2022) and MAPE (Myttenaere et al. 2015). Moreover, plots of predicted values against residuals were also created to check whether residuals (errors) are random (homoscedasticity) or follows a particular pattern (heteroscedasticity).

Results and Discussion

Crown Diameter for Sal trees were modelled using four predictors viz. Diameter, Height, Basal Area and Height-to-Diameter ratio. The neural network model indicated a good-fit ($R^2_{adj} = 0.79$) with MSE, RMSE and MAPE values of 1.72, 1.31 and 13.26% respectively. Moreover, the Pearson correlation coefficient (*r*) between actual and predicted crown diameter was found to be 0.89 ($p < 0.001$) (Figure 1a). Plots between predicted crown diameter and residuals suggested no signs of heteroscedasticity i.e., residuals were randomly scattered with no bias (Figure 1b). Before training the CD- model, hyperparameters were tuned using *tuneControl* and *tuneGrid* options.

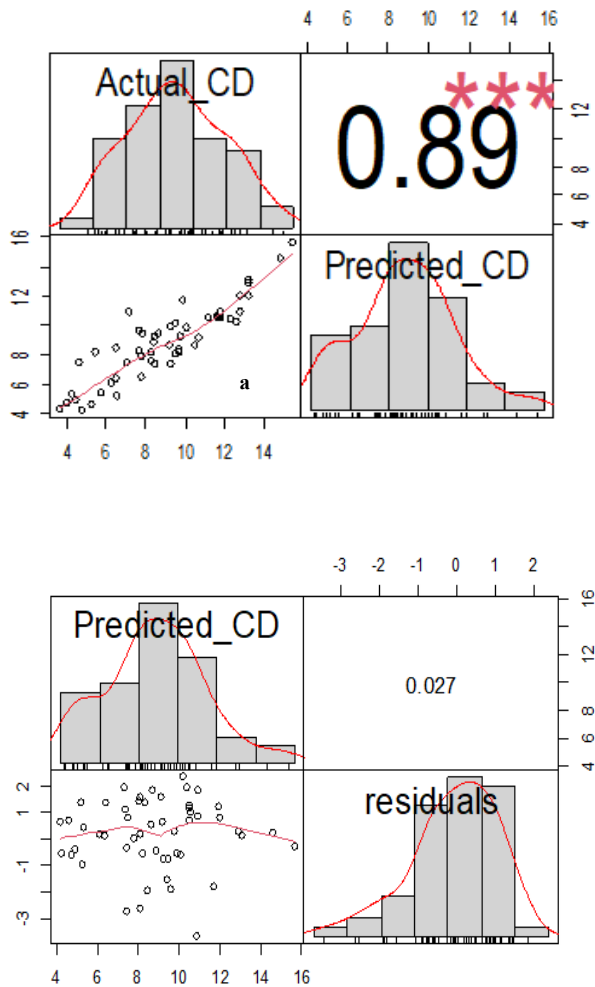


Figure 1. Plot between (a) Actual Vs Predicted CD and (b) Predicted CD Vs Residuals

Figure 2 (a) demonstrated a range of weight decay values against RMSE. RMSE was used to select the optimal model using smallest value (L2 regularization). The final values used for the model were size = 3 and decay = $1e-04$. In addition, variable importance plots (Figure 2b) suggested that HDR was the most influential predictor in the model followed by height, diameter and basal area.

Figure 3 depicted the weights and biases of the neural network model. The input layer consisted of 4 neurons; the single hidden layer consisted of 3 neurons, and finally a single output layer with a single neuron. The line thickness suggested degree of association between two neurons. Dark, thick lines indicated greater weight (stronger association) between neurons, and vice versa. B1 and B2 represented the biases in the model. One-way Partial Dependence plots suggested that diameter, basal area and tree height had a positive influence on the growth of CD (Figure 4 a-c) but HDR had a slightly peculiar curve. The CD increased with the increase of HDR up to a certain point and after that the CD decreased sharply (Figure 4d).

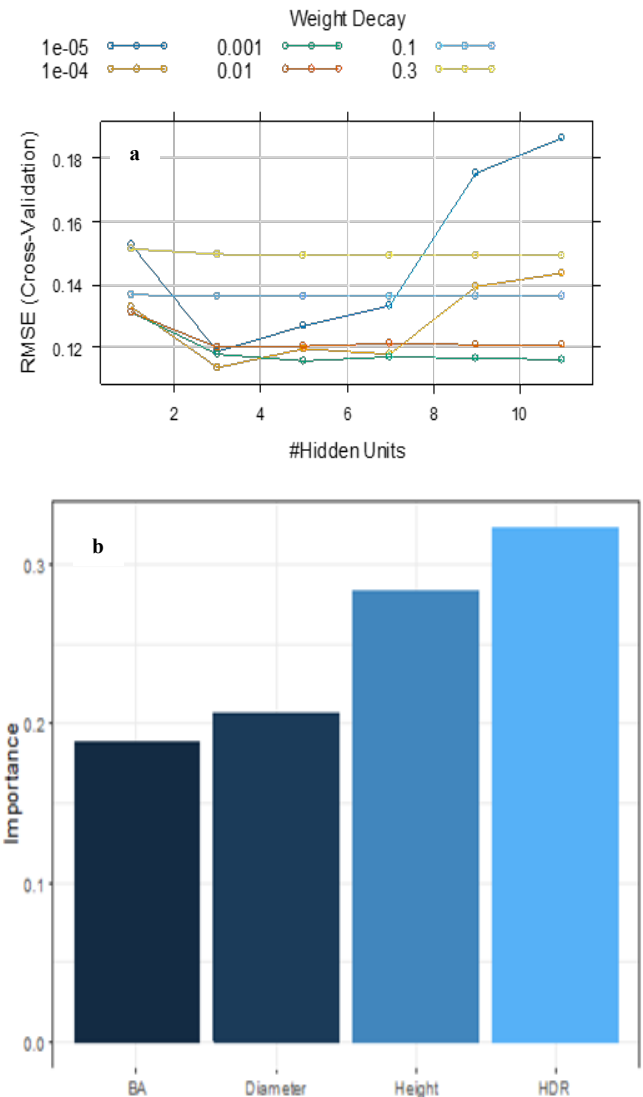


Figure 2. (a) Plot between RMSE and weight decay; 2(b) Variable Importance plot for the CD model representing various predictors and their relative contribution

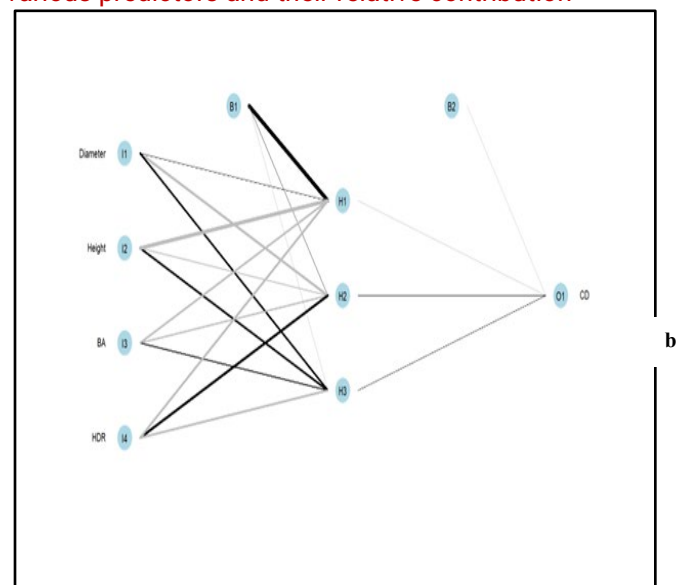


Figure 3. Artificial Neural Network (CD-model) showing weights and biases

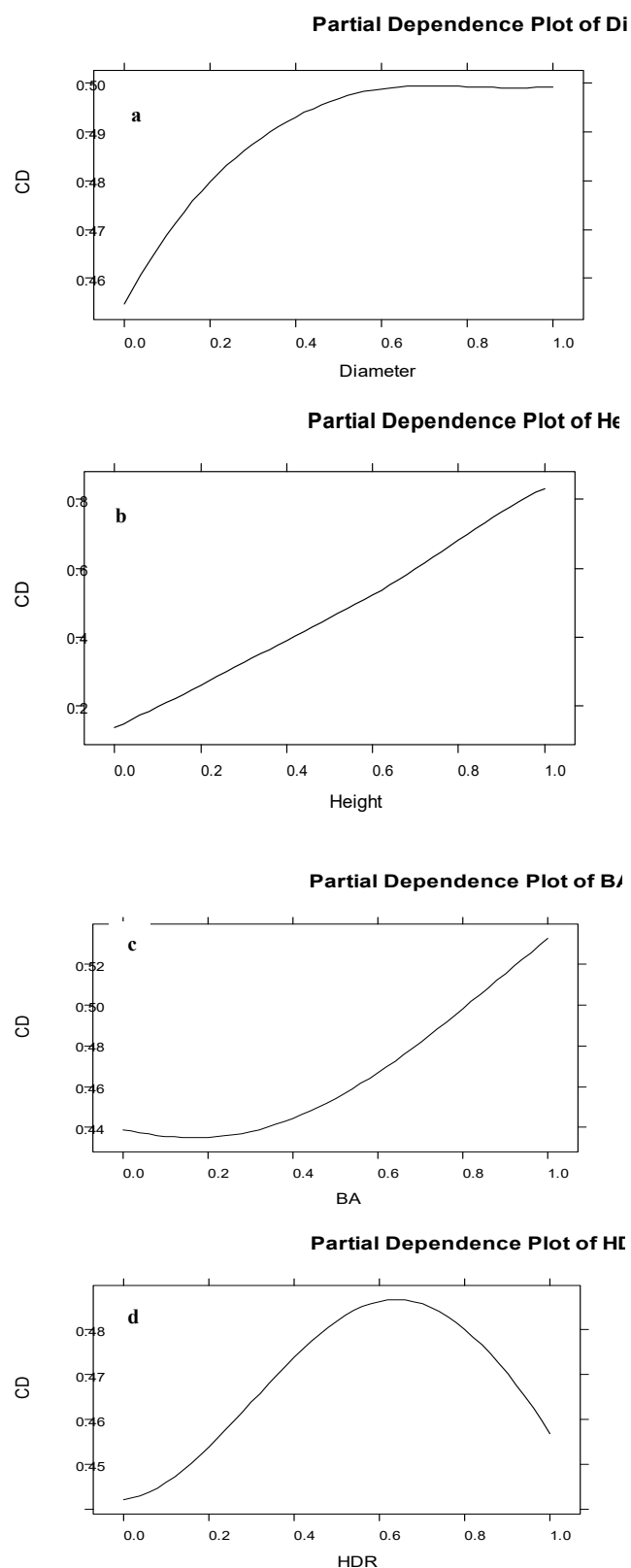


Figure 4 (a-d). One- way partial dependence plots between crown diameter and predictors

When Diameter and BA were used as a single predictor, the relationship between these two variables with CD was strong and positive but two- way PDP (Figure 5 c and e) demonstrated that when combined effect of the two predictors viz. DBH $\times$ HDR and BA $\times$ HDR on CD was investigated, it suggested a strong negative trend, i.e. HDR had masked or nullified the positive influence of DBH and BA on CD.

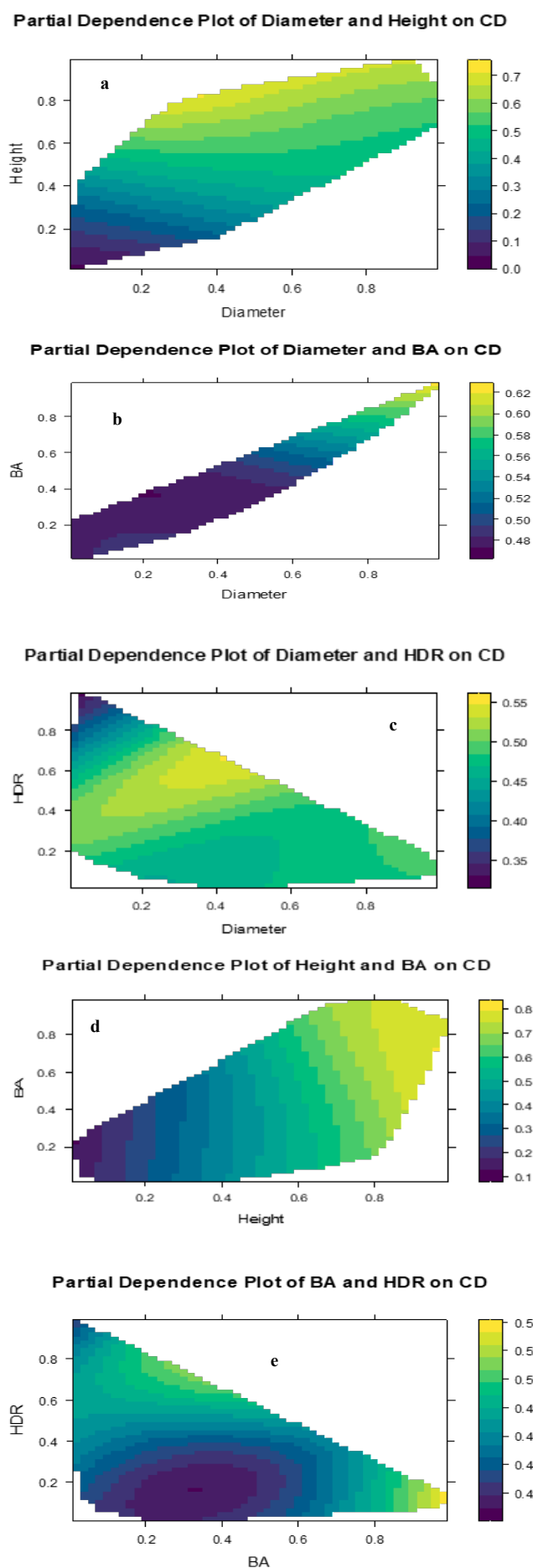


Figure 5 (a-e). Two-way partial dependence plots between crown diameter and combined predictors

In addition, two – way PDP further suggested that both *Diameter and Height* increment had a positive influence on CD (Figure 5a). Similarly, the combination between *Diameter × BA* and *Height × BA* too had a positive influence on CD growth (Figure 5b and d).

The findings that HDR is the most influential predictor for the *CD- model* followed by tree Height, DBH and BA is consistent with the complex inter- relationships of tree growth variables and highlight the utility of neural network models in capturing the non- linear relationships. The fact that, HDR a composite variable, is the most important, suggested that the relationship between height and diameter is a primary driver of crown size for the given data range, even more so than

the raw measurements of tree height and dbh individually. This indicated that the model had successfully identified a key biological or structural relationship. The neural network model suggested that in dense stands tree's slenderness or stockiness is the strongest indicator of its crown diameter (Rudnicki *et al.*, 2004; Pretzsch *et al.*, 2015; Ezenweny and Chukwu, 2017; Ahmed *et al.*, 2025). Trees with similar dbh and height might have different crown sizes based on their specific proportions. Similar pattern was also observed in *Sal* dominated forest site at Ranibagh where crown diameter growth was found out to be significantly impacted by stand competition and HDR.

Table 2. Resampling results across tuning parameters

Size	Decay	RMSE	R-squared	MAE
1	1.00E-05	0.15258	0.594924	0.126835
1	1.00E-04	0.132911	0.698358	0.106115
1	1.00E-03	0.131187	0.70687	0.104806
1	1.00E-02	0.131523	0.709044	0.105658
1	1.00E-01	0.136998	0.703861	0.108983
1	3.00E-01	0.151306	0.677942	0.120568
3	1.00E-05	0.118863	0.740662	0.094814
3	1.00E-04	0.113802	0.752973	0.089083
3	1.00E-03	0.118082	0.765548	0.093516
3	1.00E-02	0.120336	0.745084	0.095296
3	1.00E-01	0.136352	0.704166	0.108462
3	3.00E-01	0.149558	0.67622	0.119494
5	1.00E-05	0.126938	0.713732	0.101257
5	1.00E-04	0.119839	0.755362	0.093372
5	1.00E-03	0.115986	0.784548	0.089545
5	1.00E-02	0.120688	0.743649	0.095711
5	1.00E-01	0.136667	0.702132	0.108818
5	3.00E-01	0.149439	0.674782	0.119577
7	1.00E-05	0.133451	0.698296	0.10824
7	1.00E-04	0.118026	0.7535	0.096373
7	1.00E-03	0.117288	0.776523	0.091093
7	1.00E-02	0.12151	0.739023	0.096703
7	1.00E-01	0.136653	0.701623	0.108882
7	3.00E-01	0.149379	0.673881	0.119623
9	1.00E-05	0.175607	0.675097	0.126184
9	1.00E-04	0.139496	0.683016	0.112129
9	1.00E-03	0.116791	0.779375	0.090357
9	1.00E-02	0.12091	0.742335	0.095826
9	1.00E-01	0.136675	0.701334	0.108923
9	3.00E-01	0.149326	0.673663	0.119619
11	1.00E-05	0.186696	0.563765	0.136503
11	1.00E-04	0.143655	0.636471	0.113571
11	1.00E-03	0.116394	0.780644	0.090092
11	1.00E-02	0.120882	0.742547	0.095783
11	1.00E-01	0.136683	0.701164	0.108945
11	3.00E-01	0.149301	0.673148	0.119652

*RMSE was used to select the optimal model using the smallest value. The final values used for the model were size = 3 and decay = 1e-04

Further, the model illustrated that Height and DBH (standard biometric measures) are significant but less critical than their ratios. Height is more important than DBH, suggesting that vertical growth of *Sal* trees had a

slightly stronger influence on crown size than girth in the context of this specific model. In addition, BA was found to be the least important predictor. BA is a measure of tree's cross-sectional area of the stem and is highly correlated with dbh (Omijeh 2021; Sumnall *et al.* 2025). The model had likely captured most of the information related to tree size through DBH and

Height, leaving little unique variance for BA to explain. For *Sal*-forest, the prominence of HDR suggested that simply using traditional measures like DBH and Height is insufficient for accurately modelling CD and the relationship between height and diameter is a crucial factor (Opio et al. 2000; Sporek & Sporek 2023).

As far as importance of HDR is concerned, it is an indicator of competitive assessment of trees. HDR is often used as an indicator of stand density and competition. Trees in dense stands tends to be taller for their diameter (higher HDR) and often have smaller crowns (Vospernik et al. 2010; Kang et al. 2021). The model supported this argument using this ratio to understand how competition affects crown development. Tree height and dbh were found to be the next most important predictors. These are standard measure of tree size, and their high importance makes intuitive sense, i.e., larger trees generally have larger crowns. The model used three fundamental measurements to refine its predictions after accounting for the primary HDR factor.

The neural network demonstrated that HDR is intrinsically linked to crown size, as taller trees relative to their dbh, often have narrow crowns, while shorter trees (lower HDR) can support broader crowns, impacting forest models, biomass estimates and competitive dynamics. Their relationships indicated that as dbh increases, the HDR generally decreases, indicating better growth, but the crown expansion slows relative to dbh as tree matures. A higher HDR (tall trees), often signifies a tree struggling for light in a dense stand, leading to slower growth and smaller crowns relative to its height.

In dense forest, crown expansion is slow as trees compete for light. As trees grow larger (increased diameter), crown expansion slows down, while diameter growth continues as more resources go to maintain and support. When trees achieve dominance, their crown expansion accelerates relative to early growth, leading to wider crowns, but eventually, crown growth plateaus while diameter keeps increasing. In essence, a tree's form (HDR) continuously changes as the tree grows, reflecting tree's competitive environment, which directly influence how large its crown can expand relative to its trunk diameter (Wang et al. 2024). Thus, forest modelling requires accurate *Height – Diameter* and *Crown Diameter – Stem Diameter* models which are crucial for estimating forest biomass, carbon stocks and atmospheric interactions. Overall, the neural network model emphasized the geometric proportions of *Sal* trees (HDR), as the primary driver of CD, followed by tree's absolute size dimensions (height and diameter) and finally, a more general stand characteristic (BA). This suggested that the model had captured specific allometric relationships within the data.

Both one way and two- way PDPs were built to visualize the marginal effect of predictors on predicted CD, averaging all other variables in the model. One- way PDP between DBH and CD indicated a non- linear saturating relationship between the two variables. It is a common relationship and biologically sound finding in

forestry and ecological studies (Nguyen & Katabuchi 2025). When trees are young, both stem diameter and crown grows rapidly and in correlation to capture light and resources. The PDP- curve initially displayed a steep positive slope, indicating that an increase in diameter is associated with a proportional increase in CD. As the tree matures and its diameter continues to increase, the CD growth rate slows down and eventually levels off (Figure 4a). This resulted in flattening of *pdp*-curve, resembling a power- sigmoid function or a log-curve. The flattening of CD curve at larger diameter values could be due to physical constraints, resource competition, physiological limits and senescence (Mencuccini et al. 2005). Thus, the PDP - interaction between diameter and CD illustrated the relationship between the two variables is dynamic. Crown growth is strongly linked to stem growth initially, but other factor becomes dominant as the tree reaches maturity, leading to a maximum average CD, regardless of further increase in trunk diameter.

One-way PDP also indicated that as tree height increases, the CD also increases. This positive correlation is a well- established allometric relationship in forestry (Paula et al. 2001; Stoffberg et al. 2008), indicating that taller trees tend to have wider crowns to support their larger biomass and capture more sunlight (resource allocation). Moreover, with the increase of BA, the CD also increased. In forestry, a strong allometric relationship exists between a tree's stem diameter (denoting BA) and its crown dimensions, including CD and Crown Projection Area (Asigbaase et al. 2023; Bhebhe et al. 2025). A large crown generally indicated a greater capacity for photosynthesis and light interception, which in turn support a large stem diameter (BA) to transport water and nutrients and also provide mechanical support (Bartkiewicz et al. 2025). This relationship can be influenced by competition. In dense stands, with high BA, individual trees may have smaller crown widths for a given diameter, compared to open- grown trees due to competition for light. However, the general trend in a stand is that larger trees (larger BA) have larger crowns.

The relationship between HDR and CD was found to be nonlinear and non – monotonic, which is a common finding in forestry models. The initial slope of the *pdp* indicated that up to a certain threshold, as the HDR (slenderness) increases, the CD also tends to increase on average. This might occur in stands with low competition, where trees grow both in height and width. The curve reached a peak, suggesting that there is an optimal HDR for maximizing CD under the conditions represented in model training data. The subsequent sharp decrease is the most crucial feature. This suggested that beyond a certain HDR (i.e. when trees become very slender), the CD rapidly decreases. This could be interpreted that in dense forest stands trees compete heavily for sunlight. They allocate more resources to grow taller quickly (increasing HDR) while shedding lower branches (natural pruning), resulting into a smaller, narrower crown (decreased CD). Very tall and slender trees may perhaps be experiencing resource limitations (e.g. water and nutrients) or

structural stress, which limits their ability to maintain a large, wide spreading crown.

In addition, a two- way PDP visualized the average predicted CD as a function of various combinations of predictors used in the model. *Diameter and Height*, *Diameter and BA* and *Height and BA* had a positive influence on the growth of CD. The contour lines connected areas with the same average predicted CD value. The fill colors indicated the magnitude of the predicted values. Lighter and higher- valued contours represented larger CDs. Moreover, the presence of changing or non- parallel contour lines indicated an interaction between the combined predictors in predicting CD (Figure 5). When HDR was combined with tree diameter and BA, the CD displayed a negative trend. This trend could be the result of interspecific competition dynamics in the forest stand. A negative relationship between DBH and HDR, as conditioned on CD, makes a sense in a biological context. This indicated that for a given CD, trees with larger DBH tend to have a lower HDR i.e. a more stable and robust tree. Since, HDR (h/d) is a key indicator of tree's slenderness and a strong proxy for competition levels, it is frequently applied to study forest dynamics. Trees in dense stands compete strongly for light while they grow (increasing height and thus HDR), their lateral crown expansion is suppressed by neighboring trees. Therefore, for a given diameter or BA trees with higher HDR tend to have smaller, more vertical oriented crowns, leading to the observed negative relationship in a two- way PDP interaction plot. The effect of BA and DBH on CD is conditional on the level of competition indicated by HDR. ANN- based models for predicting CD offers a superior, non – parametric alternative to traditional regression methods, significantly improving the precision of forest biomass estimation, carbon stock assessments and management strategies. Thus, AI – driven models handle complex, nonlinear relationships between tree attributes leading to more accurate results and should be frequently used to study tree allometry and forest dynamics.

Conclusion

The highlight of this piece of work is developing a *CD-model* for Sal trees using ANN. Such models are capable to learn complex interactions between different tree variables with high accuracy and minimum tuning. In the present investigation, HDR was found to be the most influential predictor, even though height, diameter and BA were more fundamental and direct tree measurements. HDR is an indicator of competition intensity for light and low ratios representing better-developed trees in open stand. Higher HDR (tall and thin trees) signifies restricted diameter growth due to competition, making them less stable and more vulnerable to wind damage, whereas lower HDR indicates higher individual stability. Moreover, in the field of forestry, where biological systems involve high variability due to numerous unmeasured factors, an R^2_{adj} value of 0.79 is often considered strong. As the Ranibagh site had a dense canopy and reasonably high tree density, it was becoming increasingly difficult to

measure height and CD of larger Sal trees, the DBH range within which the model was built was kept to 10- 65 cm. The limitation of this approach is that the resulting model will be most accurate for predicting the crown diameter of trees within the 10 to 65 cm DBH range. Applying the model to significantly larger trees would be an extrapolation and might lead to less accurate predictions.

Acknowledgement

The authors would like to thank the field staff for data collection, which led to further analysis and interpretation. A big gratitude to the two anonymous reviewers for their timely suggestions and constructive comments.

Declarations of interests

All authors of this manuscript declare that they have no conflict of interest.

Data sharing

All relevant data are within the manuscript.

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