

Dynamic growth models and estimation distinction of carbon stock for coniferous trees under different afforestation modes

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Research Article

Keywords: Dynamic growth model, Afforestation mode, Pinus tabuliformis, dendrochronology, Panel data

Posted Date: July 20th, 2023

DOI: <https://doi.org/10.21203/rs.3.rs-3173487/v1>

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Additional Declarations: No competing interests reported.

Abstract

Many qualitative studies have found that mixed conifer–broadleaf forests provide higher ecological benefits than monoculture forests, and the demand for mixed forests is increasing. However, the carbon sequestration benefits of artificial mixed forests remain unclear. In particular, considering specific growth characteristics of plantation trees and capturing the dynamic changes in carbon sequestration over time are necessary. Using 456 tree disks for dendrochronological analyses, we established a dynamic growth model for the carbon stock of *Pinus tabuliformis* under three afforestation modes in the eastern Tibetan Plateau. Based on the fundamental growth model, nonlinear fixed-effect (NLFE) models with specific parameter combination constraints were established to improve model stability. Compared with other models, the NLFE model based on the Weibull equation, which uses the model parameters n and z as classification parameters, was the optimal model. This model was used to evaluate the potential contribution of afforestation modes to the growth of carbon stock in individual *P. tabuliformis* trees over 100 years and to predict the carbon sequestration benefits of mixed and pure forests. Conifer–broadleaf forests can bring lower initial returns but higher long-term returns than the other two afforestation modes, and such forests can store more carbon. In addition, this study provides a feasible method for establishing a carbon stock growth model with minimal sample damage as well as evaluation methods and basis for large-scale pure forest transformation and management strategies.

1. Introduction

Developing plantation forests have been considered as important measures to effectively mitigate the effects of climate change (Hong et al. 2020). Since the 1980s, artificial forests have contributed to approximately 80% of China's forest biomass carbon sink (Fang et al. 2001). Some scholars believe that creating mixed forests is a potential forestry management approach to replace pure forests worldwide (Liu et al. 2018). Compared with pure forests, the average aboveground biomass and soil organic carbon stock of mixed multi-species forests are 25.5% (Feng et al., 2022) and 12% (Xiang et al. 2022) higher, respectively. Mixed forests of broadleaf and coniferous species can greatly increase soil C and N storage in the organic and mineral layers (Chen et al. 2023). However, some studies have shown that productivity does not necessarily increase as the number of tree species increases, and it may even decline (Forrester and Bauhus 2016). In some forest types, increasing tree size heterogeneity can reduce stand productivity by 20% (Bourdier et al. 2016; Soares et al. 2016). Predicting changes in the rate of carbon sequestration and peak carbon stock in future forest ecosystems is crucial for adaptive management in a changing climate. Using a carbon stock growth model is an appropriate method for accurately measuring and calculating the growth trend of carbon stock in forest vegetation. A carbon stock model is an equation or system of equations that describes the relationship between the carbon stock of an individual tree or stand and other survey factors. This model is used to derive carbon stock from easily obtainable survey variables. If the model's independent variables include tree age, then it becomes a carbon stock growth model that is used to understand, explain, and predict the growth process of carbon stock. The construction of such models usually relies on forest inventory data or panel data extracted from tree rings. Analysis of tree species growth patterns based on tree ring series provides important insights into their ecology and dynamics, such as information on growth rates and long-term growth changes (Baker et al. 2005; Baker and Bunyavejchewin 2006; Brien and Zuidema 2006; Brien et al. 2010; Schoengart et al. 2015).

As a widely planted artificial tree species on the Tibetan Plateau, *Pinus tabuliformis* often appears in the form of pure pine forests and plays an important role in mitigating climate change (Niu et al. 2022). At present, little scientific and systematic empirical research has been conducted on the carbon sequestration effects of the near-natural transformation of pure coniferous forests on the Tibetan Plateau. In particular, long-term observation, simulation, and quantitative result studies after transformation are lacking. For example, should we develop artificial mixed coniferous forests or mixed conifer–broadleaf forests? At what age do pure and mixed forests show significant differentiation in

carbon sequestration capacity? On an individual scale, is the carbon sequestration capacity of each organ consistently affected by afforestation modes? These questions require further in-depth research.

In addressing these questions, this study was conducted on the basis of survey data from 18 sample plots in the eastern forest region of the Tibetan Plateau. We selected artificial pure forests, mixed coniferous forests, and mixed conifer–broadleaf forests of *P. tabuliformis* as research objects and set up fixed sample plots. We harvested 456 disks and established a nonlinear fixed-effect (NLFE) individual carbon stock growth model with parameter constraints to simulate the carbon stock changes of the whole tree and its components (leaves, branches, stems, roots, and bark). We analyzed the differences in the growth of individual carbon stock of coniferous tree under different afforestation modes. Based on these models, we aimed to study the growth characteristics of individual carbon stock of pure and mixed coniferous forests, verify the scientific hypothesis that mixed forests increase the total carbon stock accumulation and growth rate of forest ecosystems, provide basic data for carbon cycle research in mixed forests, and provide a reference for the large-scale transformation of pure coniferous forests and management of mixed coniferous forests.

2. Materials and Methods

2.1. Study Area

The study area involves three afforestation modes dominated by *P. tabuliformis*, namely, pure forests, mixed coniferous forests, and mixed conifer–broadleaf forests, with different stand characteristics. In addition, the study area is located in the northeastern part of the Tibetan Plateau (35°45′–36°43′ N, 100°51′–102°26′ E, Fig. 1), which is one of the main distribution areas of artificial forests on the northwest plateau of China, including *P. tabuliformis*, *Picea crassifolia*, and *Ulmus pumila*. The terrain is complex, with a general high elevation in the northwest and low in the southeast, ranging from 2225 to 3258 m above sea level. The climate is a typical plateau arid continental climate with evident vertical changes. The distribution of heat resources is uneven, with large diurnal temperature differences and small annual temperature differences. The average annual temperature is 0–7.8°C; the average annual precipitation is 350–820 mm, mostly concentrated in July to October, and the annual evaporation is 900–1916 mm. The main soil types include chestnut calcareous soil, gray calcareous soil, black calcareous soil, and gray–brown soil.

2.2. Carbon Stock Data

The artificial *P. tabuliformis* forests on the Tibetan Plateau are primarily distributed in the Huangshui Forest Farm, Xishan Forest Farm, and Taershan Forest Farm in Xining City in the northeastern part of the plateau. Based on historical records from forest farms, all artificial forests in farms were planted 40–55 years ago, and such forests involved afforestation modes such as pure *P. tabuliformis* coniferous forests (S1); mixed coniferous forests (S2), such as mixed *P. tabuliformis*–*U. pumila* forests; and mixed conifer–broadleaf forests (S3), such as mixed *P. tabuliformis*–*P. crassifolia* forests. We set up sample plots in each of these three types of stands and collected *P. tabuliformis* disk samples. Considering that trees of the same age in the study area have different growth potentials, we measured each tree in each sample plot and divided them into diameter classes in accordance with their diameter at breast height (DBH) to avoid selection bias of dominant tree species. We selected one standard tree for each diameter class and 3–5 standard trees with different diameter classes for each sample plot to obtain biomass data sets and disk samples. In total, 18 *P. tabuliformis* plots (28.28 m × 28.28 m) were set up, and 132 (S1), 144 (S2), and 180 (S3) disks were cut from 78 *P. tabuliformis* sample trees.

The DBH and height of sample trees were measured before felling. The specific field operations for obtaining the biomass of each organ of the sample trees and disks are as follows. First, the crown was divided into the upper and lower layers based on the length of the crown to obtain accurate crown biomass. The number of branches in each layer was recorded, and 1–2 standard branches with similar basal diameter and length to the average branch in that layer and

normal growth were selected from each layer. The fresh weight of different layers (upper and lower), different branch levels (main branch and secondary branch), and different tree species (branches and leaves) was measured. Approximately 50 g of bark and 500 g of branch and leaf samples were collected from each standard branch in each layer and weighed accurately. Then, after taking disk samples at the stump (0.1 m) and breast height (1.3 m) positions, disks were taken every 2 m above 1.3 m. When the distance from the tree end was more than 1 m but less than 2 m, disks were taken every 1 m using a hand saw. Finally, all disks and segmented trunks were weighed after disassembling the trunk. The roots were excavated as completely as possible, and soil and other adhering materials were removed before weighing the roots. All samples of each component were brought back to the laboratory, dried at 85°C, and weighed to calculate the moisture content of each component of the sample and infer the biomass of individual components and whole plants (Table 2).

The carbon content of each sample was determined by dry combustion. The sample was crushed three times, and the carbon content was measured using a Multi N/C3000 analyzer (AnalytikJena AG, Jena, Germany) with three parallel samples measured each time. The average value of the measurement results was used as the sample data with a measurement accuracy of 0.01% and an error of $\pm 0.2\%$. The carbon content (P) of the sample was calculated using formula (1), and the carbon content of the sample trees is shown in Table 1. Finally, the carbon stock of individual trees was calculated by directly measuring the carbon content in biomass. Notably, the carbon stock data obtained through field measurement and calculation were used to verify model performance, whereas the data used for model construction were obtained from time series data extracted from each tree ring. The specific method is defined as follows:

$$P = \frac{C_s}{W_s} \times 100\%$$

1

where P is the carbon content of sample; C_s is the carbon stock of sample; W_s is the dry weight of sample.

Table 1

Carbon content of each component of sample trees						
	Total	Stem	Bark	Branch	Leaf	Root
Samples	78	78	78	78	78	78
Max	0.5264	0.5353	0.5272	0.5415	0.5344	0.5381
Min	0.5101	0.4940	0.5036	0.5068	0.4960	0.4691
Mean	0.5209	0.5130	0.5267	0.5188	0.5372	0.5090
SD	0.0083	0.0170	0.0109	0.0145	0.0171	0.0331

Based on tree-ring laboratory processing procedures, tree disk samples were dried, fixed, and polished (Fritts 2012). The annual ring diameters of all disks were measured from east to west and from north to south using the LINTAB tree ring analysis system and then averaged to form a diameter series for individual trees. The diameter series data and height series data recorded at the cutting disk were entered into the *P. tabuliformis* biomass model system (2)–(3) to obtain biomass series data. Then, the result was multiplied by the carbon content to obtain carbon stock time series data (Table 2) for constructing an individual tree carbon stock growth model.

$$\begin{cases} M_A = 0.067765D^{2.18050}H^{0.43610} & (D \geq 5cm) \\ M_A = 0.398351D^{1.07994}H^{0.43610} & (D < 5cm) \end{cases}$$

(2)

where M_A is the aboveground biomass of sample tree; D and H are the DBH and tree height of the sample tree, respectively. The same below.

$$\begin{cases} M_1 = \frac{1}{1+g_1+g_2+g_3} \times M_A \\ M_2 = \frac{g_1}{1+g_1+g_2+g_3} \times M_A \\ M_3 = \frac{g_2}{1+g_1+g_2+g_3} \times M_A \\ M_4 = \frac{g_3}{1+g_1+g_2+g_3} \times M_A \end{cases}$$

(3)

where M_1 , M_2 , M_3 , and M_4 are the biomass of the stem, bark, branches, and leaves in kilograms (kg), respectively; g_1 , g_2 , and g_3 are the scale functions of the bark, branches, and leaves relative to stem biomass of 1, respectively.

Table 2
Summary statistics of individual tree age and carbon stock for sample trees.

Factors	Items	Pure coniferous forests	Coniferous mixed forests	Coniferous broadleaved mixed forest
Samples		24	24	30
Tree age (year)	Mean	52.50 ± 2.89	44.25 ± 2.06	47.80 ± 2.95
	Range	50 ~ 55	42 ~ 47	45 ~ 52
TC (kg)	Mean	27.39 ± 23.76	20.41 ± 22.26	20.84 ± 24.76
	Range	0.19 ~ 91.15	0.03 ~ 103.17	0.01 ~ 124.25
SC (kg)	Mean	11.19 ± 10.14	8.20 ± 9.03	8.77 ± 10.91
	Range	0.03 ~ 38.89	0.01 ~ 41.60	0.00 ~ 55.42
BC (kg)	Mean	1.99 ± 1.66	1.49 ± 1.43	1.61 ± 1.79
	Range	0.01 ~ 6.26	0.00 ~ 6.32	0.00 ~ 8.78
BrC (kg)	Mean	6.12 ± 5.25	4.61 ± 5.21	4.48 ± 5.26
	Range	0.05 ~ 19.96	0.01 ~ 24.15	0.00 ~ 25.90
LC (kg)	Mean	3.08 ± 2.29	2.39 ± 2.30	2.28 ± 2.26
	Range	0.07 ~ 8.67	0.01 ~ 10.36	0.01 ~ 10.61
RC (kg)	Mean	4.95 ± 4.42	3.69 ± 4.32	3.65 ± 4.53
	Range	0.14 ~ 17.02	0.05 ~ 20.38	0.05 ~ 22.97
Note: TC, SC, BC, BrC, LC and RC mean carbon stock of total, stem, bark, branches, leaves and root of individual tree, respectively. The minimum value of the carbon stock range depends on the minimum diameter at breast height and tree height at the disk cutting location, while the maximum value depends on the diameter at breast height and tree height data obtained during tree measurement.				

Individual tree diameter series does not contain information about intra-specific variability. Considering dynamic associations among the same species, panel data (a data structure commonly used in econometrics) were used. Panel data are multi-dimensional data that contain observations about different cross-sections across time. Each value in the panel data is denoted as y_{kt} , where k represents the k_{th} individual and t represents the t_{th} observation period. If the

individuals in the sample were identical in each period, then the sample is called a “balanced panel,” otherwise it is called an “unbalanced panel.” Modeling panel data can not only control the time-invariant and unobservable heterogeneous factors, but also the time-varying and unobservable homogeneous factors, which makes parameter estimation more reliable. Compared with cross-sectional or time-series data, panel data are more conducive for studying dynamic changes within datasets. In this research, the diameter data of an individual tree present a typical time series. Panel data consist of individual tree diameter series of the same tree species. Panel data are unbalanced because different individual trees have different series lengths. Taking the total carbon stock (TC) of individual tree as an example, some of the panel data included in this paper are shown in Table 3.

Table 3
Unbalanced panel data of individual total carbon stock.

Tree Numbers	TC ₀	TC(t)	TC(t + 1)	ΔTC	Time Intervals
101	0.63	0.63	3.37	2.74	5
101	0.63	3.37	6.54	3.17	10
		...			
101	0.63	44.71	/	/	55
102	0.61	0.61	1.55	0.94	5
102	0.61	1.55	2.42	0.87	10
		...			
124	1.55	80.99	/	/	50
201	0.56	0.56	1.08	0.52	5
		...			
224	1.30	70.76	/	/	47
301	0.15	0.15	0.60	0.45	5
		...			
330	0.56	78.23	/	/	52
Note: ΔTC means carbon stock increments every five years (if the tree ring increment is less than five years, the carbon stock during actual time intervals will be calculated), and TC(t) and TC(t + 1) mean the carbon stock of period t and t + 1, respectively. This table lists only part of the panel data. The symbol ‘...’ means that some data is omitted.					

2.3. Methods

2.3.1. Basic Growth Models

Taking the total carbon stock as an example and considering the data patterns (Fig. 3), seven basic versatile nonlinear functions (Table 4) were selected to fit the correlation between carbon stock and tree age. We fitted these functions to the entire data set and selected the best performing model in accordance with R² (coefficient of determination), root-mean-squared error (RMSE), and Bayesian information criteria (BIC). BIC is a selection criterion used to select among different models with different numbers of parameters. It is an asymptotic result derived from the assumption that the data distribution belongs to the exponential family and compensates for models with more parameters, being more careful. R² is used as the main criterion for model evaluation, with smaller values (except for R²) indicating a better model. All basic

models were fitted using NLS techniques with Matlab R2019b. The mentioned evaluation indicators are shown in Equations (5)–(7):

$$R^2 = \frac{\sum_{k=1}^N (\hat{C}_k - \bar{C}_k)}{\sum_{k=1}^N (C_k - \bar{C}_k)}$$

(5)

$$RMSE = \sqrt{\frac{\sum_{k=1}^N (C_k - \hat{C}_k)^2}{N}}$$

(6)

$$BIC = m \ln(N) - 2 \ln(L)$$

(7)

where C_k and $\hat{C}_k$ are the observed and estimated values of carbon stock of the k_{th} sample tree; $\bar{C}_k$ is the average value of C_k ; N is the number of samples; m is the number of model parameters; L is the likelihood function value. The same below.

Table 4
Candidate basic growth models we considered.

Basic Growth Model	Function Expression	Function Form
M1	$C = e^{m+A}$	Growth
M2	$C = m \cdot (1 - e^{-n \cdot A})^z$	Richards
M3	$C = m \cdot e^{-n \cdot e^{-z \cdot A}}$	Gompertz
M4	$C = m \cdot e^{-n \cdot A^{-z}}$	Korf
M5	$C = m \cdot e^{-n \cdot e^{-z \cdot A}}$	Logistic
M6	$C = m \cdot (1 - e^{-n \cdot A^z})$	Weibull
M7	$C = m \cdot e^{-A}$	Schumacher
Note: C is carbon stock of the different components (kg); A is the age of individual tree (years); and m , n , and z are the formal parameters to be estimated.		

2.3.2. NLFE Models

A hierarchical structure of the data results was established on the basis of the correlation of afforestation modes among observations. However, the stochastic structure was ignored, and the independence of observations was assumed by using NLS regression. On the contrary, individual trees in different afforestation modes had different values of carbon stock. Therefore, the NLFE model using afforestation modes as dummy variables based on the optimal basic function

was utilized to demonstrate the effect of afforestation modes. During this process, the fitting data were the panel data, which were composed of carbon stock series of the same plantation afforestation mode. The following dummy variable models were constructed using the Weibull equation (M6): $P = 1, C = M = 0$ for pure coniferous forests (S1), $C = 1, P = M = 0$ for mixed coniferous forests (S2), and $M = 1, P = C = 0$ for mixed conifer–broadleaf forests (S3, Table 5).

Table 5
NLFE models using regions as dummy variables.

Equations	Derivation	Model
F1	m	$C_i = (m^P \cdot P + m^C \cdot C + m^M \cdot M) \cdot (1 - e^{-n \cdot A^z}) + \epsilon_i$
F2	n	$C_i = m \cdot (1 - e^{-(n^P \cdot P + n^C \cdot C + n^M \cdot M) \cdot A^z}) + \epsilon_i$
F3	z	$C_i = m \cdot (1 - e^{-n \cdot A^{(z^P \cdot P + z^C \cdot C + z^M \cdot M)}}) + \epsilon_i$
F4	m,n	$C_i = (m^P \cdot P + m^C \cdot C + m^M \cdot M) \cdot (1 - e^{-(n^P \cdot P + n^C \cdot C + n^M \cdot M) \cdot A^z}) + \epsilon_i$
F5	m,z	$C_i = (m^P \cdot P + m^C \cdot C + m^M \cdot M) \cdot (1 - e^{-n \cdot A^{(z^P \cdot P + z^C \cdot C + z^M \cdot M)}}) + \epsilon_i$
F6	n,z	$C_i = m \cdot (1 - e^{-(n^P \cdot P + n^C \cdot C + n^M \cdot M) \cdot A^{(z^P \cdot P + z^C \cdot C + z^M \cdot M)}}) + \epsilon_i$
F7	m,n,z	$C_i = (m^P \cdot P + m^C \cdot C + m^M \cdot M) \cdot (1 - e^{-(n^P \cdot P + n^C \cdot C + n^M \cdot M) \cdot A^{(z^P \cdot P + z^C \cdot C + z^M \cdot M)}}) + \epsilon_i$
Note: $m^P, m^C, m^M, n^P, n^C, n^M, z^P, z^C$ and z^M are regression parameters related to the dummy variables (afforestation modes). P, C , and M are the afforestation modes of pure coniferous (S1), coniferous mixed (S2), and conifer–broadleaf mixed forests (S3) in the study area, respectively, and ϵ_i is a normally distributed error term associated with the i_{th} individual tree observation.		

2.3.3. Autocorrelation and Heteroskedasticity Elimination

Considering the high degree of first-order autocorrelation and heteroskedasticity of the panel data in this study, they were processed using the first-order difference method and weighted regression method, respectively. The calculation steps are shown as follows:

Step 1: Taking Equation M6 as an example, the presence or absence of autocorrelation in the error term ϵ_t was determined by comparing the Durbin–Watson (DW) statistic with two critical values (DURBIN and WATSON 1951). The DW statistic is defined using Eq. (8).

$$DW = \frac{\sum_{t=2}^n (u_t - u_{t-1})^2}{\sum_{t=1}^n u_t^2}$$

8

where u_t is the residual of the regression model. The DW statistic is related to the following value of autocorrelation coefficient ρ :

$$\rho = 1 - \frac{DW}{2}$$

9

Step 2: The generalized first-order difference method achieves the elimination of heteroskedasticity by subtracting the original model by ρ multiplied by the model with one period lag, which is developed as follows:

$$C' = m \cdot \left(1 - e^{-n \cdot A_t^z}\right) - \rho \left[m \cdot \left(1 - e^{-n \cdot A_{t-1}^z}\right) + \epsilon_t - \rho \epsilon_{t-1} \right]$$

10

where

$$C' = C_t - C_{t-1}, v_t = \epsilon_t - \rho \epsilon_{t-1}$$

11

A new model without autocorrelation was obtained by using the algorithm, and the parameters were solved by OLS regression in the new model to eliminate the autocorrelation of the variables caused by the spherical disturbance term.

Step 3: Weighted regression estimation was used to eliminate heteroskedasticity, and the key to remove heteroskedasticity by weighted regression is the choice of weight function. This study used $\frac{1}{\sqrt{f(A)}}$ as the weight function to remove the heteroscedasticity in the carbon stock growth model.

2.3.4. Evaluation and validation of models

In selecting the best-fitting NLFE carbon stock growth model, R^2 (Eq. 5), Standard Error of Estimate (SEE) (Eq. 12), and TRE (Eq. 13) were used as model evaluation indicators. An external independent data set was used to evaluate the predictive performance of the NLFE carbon stock growth model (BERK 1984; SHAO 1993). Considering that the modeling data for the NLFE carbon stock growth model in this study were obtained from tree ring series combined with publicly derived models, the 78 carbon stock data obtained by sampling were not sufficient for modeling, but this true value data can be used as a validation set (Table 2). The model was validated by comparing the estimated carbon stock from panel data with the true carbon stock obtained by sampling. Considering that the ages of the sample trees were concentrated in the middle-aged forest stage (42–55 years), the accuracy of carbon stock simulation during this period was highly credible in validating this study, indicating reference significance for the prediction accuracy of carbon stock in other age stages of the model. The accuracy of validation was calculated using mean percentage standard error (MPSE) and mean systematic error (MPE), as shown in Equations (14) and (15). MPSE indicates the accuracy of individual carbon stock estimates, while MPE indicates the size of the regression model's estimation accuracy.

$$SEE = \sqrt{\frac{\sum_{k=1}^N (\hat{C}_K - C_k)^2}{N-m}}$$

(12)

$$TRE = 100 \sqrt{\frac{\sum_{k=1}^N (C_k - \hat{C}_K)^2}{\sum_{k=1}^N \hat{C}_K}}$$

(13)

$$MPSE = \sum \left| (C_k - \hat{C}_K) / \hat{C}_K \right| / N \times 100\%$$

(14)

$$MPE = t_{\alpha} \cdot (SEE / \bar{C}_k) \cdot \sqrt{N} \times 100$$

(15)

3. Results

3.1. Optimization of the basic dynamic growth model and handling of autocorrelation

Seven carbon stock growth models were used as candidate basic growth models (Table 4). The entire data of 78 *P. tabuliformis* sample trees were used to fit the basic growth models. Based on fit statistics produced by fitting seven candidate models (Table 6), M6 had the best R^2 and RMSE, and the BIC of M6 was intermediate; therefore, M6 (Eq. 14, Table 5) was selected as the best basic growth model in this study.

$$C_k = m \cdot (1 - e^{-n \cdot A_k^z}) + \epsilon_k$$

14

where C_k and A_k are the carbon stock (kg) and age (year) of the k_{th} sample tree of *P. tabuliformis*; m , n , and z are the formal parameters of this model; ϵ_k is the error term of the k_{th} tree. Parameter m is the limit value parameter of the growth of the tree carbon stock. Parameter n is related to the tree growth rate in Weibull equations. Parameter z is a shape parameter.

Table 6
AIC and BIC score of the basic growth models

Model	Component	AIC	BIC
M1	Total	769.8985	782.8242
	Stem	641.3210	653.2467
	Bark	368.2003	380.1260
	Branch	562.4930	575.4187
	Leaf	442.3153	454.2410
	Root	538.0547	549.9804
M2	Total	770.5983	782.4868
	Stem	643.3838	655.2723
	Bark	369.9990	381.8876
	Branch	562.6203	574.5089
	Leaf	441.9220	453.8105
	Root	538.6125	550.5011
M3	Total	771.3942	783.2827
	Stem	643.1538	655.0423
	Bark	367.8758	379.7643
	Branch	564.0495	575.9380
	Leaf	442.3804	454.2689
	Root	537.8926	549.7811
M4	Total	769.5489	781.4315
	Stem	641.1945	653.9830
	Bark	367.6846	379.5731
	Branch	562.3219	574.2004
	Leaf	441.9990	453.8875
	Root	537.8698	549.7684
M5	Total	776.5437	788.4322
	Stem	649.5873	661.4758
	Bark	368.3284	380.2169
	Branch	567.8764	579.7649
	Leaf	442.7868	454.6754
	Root	538.1151	550.0036
M6	Total	769.5322	781.4207

Model	Component	AIC	BIC
	Stem	641.1208	653.0093
	Bark	367.6406	379.5291
	Branch	562.3047	574.1932
	Leaf	441.9893	453.8778
	Root	537.7733	549.6618
M7	Total	769.8985	777.8242
	Stem	641.3210	649.2467
	Bark	368.2003	376.1260
	Branch	562.4930	570.4187
	Leaf	442.3153	450.2410
	Root	538.0547	545.9804

Residuals were calculated for the carbon stock time series results of each component fitted by the M6 model, and the DW test was used to detect whether the model results were autocorrelated. At a significance level of 5%, if the DW statistic falls within the interval [0, 1.611], then the series has positive autocorrelation; if it falls within the interval [2.389, 4], then the series has negative autocorrelation, according to the DW test table (White 1992). The results showed that the DW statistics of the carbon stock series regression for individual trees and components fell within the interval [0, 1.611], and the carbon stock series data showed positive autocorrelation. Table 7 shows the DW test results before and after handling autocorrelation using the first-order difference method (Eqs. 10–11). The DW statistics after processing all fell within the interval [1.662, 2.338] (Table 7) in the non-autocorrelated region, indicating that the autocorrelation of M6 (Weibull equation) was eliminated.

Table 7
The DW statistic distribution of the individual tree diameter series regression.

Component	Sample size	Number of variables	DW ^a	DW ^b
Total	78	1	0.247	1.712
Stem	78	1	0.263	1.632
Bark	78	1	0.255	1.609
Branch	78	1	0.238	1.781
Leaf	78	1	0.214	1.79
Root	78	1	0.251	1.754
Note: DW ^a and DW ^b means DW statistic of each component of Weibull equation before and after difference method.				

3.3. NLFE dynamic growth models

The evaluation results of the NLFE model for carbon stock of individual tree and components of the *P. tabuliformis* plantation in the Tibetan plateau are shown in Table 8, which contains the results under various combinations of the derived parameters. The results showed that R^2 of the NLFE model with different derivation parameters and their combinations could reach above 0.42, and the SEE was within the range of [1.05, 17.86]. For each component, the best

fitting effect was observed in the bark ($R^2 > 0.62$), followed by the trunk ($R^2 > 0.54$), and the worst effect was observed in the roots. For different combinations of derived parameters, the NLFE model with n and z as regression parameters and afforestation mode as a dummy variable had the best performance with the smallest SEE and the highest R^2 of the parameters, and the prediction accuracy of R^2 improved by 6.39% (from 0.4727 to 0.5029) compared with NLS regression for the total carbon stock of individual tree. Meanwhile, the NLFE model with n as the regression parameter and afforestation mode as a dummy variable had a better fit and accuracy for one parameter. The NLFE model using m , n , and z as regression parameters and afforestation mode as a dummy variable for derivation did not fit better than the two regression parameters, but this model increased SEE, TRE, and MPSE. However, the NLFE model with three and two fitted parameters had significantly optimized indicators compared with the model with only one derivation parameter. For example, R^2 improved by about 3%, which shows that the correct choice of the number of derived parameters is the key to NLFE model fitting in this study. Therefore, the NLFE model using n and z as regression dummy parameters for the Weibull growth model (Equation F6) has better prediction results. The coefficients of all NLFE models are shown in Appendix A.

Table 8
Fit of different derivation parameters for the NLFE models

Equations	Derivation	Component	R ²	SEE	TRE	MPSE
F1	m	Total	0.4884	17.8471	-0.2255	57.1534
		Stem	0.5361	7.2526	-0.1242	56.1834
		Bark	0.6211	1.0662	-0.3772	47.1786
		Branch	0.4227	4.1956	-0.6122	61.1604
		Leaf	0.4378	1.8035	-0.7204	53.5301
		Root	0.4252	3.5373	-0.1515	59.4561
F2	n	Total	0.4888	17.8391	-0.0931	57.0089
		Stem	0.5364	7.2498	-0.1280	56.1051
		Bark	0.6213	1.0660	-0.1875	47.1780
		Branch	0.4236	4.1924	-0.0462	60.7942
		Leaf	0.4397	1.8004	-0.1590	52.8350
		Root	0.4254	3.5365	0.0837	59.3296
F3	z	Total	0.4879	17.8559	-0.1176	57.4077
		Stem	0.5359	7.2542	-0.0942	56.2446
		Bark	0.6208	1.0666	-0.2167	47.1363
		Branch	0.4221	4.1978	-0.0191	61.2987
		Leaf	0.4378	1.8034	-0.1115	53.5567
		Root	0.4243	3.5401	0.0476	59.9047
F4	m,n	Total	0.5011	17.7523	0.9041	57.8879
		Stem	0.5495	7.1991	1.1486	57.8824
		Bark	0.6358	1.0530	0.6560	46.8211
		Branch	0.4356	4.1792	0.4057	59.8604
		Leaf	0.4517	1.7942	0.0352	52.0665
		Root	0.4375	3.5247	0.9954	61.6209
F5	m,z	Total	0.4955	17.8516	1.4427	65.8459
		Stem	0.5454	7.2320	1.6154	66.5242
		Bark	0.6322	1.0582	0.6989	51.7801
		Branch	0.4285	4.2051	0.9841	65.3239
		Leaf	0.4452	1.8047	0.2038	55.2891
		Root	0.4307	3.5460	1.6695	73.5797
F6	n,z	Total	0.5029	17.7339	0.7600	64.7754

Equations	Derivation	Component	R ²	SEE	TRE	MPSE
F7	m.n.z	Stem	0.5471	7.2180	1.6905	83.0985
		Bark	0.6355	1.0534	-0.0563	48.5286
		Branch	0.4368	4.1747	0.0122	61.4670
		Leaf	0.4510	1.7953	-0.2331	53.2304
		Root	0.4152	0.4399	0.5125	68.2945
		Total	0.5013	17.8817	1.2150	66.4364
		Stem	0.5422	7.3117	3.2990	95.6671
		Bark	0.6367	1.0595	0.3704	48.0611
		Branch	0.4374	4.2033	0.2525	61.1410
		Leaf	0.4524	1.8062	0.0086	52.6504
		Root	0.4401	3.5428	0.7605	68.2792

The results of the best NLFE model (F6) fit for *P. tabuliformis* plantation on the Qinghai–Tibetan Plateau in this study are shown in Fig. 3. The figure includes the growth status of carbon stock for individual trees and their components. The order of carbon accumulation among the components can be observed. The carbon stock of bark is slightly lower than that of leaves, accounting for about 2–11% of the total carbon stock of trees. In addition, the growth rate of carbon stock for individual *P. tabuliformis* trees in mixed conifer–broadleaf forests (S3) is higher than that of other two afforestation modes after about 30 years. The growth rate of *P. tabuliformis* in pure coniferous forests (S1) initially slows down. Therefore, the fitting effect of the NLFE model is generally effective and consistent with the dynamic growth trend of *P. tabuliformis*.

3.4. Future growth trend forecast

Considering that tree carbon sequestration is persistent, we are interested in the long-term carbon sequestration benefits. Therefore, based on the best NLFE model obtained from fitting, this study predicted the growth trend of carbon stock for individual *P. tabuliformis* trees and their components under three afforestation modes from 0 to 100 years old. The results are shown in Fig. 4. With regard to the total carbon sequestration of individual trees, during the first 40 years, the total amount of carbon sequestration for trees in pure *P. tabuliformis* forests (S1) was the highest, followed by mixed coniferous forests (S2), and mixed conifer–broadleaf forests (S3) had the lowest carbon sequestration. With regard to the carbon sequestration rate, although the total amount of carbon sequestration for individual *P. tabuliformis* trees grown under the S3 pattern was not as high as that of the other two patterns during the first 40 years, its carbon sequestration rate increased gradually and reached its maximum growth rate at about 35 years old, making its carbon stock gradually exceed that of individual trees under the other two afforestation modes at 40–55 years old. Finally, at 100 years old, the carbon stock reached about 1.15 times that of pure forests (S1) and 1.26 times that of mixed coniferous forests (S2). With regard to components, the growth dynamics of carbon stock in the stems was consistent with that of total carbon stock, including the age points where the rate changed (accelerated or slowed down). However, the critical points of the carbon sequestration rate for other components (bark, branches, leaves, and roots) were not evident. No slowing down trend was observed within 100 years, but these four components maintained similar growth patterns. The afforestation modes had a consistent effect on the increase in carbon sequestration benefits for components as for the total carbon sequestration of individual trees. Therefore, in the long run (within 100 years), adopting the mixed conifer–broadleaf forest afforestation mode (S3) has the most evident increase in carbon sequestration benefits for *P. tabuliformis*. In addition, the mixed coniferous forest afforestation mode (S2) has a certain

negative impact on *P. tabuliformis* carbon sequestration. Moreover, the final carbon stock is lower than that of individual trees in pure *P. tabuliformis* forests.

4. Discussion

4.1. Impact of tree growth differences on model construction accuracy

Compared with pure forests, mixed forests tend to have greater stand growth, and they can effectively increase stand carbon stocks (Zheng et al. 2008). We attempted to start from the individual tree scale and use model simulation to quantitatively study the carbon sequestration benefits of three afforestation modes and explore the gain effect of mixed conifer–broadleaf forests on the carbon sequestration rate and amount of individual *P. tabuliformis* trees. The growth model method has been developed for several hundred years (Pretzsch and Pretzsch 2009). Although this method requires high-quality measured data and shows poor inference performance when exceeding input data, it still provides a powerful and reliable method for growth prediction and management purposes (Weiskittel 2014). Such models can be used to predict future yields and explore different afforestation options (Vanclay 1994).

Although the coefficient of determination (R^2) for the best NLFE model fitted for individual *P. tabuliformis* trees under different afforestation modes was only around 0.5 (Table 8), this finding does not indicate an error in the selection of the basic model or a large error in sampling data because of the large difference in growth potential between dominant and inferior trees within the stand. The slopes of different stands in the study area covered a range of 0° to 25° , and sample trees may have differences in growth potential because of factors such as topography, competition, individual genetics, disease, and pests. If the average carbon stock value of sample trees under the same afforestation mode is used as modeling data, then the R^2 of the best NLFE model constructed will increase significantly to above 0.98, and all error indicators will also decrease significantly (Table 10). However, at this time, the model can only reflect the average growth level of the stand and cannot reflect changes within the forest.

Table 10
Fitting results of the best NLFE model reflecting the average growth level of individual tree carbon stock

	Total	Stem	Bark	Branch	Leaf	Root
R^2	0.9904	0.9899	0.9943	0.9903	0.9875	0.9913
SEE	1.8598	0.8488	0.1112	0.3866	0.1946	0.3089
TRE	0.5307	0.9074	-0.1656	-0.1007	-0.2641	0.3714
MPSE	19.0821	28.4660	14.4973	14.8859	12.3612	21.4907

4.2. Description of model applicability

The applicability of this model is discussed from two perspectives: the method of model construction and model validation. First, this method was proposed for the analysis of wood disks, individual tree measurement data, biomass data, and carbon content data collected from forests. The disk can provide height and diameter sequence data for individual trees up to the present, and biomass can be calculated using publicly available biomass models. Finally, carbon stock modeling data are obtained, so this model can estimate carbon stock time series data using disk data obtained in the field. On the contrary, at present, for biomass and carbon stock model simulations, using existing recognized models can achieve ideal fitting results, reducing the need for a large amount of felling to collect biomass data. In the future, existing models must be used, and growth models must be established on this basis to predict future

tree growth trends. In addition, the time series data contained in disks or tree cores are important and convenient for establishing growth models.

Second, the study used measured carbon stock data to validate the growth model. Although the validation dataset only includes data for middle-aged forests (42–55 years) and cannot fully validate changes in carbon stock throughout the entire growth cycle of trees, the growth pattern of trees is consistent with the form of empirical models. Although only part of the data is used for validation, it is still persuasive. In addition, the model construction and validation method balances model accuracy and method convenience, ensuring that a relatively reliable model is constructed with as little destructive sampling as possible. The model results can be applied to other similar sampling environments. The model construction method based on annual ring sequence data can help researchers quickly establish new growth models with low sampling costs when large differences are observed in sampling environments.

4.3. Research on the gain effect of artificial mixed forests

Increasing studies have revealed the benefits of multi-species artificial forests with regard to productivity (Feng et al., 2022), stability (Grossman et al. 2018; Schnabel et al. 2021), community structure (Williams et al. 2017), and biodiversity (Hua et al. 2022). With regard to carbon sequestration, mixed forests also store more carbon than pure forests (Gamfeldt et al. 2013; He et al. 2013; Brandt et al. 2014). Our study also obtained similar results, suggesting that in the long-term afforestation scenario, the carbon sequestration benefits of mixed conifer–broadleaf forests are higher than those of coniferous pure forests and higher than those of mixed coniferous forests. Compared with previous studies that used observational experiments or forest inventory data, we quantified the mixed advantages of different growth stages within trees from a temporal perspective to indirectly observe the phenomenon of mixed forests. Through quantitative means, we found that the carbon sink benefits of mixed *P. tabuliformis* conifer–broadleaf forests were slightly worse in the early stages (within 40 years of tree age), which might be due to differences in root depth and distribution patterns among tree species, resulting in a certain degree of root competition in the early stages of mixed planting. *P. tabuliformis* is a coniferous tree with a deep and concentrated root system that tends to grow vertically to obtain water and nutrients from deep soil. *U. pumila* is a broad-leaved tree species with a widespread root system that includes deep and shallow soils, and it has no evident taproot. In the early stages of *P. tabuliformis* and *U. pumila* mixing, the root system of *P. tabuliformis* may need more time to adapt to the new environment and resource allocation and establish an effective water and nutrient acquisition system, so its growth rate is relatively slow. Based on the results of this study, the initial competition in mixed conifer–broadleaf forests is stronger than that in pure coniferous forests and mixed coniferous forests, affecting tree growth rates and resulting in weaker carbon sequestration benefits for *P. tabuliformis* in the early stages. However, the degree of root competition between mixed tree species depends on many factors, including soil type, water supply, nutrient distribution, and planting density. For example, Yan studied the impact of mixing ratio on stand carbon stock and found the most suitable alternate planting ratio for mixed *Larix olgensis* and *Salix babylonica* forests (Jiajie et al. 2022). Therefore, the impact of root competition can be reduced through a reasonable planting design and management measures. In the middle and late stages of mixed conifer–broadleaf forest development, *P. tabuliformis* and *U. pumila* may undergo niche differentiation in resource use and growth strategies to avoid direct competition. For example, in the initial stage, *P. tabuliformis* may focus more on root development to obtain deeper water and nutrients, whereas *U. pumila* may focus more on above-ground growth to obtain more light. Over time, this niche differentiation may promote faster growth for *P. tabuliformis* in later stages. In addition, broad-leaved trees have a relatively extensive root system that provides them strong nutrient absorption capacity. Mixing planting with broad-leaved trees can improve soil structure, increase organic matter content, and provide additional nutrient supply, thereby improving soil conditions (Chengdong 2022), which is conducive to the growth and development of *P. tabuliformis*. With regard to photosynthetic efficiency, broad-leaved trees usually have larger leaves that can utilize light energy to improve photosynthetic efficiency for entire stands. Coniferous trees such as *P. tabuliformis* can increase photosynthetic products and growth rates.

The data for this study come from time series data extracted from analyzed wood disks. Time series data from multiple trees form panel data. The acquisition of more long-term species growth data was performed through dendrochronological analysis, revealing more information about species interactions reflected in tree rings. This approach may alleviate the pressure of long-term field monitoring experiments to a certain extent, while achieving better monitoring results and natural science exploration methods in combination with experiments. This study also has certain limitations, and it only investigates the changes in carbon stock of individual trees of a single species in the sample plots. We used a large amount of time series data to ensure the credibility of the model but only considered afforestation modes as dummy variables. The next step in constructing growth models should focus on the characteristics brought by the mixed effects of tree species in artificial forests at the stand level, and the dynamics of carbon stock growth should be studied under different stand densities and cultivation conditions to promote the quantitative study of afforestation gains and form a complete system.

Declarations

Funding

This work was supported by the funding provided by the Project for Transformation of Scientific and Technological Achievements from the Qinghai Province [grant number 2020-SF-145], the "Basic Frontier Projects of Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences" [grant number E350011] and the Provincial financial support for agriculture project [grant number 2022-QFER-724].

Data availability

The datasets generated during and analysed during the current study are not publicly available due to the funding project not being completed, but are available from the corresponding author on reasonable request.

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Figures

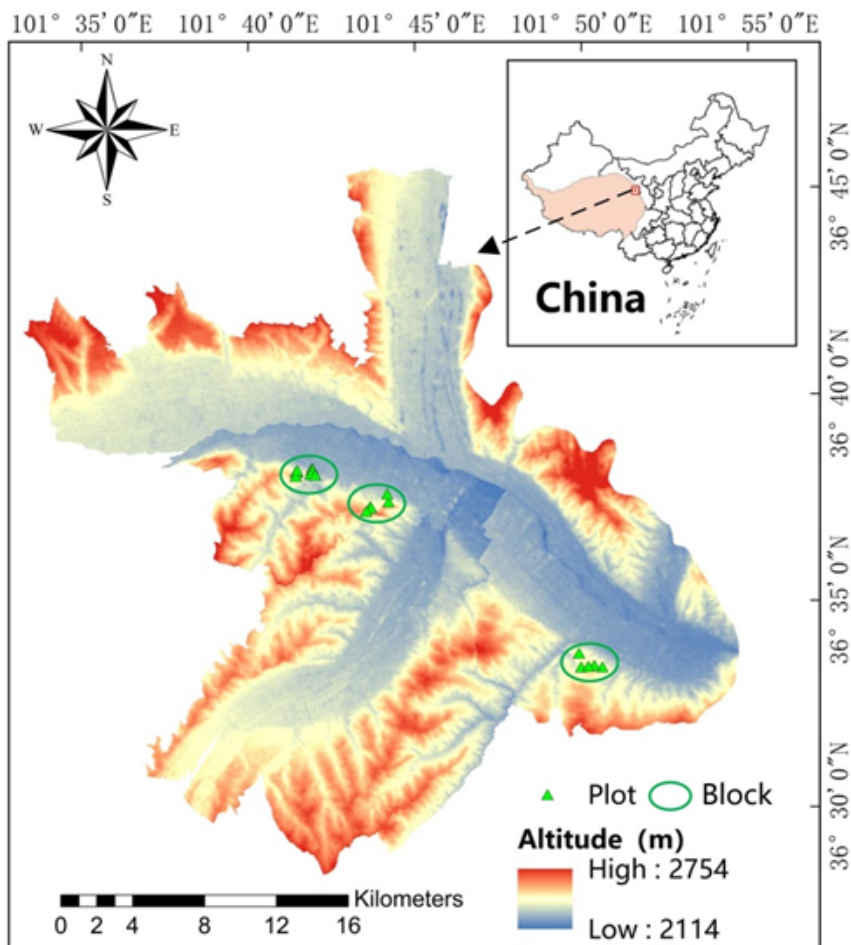


Figure 1

The regions where the tree sample data were collected.



Figure 2

Disc samples collection by segmented interception and labeling.

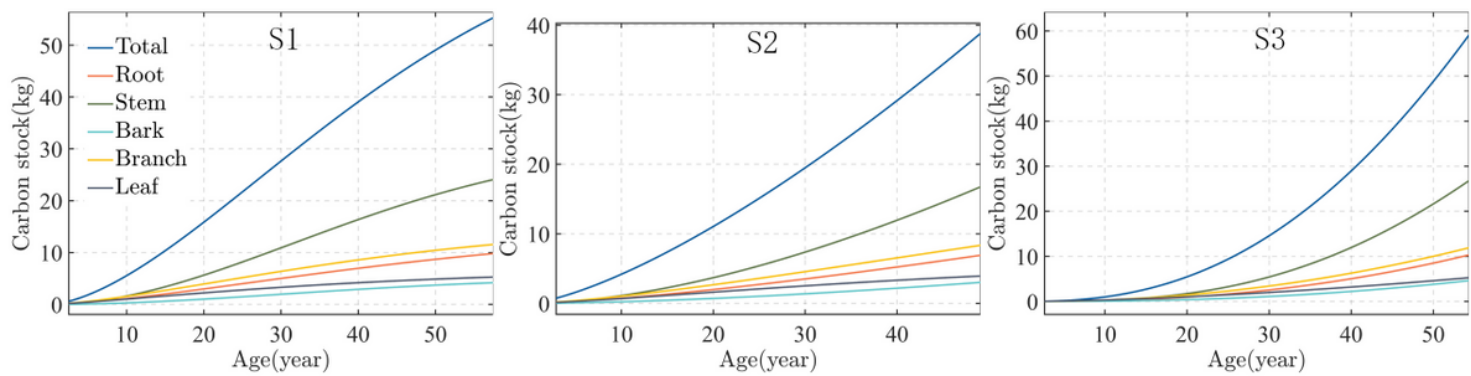


Figure 3

Fitted curve of the best NLFE carbon stock model

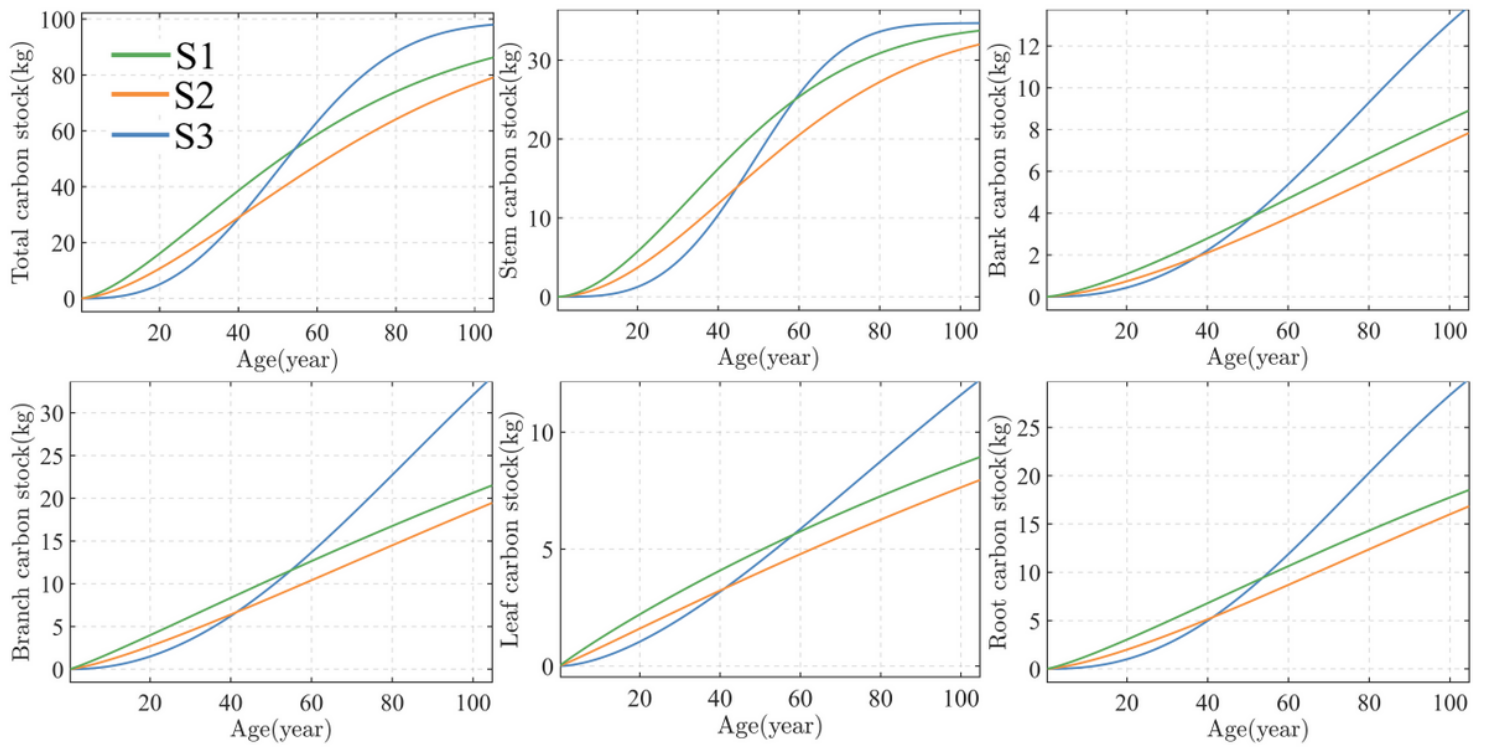


Figure 4

Predicted carbon stock growth trend over 100 years using the best NLFE model

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