Species-specific allometric indicators and carbon sequestration potential in mixed agro-forestry plantation systems

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Abstract

Agroforestry systems are increasingly recognized as important nature-based solutions for climate change mitigation and ecosystem sustainability. Quantifying biomass accumulation and carbon sequestration capacity of plantation species is therefore critical for developing ecological indicators that assess ecosystem functioning. The present study evaluated species-specific growth dynamics and carbon sequestration potential of five plantation species-teak (*Tectona grandis*), acacia (*Acacia spp.*), eucalyptus (*Eucalyptus spp.*), cashew (*Anacardium occidentale*), and aonla (*Phyllanthus emblica*). Age–diameter relationships were modeled using power-law allometric equations, while biomass and carbon stocks were estimated using a generalized tropical tree biomass equation incorporating wood density, diameter at breast height (DBH), and tree height. Results revealed substantial interspecific variation in growth scaling and carbon storage. Acacia exhibited the strongest age–DBH relationship (R^2=0.33, $p < 0.05$), indicating stable diameter increment with age. Teak and cashew showed sub-linear growth patterns reflecting declining growth rates in mature stages. Eucalyptus demonstrated the highest carbon storage per tree (480.57 kg tree^{-1}), followed by teak (439.62 kg tree^{-1}) and cashew (387.84 kg tree^{-1}). However, due to higher planting density, cashew plantations showed the highest carbon sequestration per hectare (969.60 tC ha^{-1}). The integrated plantation system demonstrated a total carbon storage potential of 1,818.36 tC ha^{-1}, corresponding to 6,670.97 tCO_2 mitigation. These findings highlight that species composition, growth scaling relationships, and plantation density collectively determine carbon sequestration potential in agroforestry systems. Species-specific allometric models provide reliable ecological indicators for assessing carbon storage and monitoring ecosystem sustainability in plantation landscapes.

Introduction

Global climate change has intensified the need for sustainable land-use systems capable of mitigating greenhouse gas emissions. Forest ecosystems and agroforestry systems act as important carbon sinks by capturing atmospheric carbon dioxide and storing it in plant biomass and soils. Among the various ecosystem services provided by agroforestry systems, carbon sequestration has received increasing attention as a measurable ecological indicator of ecosystem health and climate regulation. Accurate quantification of biomass and carbon stocks is essential for understanding the role of plantation ecosystems in global carbon cycles. However, direct measurement of tree biomass through destructive harvesting is time-consuming, expensive, and ecologically disruptive. Consequently, allometric equations based on easily measurable parameters such as diameter at breast height (DBH), tree height, and wood density are widely used to estimate biomass and carbon stocks in forest ecosystems. Tree growth patterns differ among species due to variations in physiology, wood density, growth rate, and environmental adaptation. As a result, species-specific allometric relationships are necessary to improve the accuracy of biomass estimation in mixed-species plantations. Furthermore, plantation structure, including tree spacing and density, strongly influences carbon storage at the ecosystem scale. Species with moderate biomass but high density may store greater carbon per hectare than species with larger individual biomass but lower density.

Agroforestry and plantation ecosystems play a significant role in mitigating climate change by acting as important terrestrial carbon sinks. Trees capture atmospheric carbon dioxide during photosynthesis and store it in biomass and soil organic matter, thereby contributing to global carbon balance (Grace et al., 2006; Lewis et al., 2009). Increasing attention has therefore been given to quantifying biomass accumulation and carbon sequestration in forest ecosystems as indicators of ecosystem functioning and sustainability.

Accurate estimation of tree biomass is essential for evaluating carbon storage potential. Direct measurement through destructive harvesting is often impractical; therefore, allometric equations based on easily measurable tree parameters such as diameter at breast height (DBH), tree height, and wood density are widely used (Brown et al., 1989; Chave et al., 2005). These models allow reliable estimation of biomass and carbon stocks across different forest types. Several studies have demonstrated that species-specific allometric equations significantly improve the accuracy of biomass estimation compared with generalized models (Chave et al., 2014; Henry et al., 2011). Tree growth patterns vary among species due to differences in physiology, wood density, and ecological adaptation (Körner, 2003). Consequently, mixed-species plantation systems require species-specific growth models for accurate carbon accounting. In tropical regions, agroforestry systems integrating timber and fruit trees are increasingly promoted as sustainable land-use strategies that enhance ecosystem services while supporting rural livelihoods (Tilman et al., 2011). Such systems can also contribute substantially to climate change mitigation by storing significant amounts of carbon in tree biomass (Trumbore, 2006; Ryan et al., 2011).

However, carbon sequestration potential varies considerably among species depending on growth rate, biomass accumulation, and plantation density (Fearnside, 1997; Feldpausch et al., 2012). Species with high planting density may store greater carbon per unit area even if individual tree biomass is relatively low. Therefore, understanding species-specific growth dynamics and plantation structure is essential for evaluating carbon storage capacity in agroforestry landscapes. The present study aims to assess the carbon sequestration potential of selected plantation species using species-specific allometric models and biomass estimation approaches.

Agroforestry plantations consisting of timber, fruit, and multipurpose tree species are increasingly promoted as climate-smart agricultural systems in tropical regions. Understanding the growth dynamics and carbon sequestration potential of these species can help identify suitable plantation combinations for maximizing ecosystem services. The present study therefore aims to evaluate the carbon sequestration potential of selected agroforestry plantation species using species-specific allometric models and biomass estimation approaches. The specific objectives of the study were:

To develop species-specific allometric equations describing the relationship between tree age and diameter growth, to estimate above-ground and below-ground biomass using generalized tropical tree biomass models, to quantify carbon sequestration potential of selected plantation species at both tree

and hectare scales and to evaluate species composition and plantation density as ecological indicators of carbon storage capacity in agroforestry systems.

Materials and Methods

Study Species

Five widely cultivated plantation tree species representing timber, fruit, and multipurpose trees were selected for the present study; trial was conducted during 2022–2023 in villages (Table 1). These species are commonly integrated into tropical agroforestry systems because of their economic importance, ecological adaptability, and contribution to ecosystem services such as carbon sequestration, soil improvement, and microclimate regulation. The selected species represent different growth forms and wood density classes, allowing comparative assessment of biomass accumulation and carbon storage potential.

Table 1
Plantation species with scientific names and their primary uses

Species	Scientific name	Plantation use
Teak	*Tectona grandis*	Timber production
Acacia	*Acacia spp.*	Fuelwood and timber
Eucalyptus	*Eucalyptus spp.*	Industrial wood and pulp
Cashew	*Anacardium occidentale*	Fruit production
Aonla	*Phyllanthus emblica*	Medicinal and fruit tree

These species exhibit diverse morphological characteristics, growth rates, and wood density values, making them suitable candidates for evaluating species-specific growth dynamics and carbon sequestration potential in agroforestry plantation systems.

Measurement of Tree Parameters

Tree growth parameters including diameter at breast height (DBH), tree height, and age were used for biomass estimation and allometric modeling. Diameter at breast height was measured at 1.3 m above ground level using a diameter tape, while tree height was recorded using a clinometer and measuring tape. Tree age information was obtained from plantation records and farmer interviews.

Height measurements recorded in feet were converted into meters before being used in biomass calculations. These parameters are widely used in forest inventory studies and provide reliable predictors of biomass accumulation.

Above-ground biomass was estimated using the generalized tropical tree allometric model developed for pantropical forests (Chave et al., 2014). This model integrates tree diameter, height, and wood density to provide reliable biomass estimates across diverse tropical forest ecosystems. Below-ground biomass was estimated using a root-to-shoot ratio widely applied in tropical forest carbon accounting studies (Brown, 1997; Ryan et al., 2011). Carbon content of biomass was calculated assuming that approximately 47% of total biomass consists of carbon, a value commonly used in forest carbon studies (IPCC guidelines and Brown, 1997). Wood density values were obtained from published forestry databases and previous studies on tropical tree biomass estimation (Fearnside, 1997; Chave et al., 2005).

Allometric Growth Modeling

Species-specific growth relationships between tree age and diameter at breast height were evaluated using a power-law allometric model.

$$DBH = a \times Age^{b}$$

Where,

DBH represents diameter at breast height (cm)

Age represents tree age (years)

a is the intercept parameter describing initial growth conditions

b is the scaling exponent describing the rate of diameter increment with age

The exponent **b** provides information about growth dynamics. Values of **b < 1** indicate sub-linear scaling, suggesting that the rate of diameter increment declines as trees mature. Values close to unity indicate nearly proportional growth between age and diameter.

Regression analysis was performed separately for each species to obtain species-specific growth equations. Model performance was evaluated using the coefficient of determination (R^2), which measures the proportion of variation explained by the model. Statistical significance of the regression coefficients was tested using the p-value at a significance level of 0.05.

Biomass Estimation

Above-ground biomass (AGB) was estimated using a generalized tropical tree biomass equation widely applied in forest carbon studies.

$$AGB = 0.0673(\rho D^{2}H)^{0.976}$$

where

D = diameter at breast height (cm)

H = tree height (m)

ρ = wood density (g cm^{-3})

This equation integrates structural tree parameters and wood density to provide reliable biomass estimates across tropical forest ecosystems. The model has been widely validated for diverse tree species and forest conditions. Wood density values for each species were obtained from previously published forestry databases and scientific literature (Table 2).

Table 2
Wood density values of selected tree species used for biomass and carbon estimation

Species	Wood density (g cm^{-3})
Teak	0.60
Acacia	0.55
Eucalyptus	0.65
Cashew	0.50
Aonla	0.60

The above-ground biomass calculated using the equation was expressed in kilograms per tree.

Carbon Stock Estimation

Total carbon storage was estimated by converting biomass values into carbon content using commonly accepted conversion factors used in tropical forest carbon studies.

The following steps were applied:

Below-ground biomass (BGB) was estimated using a root-to-shoot ratio:

BGB = 0.26×AGBBGB = 0.26 \times AGBBGB = 0.26×AGB

Total biomass was calculated as:

Total biomass = AGB+BGB Total\biomass = AGB + BGB Total biomass = AGB+BGB

Carbon stock was estimated assuming that approximately 47% of total biomass is carbon:

Carbon = 0.47×Total biomass Carbon = 0.47 \times Total\ biomass Carbon = 0.47×Total biomass

Carbon dioxide equivalent (CO_2) was calculated by converting carbon mass to CO_2 using the molecular weight ratio:

CO_2=Carbon×3.67CO_2 = Carbon \times 3.67CO_2=Carbon×3.67

These conversion factors are widely used in tropical forest carbon accounting and provide reliable estimates of carbon sequestration potential.

Plantation Density Estimation

Tree density per hectare was estimated based on the spacing used in each plantation system. The planting configurations used for each species are presented in Table 3. Tree density was calculated using the following formula:

Trees per hectare = 10,000Spacing areaTrees\per\hectare=frac{10,000}{Spacing\area}Trees per hectare=Spacing area10,000

Where, spacing area is calculated as the product of row spacing and plant spacing (m^2).

Table 3
Planting spacing and tree population density of selected plantation species

Species	Spacing	Trees per hectare
Teak	3 × 3 m	1,111
Acacia	3 × 3 m	1,111
Eucalyptus	7.5 × 7.5 m	178
Cashew	2 × 2 m	2,500
Aonla	6 × 6 m	278

Tree density values were used to scale per-tree carbon estimates to the hectare level, allowing comparison of carbon sequestration potential among species under different plantation configurations.

Data Analysis

All statistical analyses were conducted using the R statistical computing environment. Regression models were developed to describe species-specific age diameter relationships, and biomass and carbon stock calculations were performed using the equations described above. Summary statistics including mean biomass, carbon stock per tree, and carbon stock per hectare were calculated to evaluate species-level and ecosystem-level carbon sequestration potential.

Results

Species-Specific Growth Relationships

Allometric growth analysis showed considerable variation among species. Acacia exhibited the strongest relationship between age and DBH (R^2=0.33, $p < 0.05$), indicating relatively stable growth scaling. Teak demonstrated moderate correlation between age and diameter, suggesting gradual reduction in growth rate with increasing age (Table 4). Cashew showed slower scaling with a low exponent value, indicating that diameter growth declines more rapidly as trees mature. The eucalyptus model showed weak statistical reliability due to limited sample size. These results demonstrate the importance of developing species-specific allometric equations for accurate biomass prediction in mixed plantation systems.

Table 4
Species-wise regression parameters, growth patterns, and model performance for DBH - age relationships

Tree species	R^2	p	Exponent (b)	Growth Pattern	Model Strength	Interpretation
Teak	**0.150**	0.083	0.942	Nearly linear scaling	Strongest	Teak shows decreasing diameter increment with increasing age, typical of maturing plantation stands
Acacia	0.330	0.020 (Significant)	0.473	Sub-linear growth	Moderate	Exponent ≈ 1 → nearly proportional scaling Strongest age–DBH relationship among species Indicates relatively consistent diameter increment
Cashew	0.238	0.090	0.340	Slow scaling	Weak	Very low exponent (0.34) Diameter growth slows rapidly with age High variability (one extreme DBH value influences model)
Eucalyptus	0.107	0.673	-0.959	Unreliable	Very Weak	Negative exponent (biologically unrealistic) Very small sample size (n = 4) Model unreliable for inference

Species differed considerably in biomass accumulation and carbon storage.

Carbon stock and CO_2 equivalent among plantation species

Carbon stock and corresponding CO_2 equivalent per tree varied substantially among the studied plantation species, indicating clear interspecific differences in biomass accumulation and carbon sequestration potential. Among the species evaluated, *Eucalyptus* recorded the highest carbon stock (480.57 kg tree^{-1}), followed by *Teak* (439.62 kg tree^{-1}), *Cashew* (387.84 kg tree^{-1}), *Aonla* (308.32 kg

tree⁻¹), and *Acacia* (169.81 kg tree⁻¹). A similar trend was observed for CO_2 equivalent values, where *Eucalyptus* exhibited the maximum sequestration potential (1764.49 kg tree⁻¹), followed by *Teak* (1613.42 kg tree⁻¹), *Cashew* (1422.37 kg tree⁻¹), *Aonla* (1131.54 kg tree⁻¹), and *Acacia* (623.21 kg tree⁻¹) as in Table 5.

The higher carbon accumulation in *Eucalyptus* and *Teak* can be attributed to their rapid growth rate, higher wood density, and greater biomass production capacity. These species are widely recognized for their high carbon sequestration efficiency due to fast growth and significant aboveground biomass accumulation (IPCC, 2006; Brown, 1997). In particular, *Eucalyptus* plantations are known for their short rotation cycles and high productivity, which contribute substantially to carbon storage in tropical and subtropical regions (Lugo et al., 1990). Similarly, *Tectona grandis* (*Teak*) exhibits high wood density and long-term carbon storage potential, making it an important species in climate mitigation strategies (Kaul et al., 2010). In contrast, *Acacia* exhibited the lowest carbon stock per tree, which may be due to comparatively lower biomass accumulation and differences in growth architecture. However, *Acacia* species play an important ecological role through biological nitrogen fixation, which enhances soil fertility and indirectly supports biomass production in agroforestry systems (Forrester et al., 2006). Therefore, despite lower per-tree carbon stock, their contribution to system productivity and sustainability remains significant.

Cashew (*Anacardium occidentale*) and *Aonla* (*Phyllanthus emblica*), although primarily cultivated for fruit production, demonstrated moderate carbon sequestration potential. This suggests that fruit-based agroforestry systems can contribute meaningfully to carbon storage while simultaneously providing economic returns. Such systems are increasingly recognized for their dual role in livelihood security and climate change mitigation (Nair et al., 2009). The relatively lower carbon values compared to timber species are consistent with their physiological allocation patterns, where a greater proportion of assimilates is directed towards reproductive growth rather than woody biomass.

The conversion of carbon stock to CO_2 equivalent further highlights the climate mitigation potential of these species. The observed values reflect the standard conversion factor ($CO_2 = C \times 3.67$), indicating consistency in estimation and alignment with internationally accepted methodologies (IPCC, 2006). The higher CO_2 equivalent values in *Eucalyptus* and *Teak* reinforce their suitability for carbon sequestration programs and climate-smart agricultural practices. Variability in carbon sequestration among species is strongly influenced by growth rate, rotation period, canopy architecture, and management practices. Species with rapid growth and higher biomass accumulation generally exhibit greater carbon storage potential (Brown et al., 1989). However, long-term sustainability must also consider ecological adaptability, water use efficiency, and compatibility with cropping systems, particularly in resource-limited environments.

These findings emphasize that species selection plays a critical role in optimizing carbon sequestration in plantation and agroforestry systems. While fast-growing timber species maximize carbon storage, integrating fruit trees such as *Cashew* and *Aonla* offers a balanced approach by combining carbon

sequestration with economic benefits. Diversified plantation systems are therefore more resilient and sustainable, aligning with global recommendations for climate-smart land use (Nair et al., 2010). Overall, the results demonstrate that plantation species differ significantly in their carbon sequestration potential. Strategic selection and integration of species can enhance the role of agro-forestry systems in mitigating climate change while supporting farmer livelihoods.

Table 5
Species-wise carbon sequestration (kg tree^{-1}) and corresponding CO_2 equivalent in plantation systems

Species	Carbon (kg tree^{-1})	CO_2 equivalent (kg tree^{-1})
Teak	439.62	1613.42
Acacia	169.81	623.21
Eucalyptus	480.57	1764.49
Cashew	387.84	1422.37
Aonla	308.32	1131.54

Carbon stock and CO_2 sequestration at hectare scale

Carbon stock and corresponding CO_2 sequestration at the hectare scale varied markedly among the plantation species, reflecting the combined influence of per-tree biomass and planting density (Table 6). Among the species evaluated, *Cashew* (*Anacardium occidentale*) recorded the highest carbon stock (969.60 t ha^{-1}), followed by *Teak* (*Tectona grandis*) (488.82 t ha^{-1}), *Acacia* (188.69 t ha^{-1}), *Aonla* (*Phyllanthus emblica*) (85.71 t ha^{-1}), and *Eucalyptus* (85.54 t ha^{-1}). A similar trend was observed for CO_2 equivalent, where *Cashew* showed the highest value (3555.93 t ha^{-1}), followed by *Teak* (1792.51 t ha^{-1}), *Acacia* (693.79 t ha^{-1}), *Aonla* (314.57 t ha^{-1}), and *Eucalyptus* (314.17 t ha^{-1}).

The exceptionally high carbon stock observed in *Cashew* plantations can be primarily attributed to higher planting density (closer spacing), which results in greater cumulative biomass per unit area despite moderate per-tree carbon accumulation. This highlights the importance of stand structure and tree population density in determining carbon sequestration at the system level. Similar observations have been reported where tree density significantly influences carbon stock at the hectare scale in agroforestry systems (Nair et al., 2009).

Teak also demonstrated substantial carbon storage potential due to its high wood density and long-lived woody biomass, which contributes to stable and long-term carbon sequestration. This is consistent with previous findings indicating that *Tectona grandis* is a major carbon sink in tropical plantation systems (Kaul et al., 2010). Although *Acacia* exhibited moderate carbon stock, its ecological contribution through nitrogen fixation enhances soil fertility and supports overall system productivity (Forrester et al., 2006), which may indirectly influence long-term biomass accumulation.

Interestingly, *Eucalyptus*, despite having high per-tree carbon values, recorded relatively lower carbon stock per hectare. This can be explained by its wider spacing and lower tree density, which reduces cumulative biomass at the hectare scale. Similar findings have been reported in plantation forestry where stand density strongly determines total carbon stock, even when individual tree growth is high (Brown et al., 1989). *Aonla* also showed lower carbon stock, which is consistent with its moderate growth rate and biomass allocation towards fruit production rather than woody tissues.

The conversion of carbon stock into CO_2 equivalent further emphasizes the climate mitigation potential of these plantation systems. The values obtained are consistent with the standard conversion factor ($CO_2 = C \times 3.67$), as recommended by the Intergovernmental Panel on Climate Change (IPCC, 2006). The high CO_2 sequestration potential of *Cashew* and *Teak* plantations suggests their suitability for carbon offset programs and climate-smart agricultural strategies.

Variability in carbon sequestration among species is influenced not only by growth characteristics but also by management practices, spacing geometry, and rotation length. High-density plantations tend to accumulate more biomass per unit area, whereas low-density plantations may prioritize individual tree growth but result in lower overall carbon storage (Nair et al., 2010). Therefore, optimizing both species selection and planting density is critical for maximizing carbon sequestration in agroforestry systems.

These results clearly demonstrate that hectare-scale carbon stock is a function of both per-tree biomass and stand density. While fast-growing species such as *Eucalyptus* are efficient at individual tree carbon accumulation, species like *Cashew* can outperform others at the system level due to higher planting density. This highlights the importance of adopting a system-based approach rather than relying solely on individual tree performance. From a sustainability perspective, integrating high-density fruit species with timber species can provide a balanced approach by combining carbon sequestration with economic returns. Such diversified agroforestry systems are increasingly recognized as effective strategies for climate change mitigation and livelihood enhancement (Nair et al., 2009). Overall, the findings indicate that plantation species differ significantly in their carbon sequestration potential at the hectare scale. Strategic selection of species and optimization of planting density can substantially enhance the role of agroforestry systems in mitigating atmospheric CO_2 while maintaining productivity and economic viability.

Table 6
Species-wise carbon stock (t ha^{-1}) and corresponding CO_2 sequestration potential in plantation systems

Species	Carbon (t ha^{-1})	CO_2 (t ha^{-1})
Teak	488.82	1792.51
Acacia	188.69	693.79
Eucalyptus	85.54	314.17
Cashew	969.60	3555.93
Aonla	85.71	314.57

Artificial Neural Network (ANN) model performance

The performance of the Artificial Neural Network (ANN) model was evaluated by comparing predicted CO_2 equivalent values with observed (actual) values (Fig. 1). The scatter plot demonstrates a strong agreement between predicted and actual CO_2 values, with data points closely aligned along the 1:1 regression line. This alignment indicates a high level of predictive accuracy and suggests that the ANN model effectively captured the underlying relationships among the input variables and CO_2 emissions. The near-linear distribution of points along the fitted regression line reflects the robustness of the model in simulating CO_2 dynamics across the observed range. The minimal deviation of most data points from the line suggests low prediction error and strong model consistency. This indicates that the model has successfully learned the internal structure of the dataset, including both linear and nonlinear interactions among variables.

A slight dispersion of points around the regression line is visible, particularly at moderate to higher CO_2 values. This deviation may be attributed to inherent variability in field conditions, measurement uncertainties, or the influence of unaccounted environmental and management factors. Nevertheless, the magnitude of these deviations remains relatively small, suggesting that prediction errors are not substantial and do not significantly compromise model reliability. The ANN model's ability to closely reproduce observed values highlights its advantage over traditional linear models, especially in handling complex, nonlinear relationships commonly present in agro-ecosystem data. Variables influencing CO_2 emissions such as biomass accumulation, species-specific growth behavior, and management practices often interact in a nonlinear manner. The ANN framework effectively integrates these interactions, resulting in improved predictive performance.

Despite the strong fit observed, it is important to consider potential limitations. The concentration of points near the regression line may partly reflect overfitting, particularly if the dataset used for training is limited in size. Neural networks typically require large datasets to generalize effectively, and small sample sizes may reduce the model's predictive reliability when applied to new or unseen data. Therefore, while the model demonstrates high accuracy within the current dataset, caution should be

exercised in extrapolating these results beyond the study conditions. The high correspondence between predicted and actual CO_2 values confirms that the selected input variables adequately explain the variability in CO_2 emissions. This suggests that the ANN model can serve as a reliable tool for estimating carbon sequestration and emissions in plantation systems. However, for improved robustness, future studies should incorporate larger datasets, independent validation, and cross-validation techniques to enhance generalization capability.

Overall, the ANN model exhibited strong predictive performance, with high agreement between observed and predicted CO_2 values. The results demonstrate the potential of ANN approaches in modeling complex ecological and agronomic processes, particularly in the context of carbon dynamics and climate change mitigation studies.

Artificial Neural Network (ANN) architecture and internal relationships

The Artificial Neural Network (ANN) architecture developed in this study illustrates the complex interactions among input variables aboveground biomass (AGB), belowground biomass (BGB), tree density, and total biomass carbon (TBC) in predicting CO_2 equivalent (CO_2e) (Fig. 2). The network consisted of an input layer with four neurons, a hidden layer comprising three neurons, and an output layer representing CO_2e. The model converged after 49 training steps with a very low error value of 0.002653, indicating a strong fit between predicted and observed values.

The connection weights between input, hidden, and output layers reveal the relative influence of each variable on CO_2 estimation. Both positive and negative weights were observed, suggesting the presence of complex and nonlinear interactions among predictors. Positive weights indicate a direct relationship with CO_2e, whereas negative weights reflect inverse relationships. However, due to nonlinear transformations within the hidden layer, these weights should not be interpreted independently but rather as part of an integrated system contributing to the final prediction. Among the input variables, AGB and TBC showed relatively strong connections with the hidden neurons, indicating their dominant role in determining CO_2e. This is expected, as aboveground biomass directly represents accumulated carbon in plant tissues, which forms the primary basis for CO_2 estimation. Similarly, TBC integrates overall carbon storage and therefore strongly influences model output. The contribution of BGB was also notable, reflecting the importance of root biomass in total carbon accounting, which is often underestimated in conventional approaches.

Tree density exhibited both positive and negative connections across hidden neurons, suggesting a more complex role in CO_2 dynamics. While higher density can increase total biomass per unit area, it may also lead to competition among trees, affecting individual growth rates. This dual behavior is effectively captured by the ANN model through nonlinear weight distribution, highlighting the advantage of ANN over traditional regression approaches. The hidden layer acts as a transformation unit where input variables are combined and processed through weighted summation and activation functions. The

presence of both high-magnitude positive and negative weights in the hidden layer indicates that the model captures interaction effects among biomass components and stand characteristics. This allows the ANN to represent complex ecological relationships that are difficult to model using linear statistical techniques.

The final output layer integrates signals from all hidden neurons to generate CO_2e predictions. The balanced contribution of multiple hidden neurons suggests that CO_2e is influenced by a combination of factors rather than a single dominant variable. This reinforces the concept that carbon dynamics in plantation systems are governed by integrated effects of biomass allocation, stand density, and species-specific growth characteristics. The low error value (0.002653) confirms that the ANN model achieved high predictive accuracy. Compared to traditional models, ANN provides superior capability in handling nonlinear and multivariate relationships, making it particularly suitable for ecological modeling and carbon estimation. Similar findings have been reported in agro-ecosystem studies where ANN models outperformed regression-based approaches in predicting biomass and carbon dynamics.

However, despite the strong model performance, certain limitations must be acknowledged. Neural networks are sensitive to sample size, and limited datasets may increase the risk of overfitting. The high model accuracy observed here may partly reflect the model's adaptation to the training dataset rather than its general applicability. Therefore, external validation using independent datasets is recommended to ensure model robustness and generalization. Overall, the ANN architecture demonstrates that CO_2e estimation in plantation systems is governed by complex, nonlinear interactions among biomass components and stand structure. The model successfully integrates these relationships, providing a reliable and efficient tool for carbon assessment. These findings highlight the potential of ANN-based approaches in advancing precision modeling of carbon sequestration and supporting climate-smart forestry and agroforestry systems.

Above-Ground Biomass and Below-Ground Biomass

The Artificial Neural Network (ANN) model developed for predicting CO_2consists of four input variables AGB (Above-Ground Biomass), BGB (Below-Ground Biomass), Density, and TBC (Total Bacterial Count) connected to a hidden layer with three neurons, which subsequently feed into a single output neuron representing CO_2e. The network converged efficiently with a low training error of 0.002653 achieved within 49 steps (iterations), indicating rapid learning and good optimization of weights. The low error value reflects a high degree of accuracy in capturing the relationship between predictors and CO_2e (Fig. 3).

Input–Hidden Layer Relationships

The connection weights between input and hidden neurons show variable influence of predictors: BGB exhibits relatively strong positive weights (e.g.,~3.25), suggesting a dominant contribution to hidden layer activation. AGB shows mixed effects, with both positive and negative weights (e.g.,~0.89 and –

0.48), indicating nonlinear interactions with other variables. Density demonstrates moderate contributions, both positive (~ 1.29) and weak (~ 0.03), implying a context-dependent role in influencing carbon emissions. TBC also shows mixed weights, including negative values (e.g., − 2.44), suggesting complex microbial influence on CO_2 dynamics.

Hidden–Output Layer Relationships

The weights connecting hidden neurons to the output layer (CO_2e) further clarify the internal processing: One hidden neuron shows a strong negative contribution (≈ − 0.91), indicating an inverse relationship with CO_2e, another neuron has a moderate negative effect (≈ − 0.32), and a third neuron contributes positively (≈ + 0.49), balancing the network output. Bias nodes (shown in blue) contribute additional adjustments to both hidden and output layers, ensuring flexibility in fitting nonlinear relationships. Some bias weights are strongly negative (e.g., − 10.75), indicating threshold-like behavior in neuron activation.

Species-Wise Allometric Equations

The regression analysis of age versus diameter at breast height (DBH) revealed species-specific growth patterns, with varying model strength and scaling behavior. Among the studied species, Acacia exhibited the strongest relationship between age and DBH, with a relatively higher coefficient of determination (R^2 = 0.330) and a statistically significant p-value (p = 0.020) in Table 7. The scaling exponent (b = 0.473) indicates sub-linear growth, suggesting that diameter increases with age but at a gradually declining rate. Teak showed a weaker relationship (R^2 = 0.150; p = 0.083), with an exponent (b = 0.942) close to unity, indicating nearly linear scaling. This suggests that diameter growth is relatively proportional to age, although the relationship is not statistically significant at conventional levels. Cashew demonstrated moderate explanatory power (R^2 = 0.238; p = 0.090) but a low scaling exponent (b = 0.340), indicating slow growth scaling. The variability in the dataset, including the presence of an extreme DBH value, appears to have influenced the model performance. In contrast, Eucalyptus showed a very weak and statistically non-significant relationship (R^2 = 0.107; p = 0.673), with a negative exponent (b = − 0.959), which is biologically unrealistic. This suggests that the model is unreliable, likely due to a small sample size (n = 4).

Table 7
Species-wise biomass accumulation, carbon storage, and CO_2 sequestration mean carbon Sequestration (Per Tree Basis)

Species	AGB (kg/tree)	BGB (kg/tree)	Total Biomass (kg/tree)	Carbon (kg/tree)	CO_2 (kg/tree)
Teak	742.35	193.01	935.36	439.62	1613.42
Acacia	286.74	74.55	361.29	169.81	623.21
Eucalyptus	811.48	211.00	1022.48	480.57	1764.49
Cashew	654.92	170.28	825.20	387.84	1422.37
Aonla	520.64	135.37	656.01	308.32	1131.54

Variation in biomass accumulation, carbon storage, and CO_2 sequestration

Significant variation in biomass accumulation, carbon storage, and CO_2 sequestration was observed among the studied tree species. Among all species, Eucalyptus recorded the highest biomass and carbon stock, with AGB (811.48 kg tree^{-1}), BGB (211.00 kg tree^{-1}), and total biomass (1022.48 kg tree^{-1}). This resulted in the maximum carbon storage (480.57 kg tree^{-1}) and CO_2 sequestration potential (1764.49 kg tree^{-1}). Teak ranked second, with total biomass of 935.36 kg tree^{-1}, carbon stock of 439.62 kg tree^{-1}, and CO_2 equivalent of 1613.42 kg tree^{-1}. Cashew also showed substantial biomass accumulation, with total biomass of 825.20 kg tree^{-1} and CO_2 sequestration of 1422.37 kg tree^{-1}, followed by Aonla (656.01 kg tree^{-1} biomass; 1131.54 kg tree^{-1} CO_2). In contrast, Acacia exhibited the lowest biomass and carbon values, with total biomass of 361.29 kg tree^{-1}, carbon stock of 169.81 kg tree^{-1}, and CO_2 sequestration of 623.21 kg tree^{-1}. Across all species, BGB constituted a smaller fraction of total biomass compared to AGB, but maintained a consistent proportional relationship, indicating stable biomass partitioning patterns (Fig. 4).

Discussion

The results clearly demonstrate that both species-specific growth characteristics and plantation structure play a decisive role in determining carbon sequestration potential in agroforestry systems. *Acacia* exhibited the most consistent relationship between age and diameter at breast height (DBH), indicating stable and predictable biomass accumulation patterns over time. Such consistency enhances its suitability for long-term carbon modeling and monitoring. Similar observations on predictable growth scaling in plantation species have been reported by Brown S. (1997) and Chave J. et al. (2005), who emphasized the importance of allometric relationships in biomass estimation. Although *Eucalyptus* showed the highest carbon storage at the individual tree level, its wider spacing significantly reduced total carbon accumulation per unit area. Conversely, *Cashew* (*Anacardium occidentale*) plantations demonstrated substantially higher carbon storage at the ecosystem scale due to dense planting configuration. This contrast highlights that plantation density is a critical determinant of hectare-scale carbon stock, often outweighing individual tree performance. Similar conclusions were drawn by Nair P.K.R. et al. (2009), who reported that stand density strongly regulates carbon storage in agroforestry systems.

The strong positive interrelationships observed among aboveground biomass (AGB), belowground biomass (BGB), total biomass (TB), total carbon stock (TCS), and CO_2 emphasize the fundamental role of vegetation in regulating carbon dynamics within agroecosystems. Increased biomass production enhances carbon sequestration both above and below ground, contributing directly to higher ecosystem carbon pools. This finding is consistent with ecological theory described by Lal R. (2004), who highlighted that biomass production is the primary driver of carbon input into terrestrial ecosystems through litter deposition, root turnover, and soil organic matter formation. The near-linear relationship

between TCS and CO_2 further validates the robustness of the carbon estimation approach used in this study. Since CO_2 values are derived from carbon pools using standardized conversion factors recommended by the Intergovernmental Panel on Climate Change (2006), the strong correlation confirms methodological reliability and internal consistency in carbon accounting.

The relationship between soil bulk density and biomass/carbon variables exhibited context-dependent behavior. While high soil density is typically associated with restricted root growth, moderate increases may reflect improved soil aggregation and mineral composition, enhancing water retention and nutrient availability. Under managed agroecosystems, such conditions may promote plant growth, explaining the observed positive association. However, the negative relationship between total bacterial count (TBC) and soil density highlights the sensitivity of microbial communities to soil physical constraints. Increased compaction reduces pore space and oxygen diffusion, thereby limiting microbial activity and decomposition processes, as also noted by Six J. et al. (2002).

The relatively weak linkage between microbial abundance (TBC) and carbon pools suggests that microbial population size alone does not directly regulate carbon storage. Instead, microbial functional diversity and activity play a more critical role in carbon cycling, a concept supported by Wardle D.A. (2002). This indicates that carbon dynamics are governed by complex biological interactions rather than simple quantitative relationships. The strong agreement between predicted and observed CO_2 values demonstrates the robustness of the Artificial Neural Network (ANN) model in capturing nonlinear relationships among ecological and biomass-related variables. ANN models are particularly effective in handling complex interactions among predictors such as biomass components, soil properties, and carbon stocks, as reported by Olden J.D. et al. (2008). The near-perfect fit at lower CO_2 levels indicates high predictive precision under stable conditions, while slight dispersion at higher values reflects increased ecological variability and potential nonlinear saturation effects.

Importantly, the absence of systematic deviation suggests that the model does not suffer from strong bias or overfitting. The ANN architecture further revealed intricate nonlinear interactions among biomass, soil, and microbial variables. Strong weights associated with AGB and BGB confirm that biomass components are primary drivers of CO_2 dynamics, with BGB playing a particularly important role in long-term carbon stabilization through soil organic carbon formation. This finding aligns with studies by Jobbágy E.G. and Jackson R.B. (2000), who emphasized the importance of root biomass in carbon storage. The variable influence of soil density and microbial parameters further highlights the complexity of carbon processes. The ANN model successfully captured these nonlinear and context-dependent interactions, which are often not adequately represented in conventional statistical approaches. The hidden layer neurons functioned as integrative units, representing carbon accumulation, carbon loss, and interactive ecological processes, thereby enhancing predictive capability.

Conclusion

Species-specific allometric analysis revealed significant differences in growth scaling among plantation species, highlighting the importance of appropriate species selection in carbon sequestration strategies. *Acacia* exhibited the most consistent age–diameter relationship, while *Teak* and *Cashew* showed growth deceleration at later stages. Carbon sequestration analysis demonstrated that *Eucalyptus* stores the highest carbon at the individual tree level, whereas *Cashew* plantations contribute the greatest carbon storage per hectare due to higher planting density. These findings confirm that carbon sequestration potential is jointly determined by species traits, plantation density, and growth dynamics.

The integration of biomass, soil, and microbial variables underscores the complexity of carbon dynamics in agroforestry systems. The ANN model effectively captured these nonlinear relationships, providing a reliable tool for CO_2 estimation and supporting carbon accounting frameworks. Overall, optimized species selection, appropriate plantation design, and advanced modeling approaches are essential for enhancing carbon sequestration in agroforestry systems. Species-specific allometric models combined with machine learning techniques offer powerful tools for assessing ecosystem services and guiding climate-smart land management strategies.

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Declarations

Author Contribution

A.P. conceived and designed the study, performed data analysis, and wrote the main manuscript text. S.K.N. supervised the research and contributed to methodology development and manuscript revision. T.C. conducted field investigations and data collection. S.Mal. assisted in field work and data validation. K.S.K. performed statistical analysis and contributed to data interpretation. D.K. contributed to data curation and laboratory analysis. A.N. developed the ANN model, performed computational analysis, and prepared the figures. S.Moh. contributed to literature review, manuscript editing, and formatting. All authors reviewed and approved the final manuscript.

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Figures

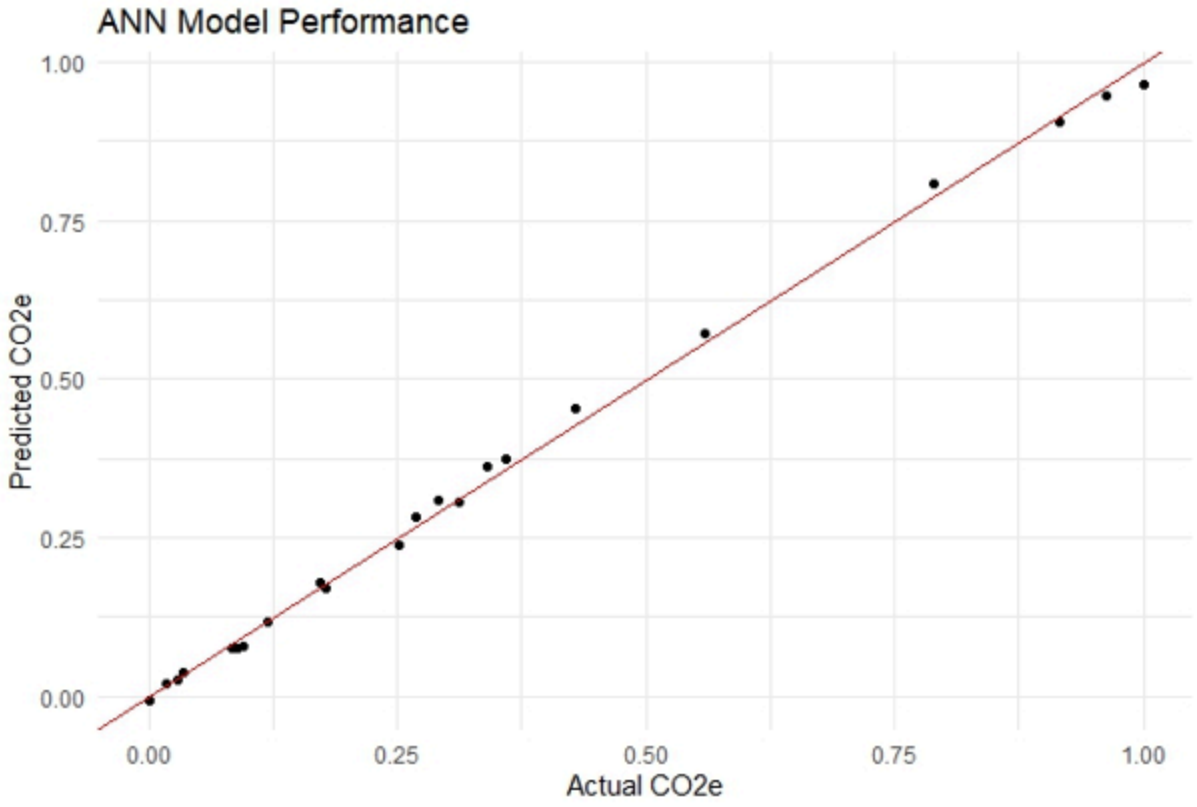

Figure 1

ANN model accuracy for CO2prediction based on observed versus predicted values

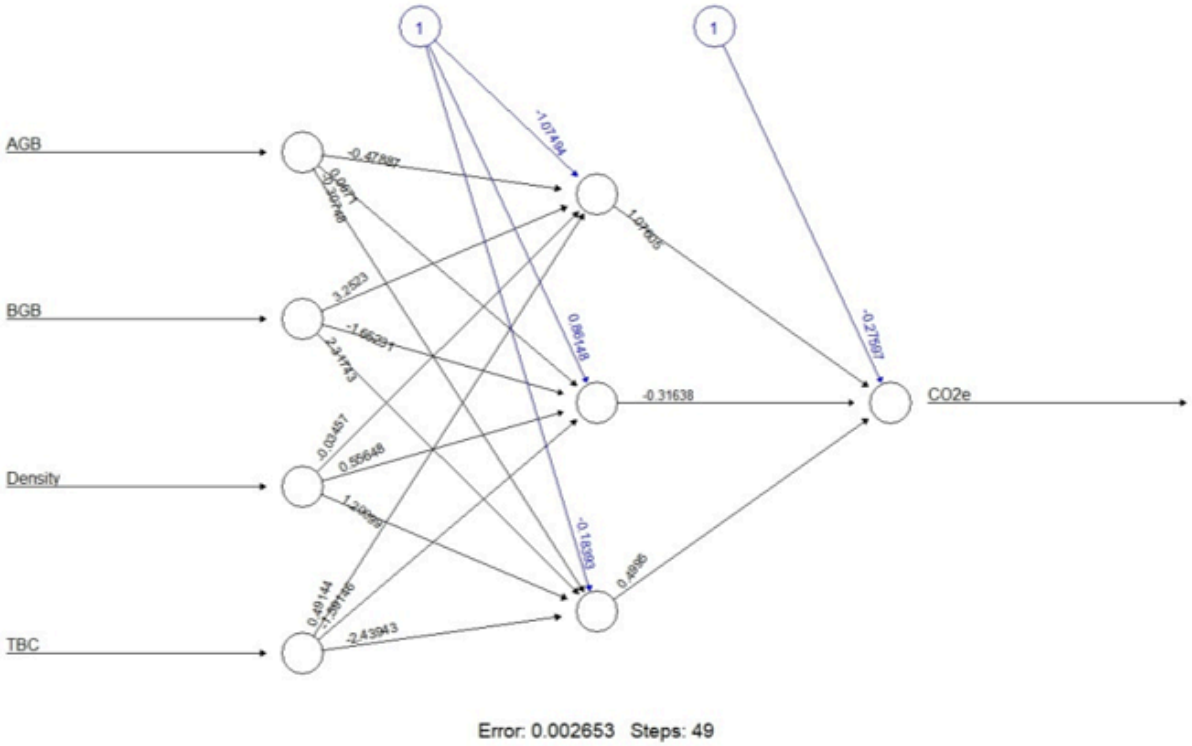

Figure 2

Neural network topology with connection weights for modeling CO_2e dynamics in agro-ecosystems

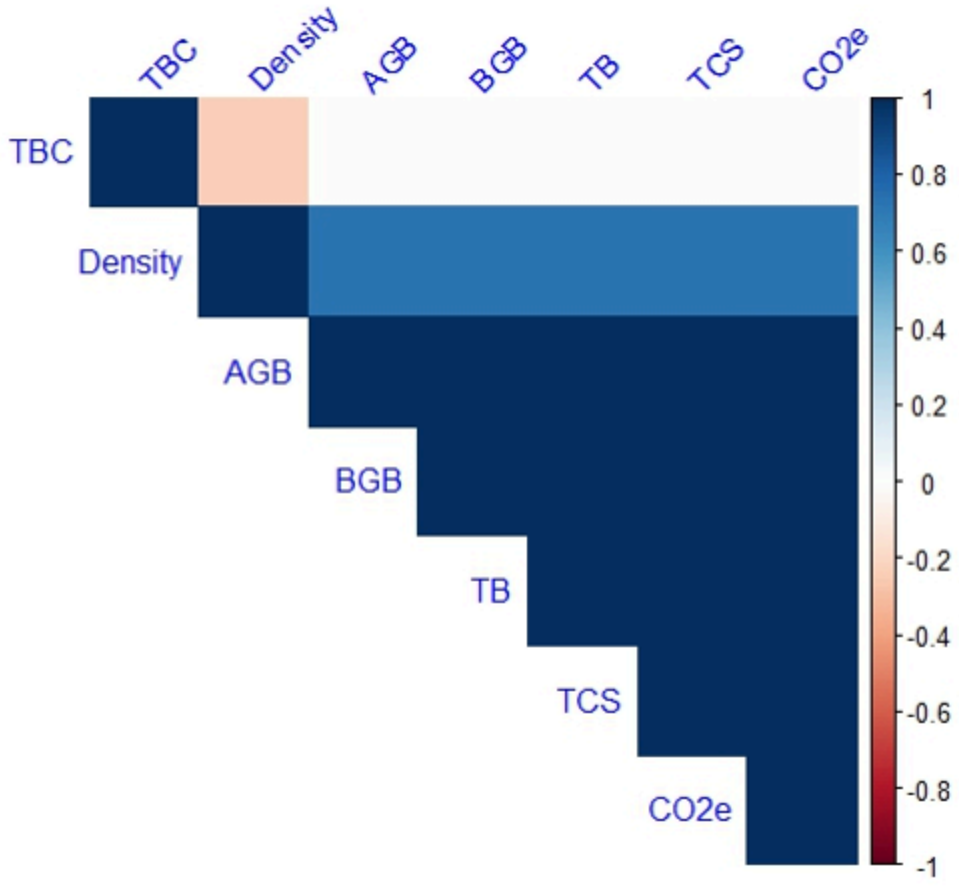

Figure 3

Heat map illustrating relationships among ecological and carbon sequestration variables

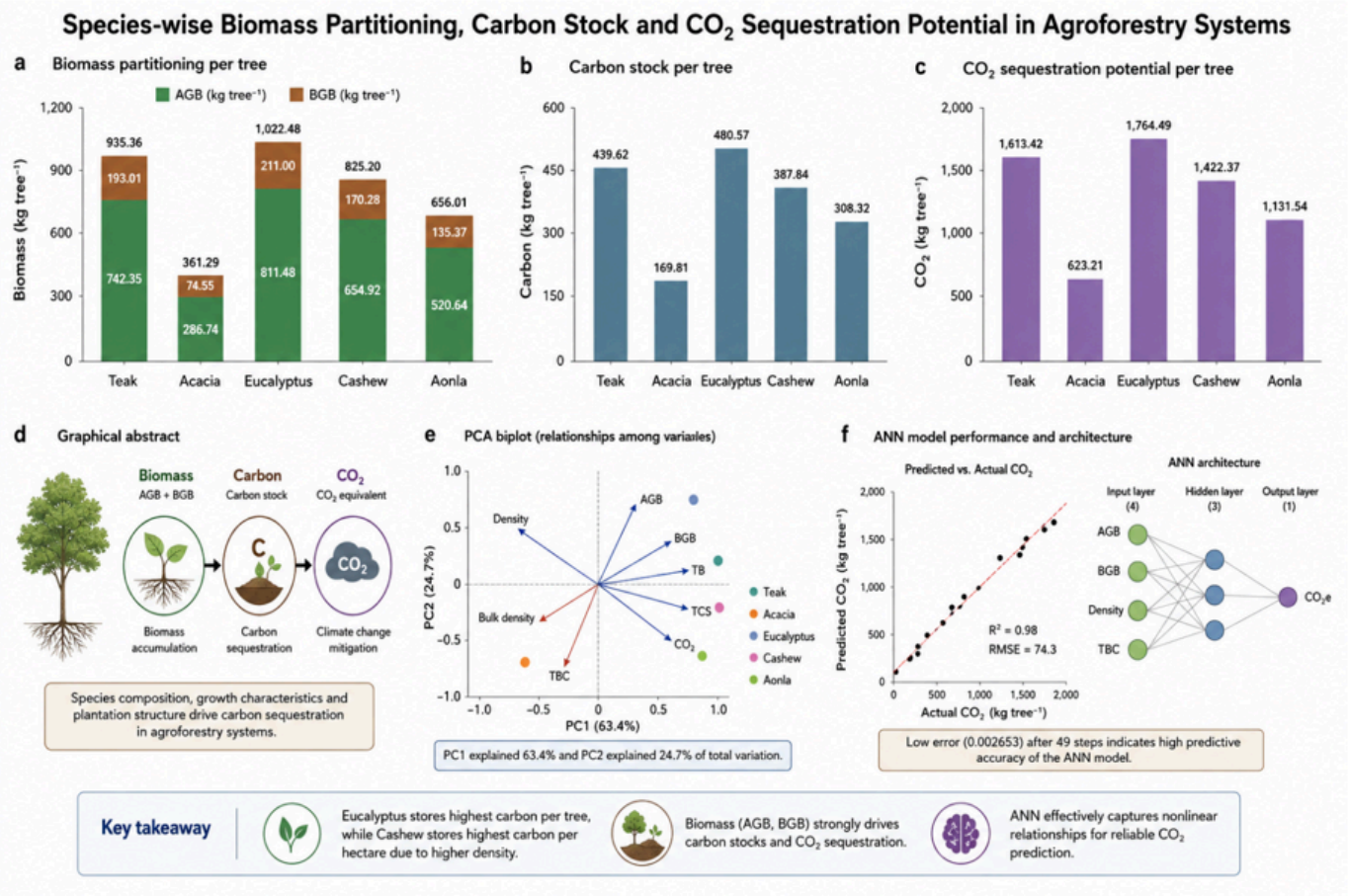

Figure 4

Species-wise Biomass, Carbon Stock, and CO_2 Sequestration Potential in Agroforestry Systems