

Article

Optimizing Carbon Sequestration Potential for Chinese Fir Plantations Using Genetic Algorithm

Zhiqiang Min ¹, Yingze Tian ², Chen Dong ^{1,3,*} and Yuling Chen ⁴

¹ College of Mathematics and Computer Sciences, Zhejiang A&F University, Hangzhou 311300, China; minzq1026@163.com

² Sichuan Forestry and Grassland Survey and Planning Institute, Chengdu 610084, China; tianyingze@icloud.com

³ Zhejiang Provincial Key Laboratory of Forestry Intelligent Monitoring and Information Technology, Zhejiang A&F University, Hangzhou 311300, China

⁴ Institute of Remote Sensing and Geographic Information System, School of Earth and Space Sciences, Peking University, Beijing 100871, China; chenyling92@pku.edu.cn

* Correspondence: dongchen@zafu.edu.cn; Tel.: +86-15867180919

Abstract: Carbon sequestration management of plantation forests has become an important topic in the current context of vigorously promoting carbon peaking and carbon neutrality goals and will be the goal and task of the forest industry for a long time. The objective of this study was to explore the applications of genetic algorithm (GA) in both near-optimal thinning regimes at stand level and near-optimal forest management planning at the regional level under the forest management objectives of carbon sequestration. This research integrates a carbon assessment technique with GA optimization to effectively enhance the management of carbon sequestration within plantation forests. Results indicate that the density effect model was an accurate and reliable carbon assessment method ($R^2 = 0.8701$, RMSE = 7.548). The GA optimization approach is efficient in the near-optimal thinning regime and the appropriate forest management planning schedule under the forest management objectives of carbon sequestration. In the research area, the near-optimal carbon sequestration is 38,045.71 t, and in the 15 years from 2016 to 2030, the carbon sequestration of 20 Chinese fir stands should meet the annual thinning constraint condition of not less than 50 t. A near-optimal decision of the carbon sequestration management of plantation forests based on GA provides a theoretical basis and technical support for the compilation of a forest management plan at the stand and regional scales in the plantation operation management of carbon sequestration.

Keywords: carbon sequestration; genetic algorithm; carbon density effect; optimal thinning; forest planning



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1. Introduction

With the increasing intensification of plantation management, the use of stand growth and management models has become an important technical measure to guide forest management decisions [1–3]. In the current context of vigorously promoting the carbon peaking and carbon neutrality goals, forest management focuses on carbon balance, while intensive forest management involves silvicultural treatments and their effects on carbon sequestration and emissions [4]. Forests hold immense promise. It is imperative to precisely measure forest carbon storage and integrate carbon sink management into forest management to effectively capture and store carbon that is in the atmosphere [5]. Exploring the research and practical significance of implementing an optimal decision scheme for plantation management based on carbon sequestration technology holds immense value for foresters and plantation management units [6–8].

Decisions in forest management can be classified according to three main levels: the tree, the stand, and forest and regional levels [9]. As the smallest operational unit, the

stand level is the appropriate level for studying the carbon balance of stand management activities [10]. Forest operation management decisions mainly include tree species selection, rotation length selection, thinning regime selection, and management planning decisions [11–13]. Operation thinning regimes and operation management planning decisions are the most frequently implemented stand management activities by forestry managers [14]. The objective of forest operation management under climate change is to change from timber yield to carbon sequestration [15]. Thus, the measures for stand management activities will change accordingly. The main optimization problems associated with stand-level optimization are the rotation length, thinning regime, and stand density management problems [16]. Near-optimal thinning regimes, such as structured forest management and near-nature forest management, play a key role in formulating a forest management strategy for adapting to climate change [17]. Starting from the stand level, we studied operation thinning regimes of single stands and the operation management planning of multiple stands.

Large carbon sequestration in forests can be achieved by increasing the rotation length, applying the appropriate stand density, and other silvicultural treatments [18]. At present, the forest management of carbon sequestration research typically centers on the optimal rotation length problem for economic and commodity production objectives [19,20]. The most frequently set objectives involve maximizing the carbon net present value (NPV) of either a single rotation or a defined period [2,13,21–23]. In the estimation of forest carbon storage, remote sensing data are mostly used for large-scale estimation [24]. Due to the challenges in conducting on-site investigations of forest biomass and carbon storage to estimate carbon sequestration, frequent on-site inspections may exacerbate damage to forest ecosystems. Therefore, evaluating forest carbon sequestration potential is complex, as is assessing its spatial and temporal variability [25]. When studying carbon sequestration management, most research in natural science examines the impact of thinning density on carbon sequestration by comparing control and experimental plots [26–32]. About the stand optimal density management problem, the forest resource planning system developed combines thinning measures with model prediction, in which the multi-functional operation planning model and simulation algorithm have been built to achieve optimal operation goals [33–36]. However, relatively little research on the compilation of a forest management plan (CFMP) [37] about carbon sequestration exists, especially from the perspective of thinning density.

With respect to the optimization methods applied to both stand and forest management decisions, a wide range of methods have been explored recently, mainly including mixed-integer programming, linear programming, goal programming, heuristics, and dynamic programming [16,38]. Heuristic methods provide assurance that the best result of these is the near-optimal (with high probability). Three main heuristic methods have been explored, as follows: genetic algorithms (GAs) [39,40], simulated annealing [41,42] and particle-swarm optimization [43]. Among these methods, GAs, which have the advantages of modularization and being able to find the global near-optimal solution to the optimization problem, have been widely used in the thinning problem at the stand level and the rotation length problem at the regional level. Nonetheless, robust research on near-optimal thinning regimes combining single stands and multiple stands based on GAs for the forest operation management of carbon sequestration is lacking.

The study aimed to extend the management of forest ecosystems by incorporating carbon assessment techniques into an optimization framework. The objective of this study is to address the deficiencies in carbon sequestration management concepts and methodologies within forest management processes, which result in the challenging and time-intensive task of solving carbon sequestration management models. Genetic algorithms are employed to implement nearly optimal thinning strategies at the stand level and to formulate effective forest management plans at the regional level that align with enhanced carbon sequestration objectives. The result is anticipated to offer theoretical insights and prac-

tical tools for CFMP, applicable to both stand and regional scales within the operational management of carbon sequestration plantations.

2. Materials and Methods

2.1. Data Source

Nanping city is in the northwest of Fujian Province, China from 117°00' to 119°25' east longitude and from 26°30'–28°20' north latitude (Figure 1). The data are derived from Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook.) plantations located in the Dali, Lanxia, and Jiangle forest farms, Nanping city (China). Specifically, subcompartments of the Chinese fir plantations were chosen based on varying age groups (young, middle-age, and near-mature forests (spanning 21–25 years)), density (sparse, medium, and dense), and site conditions (good, medium, and poor). In the selected subcompartments, 84 circular standard plots representing the average growth state of the subcompartments were set, and the radius of the circular standard plots is 5 m. According to the forest resources inventory and planning data of the local forest farm, some stand factors for each subcompartment were recorded, such as elevation (HB), slope (PD), aspect (PX), soil thickness (TRHD), humus thickness (FZZHD), average diameter at breast height (D), average tree height (H), average tree age (A), area (Area), stand volume per hectare (M1) and number of trees per hectare (N). In each circular standard plot, two to five trees with well-balanced canopy growth were selected as the standard trees, and two to three trees with good height and little competition with the surrounding trees were selected as the dominant trees. The diameters at breast height and tree height were measured for standard and dominant trees within the boundary of the sample circular plot. The measurement accuracy of diameter at breast height was 0.1 cm, and that at tree height was 0.1 m.

N

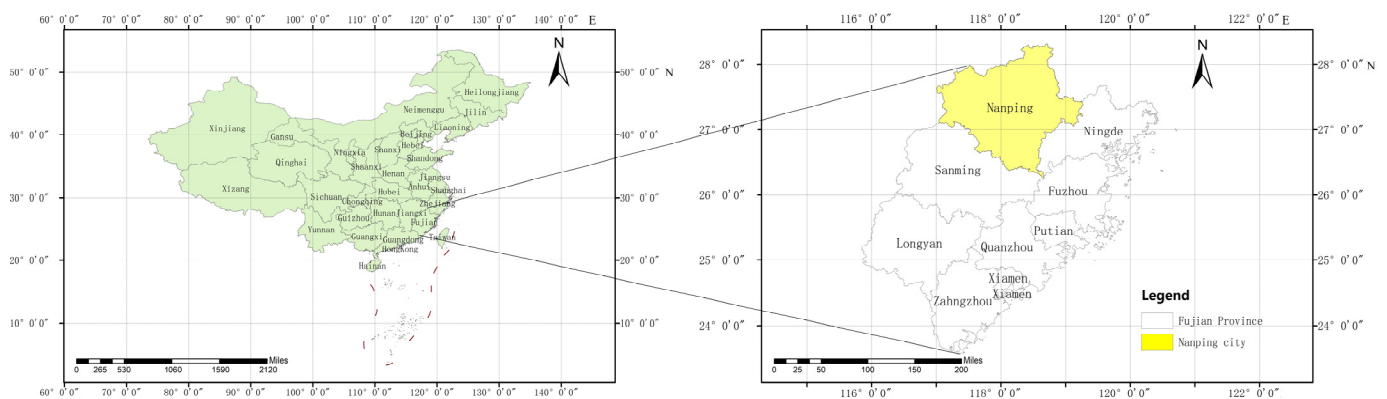


Figure 1. Research area map. The English text on the left image shows the names of provinces in China, while the Chinese and English on the right represent the names of cities in Fujian Province.

Each sample plot's dominant height (HT) was calculated using the average height of the dominant trees in the sample plot. In combination with the biomass regression models in Equations (1)–(5) [44], the biomass of the sample plot was calculated and then multiplied by the carbon content rate of Chinese fir (=0.5201) to obtain the carbon density data of the sample plot. The carbon density of the sample plot is used to represent the carbon sequestration per hectare (C).

$$W_S = 0.073429(D^2H)^{0.86262} \quad (1)$$

$$W_P = 0.013775(D^2H)^{0.84463} \quad (2)$$

$$W_B = 0.000482(D^2H)^{1.23314} \quad (3)$$

$$W_L = 0.019638(D^2H)^{0.78969} \quad (4)$$

$$W_T = W_S + W_P + W_B + W_L \quad (5)$$

where W_S is the stem biomass, W_P is the bark biomass, W_B is the branch biomass, and W_L is the aboveground biomass.

All the factors related to carbon density modelling and their descriptions are shown in Table 1. This article utilizes ArcMap 10.8 to generate a thematic map, and the software employed for the density effect model and genetic algorithm optimization planning is Python 3.7.

Table 1. Data characteristics of 84 sample plots for carbon density modeling.

Variable	Min	Max	Mean	Std Dev	CV
A (years)	5	30	13.8	7.7	0.56
D (cm)	6.5	21.7	10.9	3.2	0.29
H (m)	4.3	16.3	8.4	2.6	0.31
HT (m)	5.5	18.2	10.5	2.7	0.26
N (trees ha ⁻¹)	1245	4950	2124.0	949.8	0.45
M1 (m ³ ha ⁻¹)	16.089	330.675	84.776	63.597	0.75
C (t ha ⁻¹)	5.689	126.900	24.799	20.558	0.83

2.2. Density Effect Model

The density quadratic effect model has good mathematical properties in the optimization process of dynamic programming. It models the relationship between stand density and yield (mainly including the average basal area, the stand volume per hectare, and the carbon sequestration per hectare) and reflects the parabolic trend between the stand yield per hectare and stand density.

On the basis of the density quadratic effect model, the stand density was used as the control variable, and the stand biomass was used as the target variable. The density effect model was constructed as follows (Equation (6)):

$$C = a_1HT^{b_1}N - a_2HT^{b_2}N^2 \quad (6)$$

where HT is determined by using the site index model (Equation (7)) established by Wu Chengzhen et al. [45].

$$HT = SI * 10^{(0.1809 - 3.7654A^{-1} + 2.9602A^{-2})} \quad (7)$$

where SI is the height in meters of trees of standard-age dominance in the forest stand. It is used as an indicator to evaluate forest soil productivity.

The density effect model corresponding to the density effect of average carbon sequestration per tree is Equation (8).

$$V = a_1HT^{b_1} - a_2HT^{b_2}N \quad (8)$$

The density effect model of Chinese fir was fit using nonlinear least-square estimates through a Gauss–Newton algorithm, which was implemented in PROC MODEL. Considering that the leave-one-out approach effectively showed the independence of the validation data set, the leave-one-out approach was selected for model verification in this experiment.

The production elasticity coefficient plays a pivotal role in economics, serving as a measure of the responsiveness of output to changes in input variables such as labor or capital. Within the scope of this article, we delve into the analysis of the production elasticity coefficient for Chinese fir, specifically within the framework of the density effect model. The examination of this coefficient provides valuable insights into the efficiency of resource allocation and the potential for yield improvement in the context of Chinese fir cultivation.

By employing the production elasticity coefficient, we can identify the most influential factors affecting production and make informed decisions to optimize forestry management practices. The relevant calculation formulas are as follows (Equations (9)–(12)).

$$\overline{EP(HT)} = \frac{\partial V / \partial HT}{V / HT} = \frac{a_1 b_1 HT^{b_1-1} - a_2 b_2 HT^{b_2-1} N}{V / HT} \quad (9)$$

$$\overline{EP(N)} = \frac{\partial V / \partial N}{V / N} = \frac{-a_2 HT^{b_2}}{V / N} \quad (10)$$

According to the multi-factor production elasticity analysis, $\sum EP = 2.109 > 1$ of Chinese fir indicates that the site condition and the density increased by $X\%$ and the carbon sequestration per tree increased by more than $X\%$.

$$MPP(HT) = \frac{\partial V}{\partial HT} = a_1 b_1 HT^{b_1-1} - a_2 b_2 HT^{b_2-1} N \quad (11)$$

$$MPP(N) = \frac{\partial V}{\partial N} = -a_2 HT^{b_2} \quad (12)$$

2.3. Thinning Regime for Carbon Sequestration Goal

Based on the density effect model, the dynamic programming mathematical model of the continuous state in the discrete stage was established to study the stand density control of the multi-stage decision. Genetic algorithm (GA) was applied to calculate the near-optimal thinning regime.

2.3.1. Dynamic Programming Mathematical Model

According to the established density effect model, stand density is the control variable, and carbon density is the target variable. The thinning of Chinese fir plantations was carried out at multiple time points, and the control of stand density was a multi-step decision-making process. In the process, m decisions were assumed; the first $m-1$ decisions were the thinning decisions, and the m th decision was the final planning time point decision. The state transition equations are Equations (13) and (14).

$$N_{i+1} = N_i - n_i = N'_i \quad (13)$$

$$C_{i+1} = C_i + v_i * Sgn + \Delta C_{i,i+1} \quad (14)$$

where N_i is the number of trees per hectare before the i th ($i = 1, 2$) thinning, N'_i is the number of trees per hectare after the i th thinning, n_i is the number of trees of the i th thinning, C_i is the carbon sequestration before the i th thinning, v_i is the carbon sequestration of the i th thinning, and $\Delta C_{i,i+1}$ is the net increment of carbon sequestration during the i th thinning and the $(i + 1)$ th thinning. When the D of the harvested wood is less than or equal to 6 cm, the harvested wood is placed in the forest as the residue, which is regarded as carbon emission, and then Sgn is -1 ; when the variable D of the harvested wood is greater than 6 cm, the harvested wood is used for solid wood or paper products as carbon storage, and then Sgn is 1. D was determined by using the D model (Equation (15)) established by Dong Chen [4].

$$D = 7.697 * SI^{0.547} \left(1 - e^{-0.213 * N^{-0.221} * A} \right)^{1.078} \quad (15)$$

The boundary condition represents the initial and terminal states under the action of density control during stand growth. The initial state refers to the number of trees per hectare and stand carbon sequestration before the first thinning (Equation (16)), and the terminal state refers to the number of trees per hectare and stand carbon sequestration after the final planning time point (Equation (17)).

$$(N_1, C_1) = (N_0, C_0) \quad (16)$$

$$(N_{m+1}, C_{m+1}) = (0, 0) \quad (17)$$

The optimal stand density control is to find the optimal number of retained trees at each thinning or the final planning time point N_i^* ($i = 1, 2, 3, \dots, m$), so that the stand status (N_1, C_1) is transferred to (N_2, C_2) ... until it is transferred to (N_{m+1}, C_{m+1}) . The objective function obtains the largest value (Equation (18)).

$$J_m^* = \max_{N_1^*, N_2^*, \dots, N_m^*} \sum_{i=1}^m v_i * Sgn \quad (18)$$

2.3.2. Genetic Algorithm for Near-Optimal Thinning Regime

Assuming that the operation period of Chinese fir is M years and considering the actual forest operation situation in Fujian Province, the first thinning in the plantation operation process occurs in 6–10 years, the number of thinnings in the plantation operation period is 1–2, the thinning interval is 5–10 years, and the range of thinning intensity is 0%–40%. GAs can provide a probabilistic guarantee of the global optimal solution [29,30]. The specific process of the GA is as follows:

Step 1. Plantation parameter chromosome encoding and decoding. The plantation parameters involved in this study are as follows: first thinning time, thinning interval, and thinning intensity. The value range of the first thinning was from 6 years to 10 years, and the binary code length is 2. The thinning interval range is from 5 years to 10 years, and the binary code length is 3. The value range of the thinning intensity is 0%–25%, the binary code length is 5, and the binary code length of thinning twice is $5 \times 2 = 10$. The binary coding method was used to determine the length of chromosomes $L = 2 + 3 + 10 = 15$. Each chromosome contained four genes (decision variables), which correspond to a thinning regime.

For example, the first thinning is 6 years, the thinning interval is 10 years, the first thinning intensity is 10%, the second thinning intensity is 20%, and the operation parameter chromosome encoding is as follows (Figure 2).

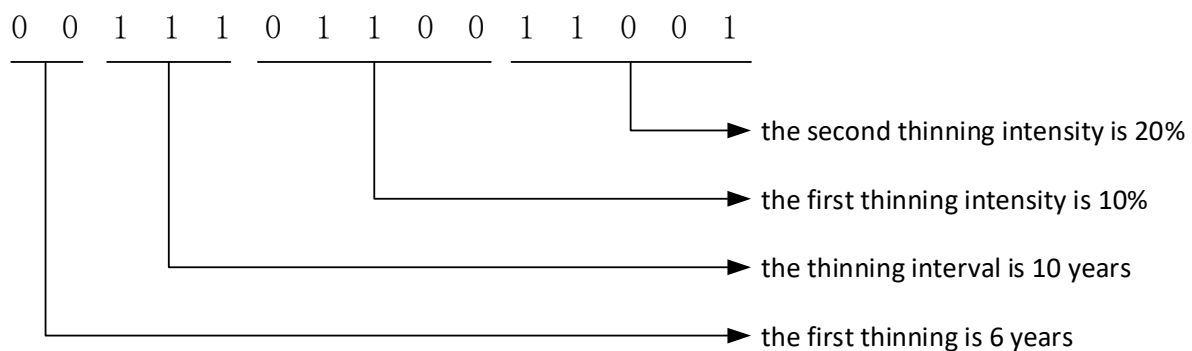


Figure 2. Example diagram of the operation parameter chromosome coding.

The chromosomes were decoded according to Equation (19), and the four operating parameters were decoded separately during chromosome decoding. The first two bits are the first thinning, the third to fifth bits are the thinning interval, the sixth to tenth bits are the first thinning intensity, and the last five bits are the second thinning intensity.

$$x = a + \frac{T(b-a)}{2^l - 1} \quad (19)$$

where T is the binary code of length l corresponding to a decimal value, and a and b are the respective upper and lower limits of decision variable x .

Step 2. Determination of initial population. Population length $POP = 100$ (corresponding to 100 thinning regimes); that is, the population is composed of 100 individuals (chromosomes), and each can be generated by the random method.

Step 3. Construction of fitness function. Four operation parameters were obtained after decoding the chromosomes and fed to the Chinese fir growth harvest model and the density effect model to calculate the fitness value of each chromosome. The objective function is the maximum carbon sequestration in the entire stand decision-making period.

Each chromosome was decoded into phenotypes (a, b, c, d), and then the fitness function was introduced. The calculation process is as follows. Given a certain stand, its site condition is SI, the initial stand density is N_0 , the first thinning time is a, the first thinning intensity is c%, the thinning interval is b, and the second thinning intensity is d%. The changes in the state variables in the two thinning processes are as follows:

(1) First thinning

Before thinning: Age = a, site index = SI, stand density = N_0 , average diameter at breast height $D_a = f(a, SI, N_0)$, dominant height $HT_a = f(a, SI)$, stand stock $C_a = f(TH_a, N_0)$, average carbon sequestration per tree $V_a = f(HT_a, N_0)$.

Number of thinned trees: $N_0 * c\%$.

Number of trees after thinning: $N_1 = N_0 - N_0 * c\%$.

Thinned carbon sequestration: If $D_a \leq 6$ cm, then $C_1 = -V_a * (N_0 * c)$; if $D_a > 6$ cm, then $C_1 = V_a * (N_0 * c)$.

(2) Second thinning

Before thinning: Age = a + b, site index = SI, stand density = N_1 , average diameter at breast height $D_{a+b} = f(a + b, SI, N_1)$, dominant height $HT_{a+b} = f(a + b, SI)$, stand stock $C_{a+b} = C_a + C_1 + \Delta C_{a,a+b}$ (where $\Delta C_{a,a+b} = C_{a+b}(HT_{a+b}, N_1) - C_a(HT_a, N_1)$), average carbon sequestration per tree $V_{a+b} = f(HT_{a+b}, N_1)$.

Number of thinned trees: $N_1 * d\%$.

Number of trees after thinning: $N_2 = N_1 - N_1 * d\%$.

Thinned carbon sequestration: if $D_{a+b} \leq 6$ cm, then $C_2 = -V_{a+b} * (N_1 * d)$; if $D_{a+b} > 6$ cm, then $C_2 = V_{a+b} * (N_1 * d\%)$.

The final decision time is set as M (corresponding to forest age is M), and the stand stock $C_M = C_{a+b} + C_2 + \Delta C_{a+b,M}$ (where $\Delta C_{a+b,M} = C_M(HT_M, N_2) - C_{a+b}(HT_{a+b}, N_2)$). The carbon sequestration of the entire stand decision-making period includes the carbon sequestration during the first thinning, the carbon sequestration during the second thinning and the carbon growth increment after two thinnings. Therefore, the fitness function can be calculated as Equation (20).

$$\begin{aligned} J(X_i) &= C_a + C_1 + \Delta C_{a,a+b} + C_2 + \Delta C_{a+b,M} \\ &= C_a + C_1 + C_{a+b}(HT_{a+b}, N_1) - C_a(HT_a, N_1) + C_2 \\ &\quad + C_M(TH_M, N_2) - C_{a+b}(TH_{a+b}, N_2) \end{aligned} \quad (20)$$

Similarly, if only one thinning is performed, the fitness function can be calculated as Equation (21).

$$J(X_i) = C_a + C_1 + \Delta C_{a,M} = C_a + C_1 + C_M(HT_M, N_1) - C_a(HT_a, N_1) \quad (21)$$

Step 4. Genetic operator. The basic genetic operators of a GA are mutation, crossover, and selection. In this paper, the selection operation adopted the roulette algorithm, with crossover probability $P_c = 0.3$ and mutation probability $P_m = 0.05$. The fitness values of each individual in the new population after crossover and mutation were calculated, and then the selection operation was carried out until $MAXGEN = 1000$.

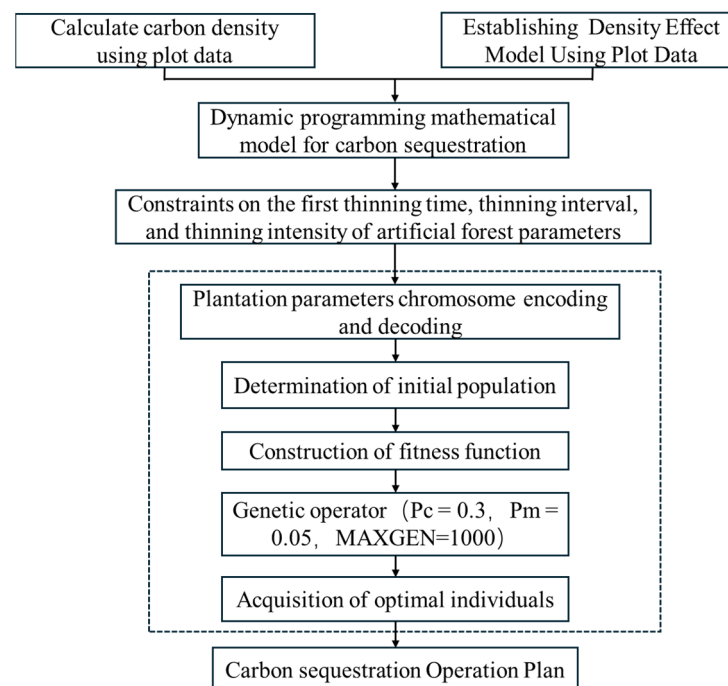
Step 5. Acquisition of optimal individuals. To avoid the loss of the optimal individuals of each generation in the evolution, the optimal individuals of each generation were stored in an array. After the iteration, these individuals were compared, and the optimal individuals were output as the result.

The information of the near-optimal thinning regime code was restored, and the thinning regime decision of the Chinese fir stand was obtained.

The pseudocode of GA for optimizing the thinning regime is as follows (Algorithm 1), and the research flowchart is shown in Figure 3.

Algorithm 1: GA for near-optimal thinning regime (GA-OTR)**Input:** SI, N, M**Output:** Near-optimal thinning regime, maximum carbon sequestration

1. GA parameter setting
2. Initialization of population (according to chromosome code)
3. Iteration through the individuals in the population
 - Chromosome decoding
 - Calculate individual fitness (based on input parameters)
 - Selection operation
 - Crossover operation
 - Mutation operation
 - Calculation of the effect of one iteration and saving the near-optimal result
4. Output of the near-optimal thinning regime and maximum carbon sequestration after all the iterations

**Figure 3.** Research flowchart.**2.4. Forest Management Planning for Carbon Sequestration Goal**

Assuming that the region has 20 Chinese fir stands (numbered 1–20), their basic situation at the end of 2015 is shown in Table A1. Each stand has three management regimes, namely no thinning, thinning once and thinning twice. The total carbon sequestration of all the stands in the region is required to reach the maximum value at the end of the year 2030, and the carbon sequestration of the annual thinning must be no less than 50 t in the next 15 years.

2.4.1. Forest Management Planning Model

The forest management planning model formulation of this study was conducted according to three guidelines. First, the area control of the thinned forestland in each period is required. Then, the carbon sequestration in the thinning should not be less than 50 t every year. Finally, the aim to maximize carbon sequestration is established, depending on the option of the thinning regimes, including no thinning, thinning once, and thinning twice. The model formulation details are expressed as follows.

Objective equation:

$$\max Z = \sum_i^I \sum_j^J u_{ij} X_{ij} \quad (22)$$

Constraints:

$$\begin{cases} \sum_j X_{ij} = A_i \\ \sum_i \sum_j v_{ijt} X_{ij} \geq 50 \\ X_{ij} \geq 0 \end{cases} \quad (23)$$

Variable u_{ij} is the carbon sequestration per hectare of the i_{th} stand under the j_{th} management scheme. Variable v_{ijt} is the carbon sequestration per hectare of the i_{th} stand in t period under the j_{th} management scheme. Variable X_{ij} is the area of the i_{th} stand under the i_{th} management scheme. Variable A_i is total area of the i_{th} stand.

In this study, stand segmentation is prohibited; that is, a stand can only adopt one of the three thinning regimes. If the i_{th} stand adopts the i_{th} management scheme, then $X_{ij} = A_i$, and $X_{ik} = 0$ ($k = 1 \dots 3, k \neq j$).

2.4.2. Genetic Algorithm to Solve Operation Management Planning

GA was applied to multi-stand carbon sequestration management planning. Each stand near-optimal thinning regime is regarded as a gene, and the binary code length is 2. Then, the combination of 20 stand management modes uses an individual with a binary length of $2 \times 20 = 40$ bits. Any individual in the group is a combination of management modes of 20 stands, which corresponds to a management planning scheme for the region.

Initial population number POP is set, and 40-bit binary numbers are randomly generated to represent the genotype of the POP individuals. The fitness function is a key element of a forest management planning model. After decoding the genotypes, the annual carbon sequestration and objective equation values of the POP individuals are calculated. The fitness function should be constructed to maximize the objective equation values under the annual carbon sequestration constraints. The fitness values of each individual in the new population after crossover and mutation are calculated, and then the selection operation is carried out until MAXGEN = 800. After selecting and adjusting the appropriate parameters, the GA can quickly converge the near-optimal solution to a similar degree.

3. Results

3.1. Density Effect Model Results

The statistics in Table 2 indicate that the density effect model exhibits good performance in terms of the fitting ($R^2 = 0.8701$, RMSE = 7.548) and test ($R^2 = 0.8291$, RMSE = 8.447) results.

Table 2. Parameters and evaluation indicators of carbon density effect model.

Parameter	Estimated Value	S.E.	Fitting Indicators	Test Indicators
a1	0.00004	0.00002	$R^2 = 0.8701$ RMSE = 7.548	$R^2 = 0.8291$ RMSE = 8.447
b1	2.6096	0.1942		
a2	1.38×10^{-8}	1.17×10^{-8}		
b2	2.3542	0.3228		

In the context of Chinese fir cultivation, the production elasticity coefficients, as derived from the density effect model, are encapsulated within Equations (9) and (10). These coefficients are pivotal for understanding the sensitivity of Chinese fir production to variations in input factors, such as planting density or other cultivation practices. As shown in Table 1, the average dominant height of each stand in this region is 10.5 m, with an average of 2124 trees per hectare. The average EP(TH) is 2.781, while the average EP(N) is -0.672 . A higher EP(TH) value indicates that the site condition effect is at an increasing stage, implying that better site conditions lead to improved outcomes. Conversely, a negative EP(N) value suggests that the density effect is also at a negative stage. It is

noteworthy that a 1% decrease in density results in a 0.672% increase in carbon sequestration per Chinese fir tree. This indicates that the stand density of Chinese fir plantations in the surveyed area of Fujian Province is relatively high and should be appropriately reduced.

The $MPP(TH) = 0.003$ (Equation (11)) and $MPP(N) = -0.0000035$ (Equation (12)) reveal crucial insights from the multi-factor marginal product analysis. These findings demonstrate that, under current conditions, adding one tree per hectare will result in a reduction in carbon sequestration per tree by 0.0000035 tons. Furthermore, the data show that for every 1 m increase in the site index, the carbon sequestration per tree increases by 0.003 tons. This emphasizes the considerable influence of site density on carbon sequestration per tree.

3.2. Near-Optimal Thinning Regime for Carbon Sequestration Goal

Based on the basic situation of 20 stands at the end of 2015 in Table 2, GA was used to calculate the near-optimal thinning regime for thinning once and thinning twice for each stand and carbon sequestration per hectare at 30 years of age (Table A2). Taking stand No. 1 as an example, the near-optimal output of thinning twice is as follows:

Near-optimal thinning regime: (10.0, 10.0, 20.0, 25.0).

Carbon sequestration goal values: 139.573.

It can be interpreted as follows: the first thinning age is 10 years (the first number), the first thinning intensity is 20% (the third number), the second thinning age is 20 years (the first number + the second number), the second thinning intensity is 25% (the fourth number), and the carbon sequestration per hectare is 139.573 t ha⁻¹ when the decision time is 30 years. Figure 4 shows the changes in the stand carbon sequestration and stand density with age during the entire decision-making period, covering an appropriate forest management planning schedule for carbon sequestration goals.

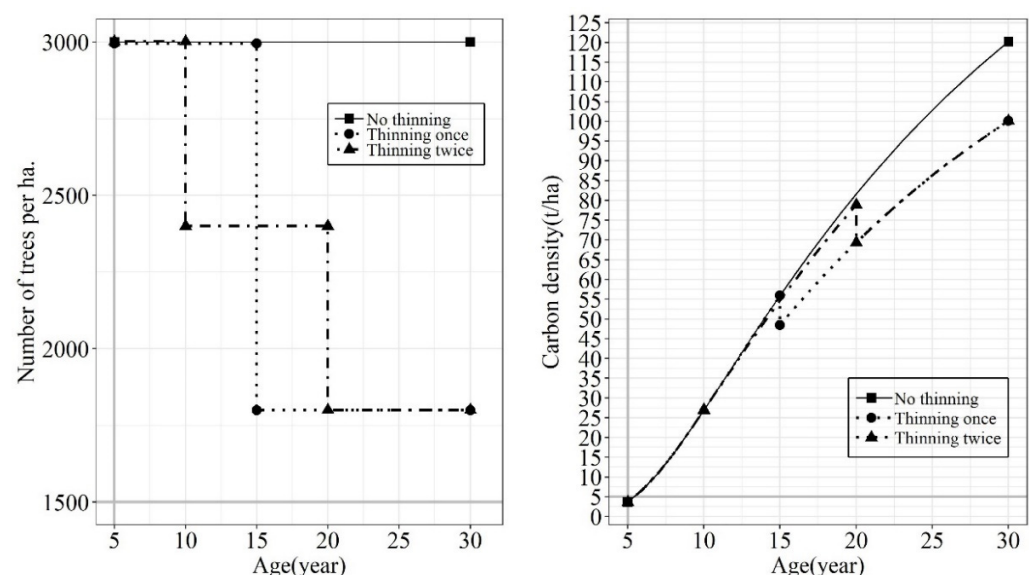


Figure 4. Schematic diagram of stand density and carbon density changing with age under near-optimal thinning regime (stand No. 1).

Figure 5 illustrates the convergence process of the genetic algorithm (GA) with initial population sizes of 500 and 1000. Additionally, Table 3 demonstrates that using crossover and mutation probabilities of 0.5 and 0.01, respectively, with an initial population size of 1000 yielded favorable results. It is important to note that different parameter settings can impact the convergence rate, runtime, and the quality of the near-optimal solution. After adjusting and selecting appropriate GA parameters (iteration number = 800, initial

population number = 1000, crossover probability = 0.5, mutation probability = 0.01), a forest management plan for achieving the carbon sequestration goal was generated, as shown in Table 4. The near-optimal carbon sequestration amount is 38,045.71 tons. Over the 15-year period from 2016 to 2030, 20 Chinese fir stands are expected to meet the annual thinning constraint condition of not less than 50 tons of carbon sequestration. The corresponding near-optimal scheme is denoted by the sequence (1, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2, 2, 1, 1, 2, 1, 2, 2, 2, 2), where 1 represents the stand choosing a once-thinning regime, 2 represents the stand choosing a twice-thinning regime, and 0 represents the stand choosing no thinning regime.

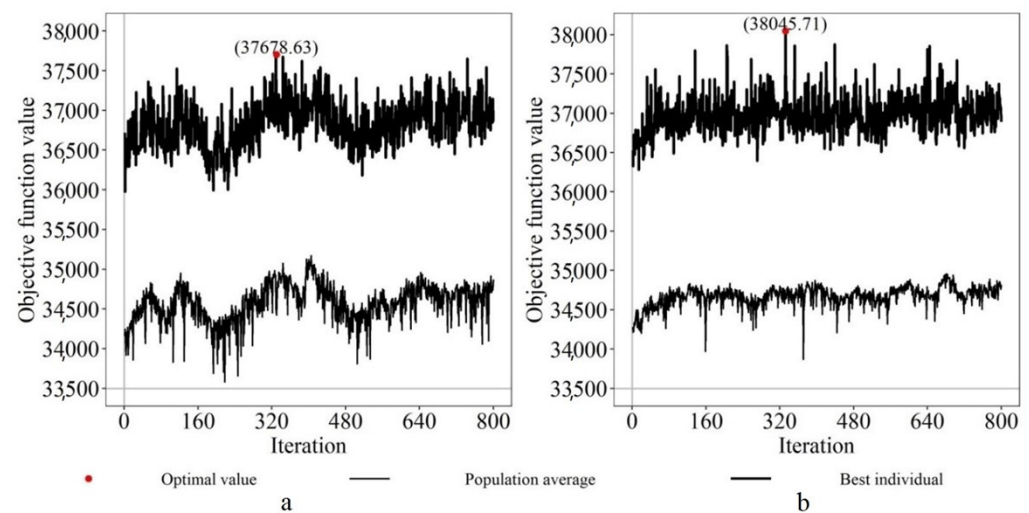


Figure 5. GA running with the data sets of two examples ((a) population size = 500, (b) population size = 1000).

Table 3. Convergence effect of GA with different parameter settings.

Pc	Pm	Objective Function Value	CPU Time (Seconds)
0.3	0.05	37,541.21	378.0291
0.5	0.05	37,749.59	375.9889
0.9	0.05	37,399.01	343.8089
0.5	0.01	38,266.94	273.5580
0.5	0.1	37,439.11	274.9308

Table 4. Appropriate forest management planning schedule for the carbon sequestration goal.

Stand No.	Option	Thinning Time and Carbon Sequestration															Final Carbon Sequestration
		2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	
1	Thinning once										131.96						766.50
2	Thinning twice		21.00										184.92				1143.59
3	Thinning once						119.03										680.87
4	Thinning twice			44.97										440.50			2743.22
5	Thinning twice				82.25										560.83		3393.09
6	Thinning twice			10.09										153.19			972.82
7	Thinning twice					90.74										432.05	2285.78
8	Thinning twice					16.37										595.96	3830.56
9	Thinning twice				119.19										494.83		2654.55
10	Thinning once						147.61										817.86
11	Thinning twice			36.25											264.11		2167.59

Table 4. Cont.

Stand No.	Option	Thinning Time and Carbon Sequestration															Final Carbon Sequestration
		2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	
12	Thinning twice	62.12										258.12					1385.40
13	Thinning once								309.44								1749.01
14	Thinning once							300.26									985.24
15	Thinning twice		23.66										262.01				1642.68
16	Thinning once							147.51									849.21
17	Thinning twice	66.58										426.11					2558.69
18	Thinning twice			52.79										359.61			2175.48
19	Thinning twice	58.58										648.78					4067.46
20	Thinning twice		28.51										194.39				1176.09
Total: 20 stands		187.28	73.17	107.84	237.69	107.11	266.64	147.51	300.26	309.44	131.96	1333.00	641.32	953.30	1319.78	1028.01	38,045.71

4. Discussion

4.1. CFMP in Carbon Sequestration Management of Plantation

As forest management objectives shift from timber yield to carbon sequestration under climate change, optimal thinning plays a pivotal role in developing a climate change adaptation strategy for forest management. However, relatively few studies on the CFMP in the carbon sequestration management of plantations have been conducted, especially from the perspective of thinning density. Nutrient removal and reduced organic matter inputs to forest soils through different thinning regime practices may affect the long-term forest soil fertility and stand productivity, affecting the carbon sink capacity of forest ecosystems [46]. Measuring the effectiveness of thinning practices in carbon sequestration is a complex process that involves numerous considerations. This includes estimating forest carbon sequestration potential, simulating forest carbon cycling, optimizing forest management strategies, assessing forest carbon sink functions, and establishing sustainable forestry carbon finance markets. Studying the status, driving factors, and ways to enhance the global forest carbon sink function, as well as the distribution of and changes in forest soil carbon storage, are important aspects for measuring the effectiveness of thinning practices. It is essential to establish a sound carbon finance market, promote the increase in forest carbon sinks through policy guidance and international cooperation, and improve the quality and efficiency of the forestry carbon finance system.

This study explored the application of GAs in near-optimal thinning regimes at the stand level and near-optimal forest management planning at the regional level under the forest management objectives of carbon sequestration. The field of near-optimal carbon sequestration focuses on sequestering 38,045.71 tons of carbon. Over the 15-year period from 2016 to 2030, it is crucial for 20 Chinese fir stands to consistently meet the requirement of sequestering a minimum of 50 tons of carbon annually through thinning. When compared to traditional methods, the GA algorithm not only significantly enhances carbon sequestration but also offers comprehensive guidance for real-world operations. Following the CFMP in the carbon sequestration management of plantations will also help China achieve its carbon neutrality target for 2060, because doing so will effectively improve the forest carbon sinks [46].

4.2. Effect of Thinning on Carbon Sequestration of Chinese Fir

Our results confirm that thinning is better than no thinning when analyzing the near-optimal thinning scheme of each stand, because our tree age is between 5 and 9 years. In the seedling stage, the forest has not formed a stable ecological structure, and thinning at this time reduces the competition between organisms for resources, which not only plays a positive role in promoting the growth of Chinese fir but also lays a good foundation for

ecological development. Therefore, after thinning, the forest carbon sequestration shows a rapid growth trend. A previous study demonstrated that thinning a Chinese fir forest in 6–10 years played a fundamental role in the formation of a stand structure in the later period of the forest and significantly increased the biomass in the forest area in Fujian Province [47]. This report is consistent with our finding that thinning at a young age has played a positive role in promoting the carbon sequestration of Chinese fir. Wang Zichun et al. [48] believed that thinning reduces the stand density but can increase the biomass of a single tree, so it does not necessarily reduce the stand biomass, which is related to the growth years after thinning. However, Xu Jinliang et al. [49] found that 15 years of thinning had no significant effect on the carbon sequestration of Chinese fir. Therefore, the effect of thinning on the carbon sequestration of Chinese fir also requires further monitoring.

At both the stand and regional levels of forest optimization, time is an important factor due to the length of the planning horizon [16]. The stand-level near-optimal regime (timing of management activities) can be perceived to change considerably as the final decision time point is varied. These effects, such as site index and stand density, are more closely related to stand optimization problems. At other scales, a limited set of stand-level decisions is typically available for addressing regional level goals. Table 4 shows that the objective equation value of thinning twice is better than that of thinning once. However, the constraint seems to be that after thinning, the amount of carbon remaining (residual) in a stand should be 50; thinning once and the stand area should be considered in the forest management planning. The greater the number of decision variables, the more thinning regimes will be generated for simulation, resulting in additional loads and entailing additional computational resources. GA was studied for optimization, and other heuristic methods, such as simulated annealing and particle swarm optimization or some reinforcement learning algorithms, require further exploration.

4.3. Research Forecast

This study focused on thinning and density control for the carbon sequestration management of plantations, excluding the influence of the optimal rotation length problem for economic and commodity production objectives, fertilization intensity, and other silvicultural treatments on the carbon sequestration management of plantations. Forest ecosystem management and carbon balance take into consideration carbon sequestration and emissions. The comprehensive evaluation of the change mechanism of forest management measures for carbon sequestration and the effect of the carbon sequestration capacity of Chinese fir on offsetting carbon emissions from fossil energy are potential directions of future research on carbon sequestration management.

5. Conclusions

This study analyzed how near-optimal thinning for carbon sequestration goals depends on the carbon assessment method and the optimization technique. Our results indicate that the density effect model is a reliable carbon assessment method, which is crucial for optimizing thinning regimes and generating an appropriate forest management planning schedule. For complicated forest decision-making problems, the heuristic optimization technique GA is a promising alternative. The GA optimization approach, designed in this study for the forest decision problems (thinning and forest management planning) of carbon sequestration management under single stands (stand level) and multiple stands (regional level) is valuable. Implementing the Carbon Forest Management Plan (CFMP) for carbon sequestration in plantations can help China achieve its 2060 carbon neutrality target by enhancing forest carbon sinks.

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Appendix A

Table A1. Basic status of 20 stands at the end of the year 2015.

Stand No.	Area (ha)	SI (m)	A (Year)	N (Trees ha ^{−1})
1	5.9	16	5	3000
2	6.1	18	8	2700
3	2.8	20	9	3000
4	30.2	14	7	2500
5	25.1	16	6	2700
6	5.3	18	7	2550
7	15.9	16	5	3750
8	16.5	20	5	2250
9	18.6	16	6	3330
10	4.8	18	9	2500
11	6.5	22	6	1667
12	9.7	16	9	3333
13	7.3	20	6	2850
14	11.3	14	7	2700
15	12.4	16	8	2550
16	15	12	8	2700
17	13.4	18	9	2850
18	8.5	20	7	2850
19	16.2	20	9	2700
20	8.7	16	8	2700

Table A2. Possible alternative options and their carbon output for each stand during the entire decision-making period.

Stand No.	Option	Thinning Regime	Thinning Time and Carbon Density															C Goal Values
			2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	
1	No thinning	/																120.236
1	Thinning once	(15.0, 40.0)										22.366						129.916
1	Two thinning	(10.0, 10.0, 20.0, 25.0)					5.378										24.657	139.573
2	No thinning	/																165.241
2	Thinning once	(15.0, 40.0)							31.238									175.561
2	Two thinning	(10.0, 10.0, 9.0, 25.0)		3.443										30.314				187.473
3	No thinning	/																226.818
3	Thinning once	(15.0, 40.0)						42.512										243.169
3	Two thinning	(10.0, 10.0, 15.0, 25.0)	7.734										44.031					260.200
4	No thinning	/																80.169
4	Thinning once	(15.0, 40.0)								15.174								85.064
4	Two thinning	(10.0, 10.0, 8.0, 25.0)			1.489										14.586			90.835
5	No thinning	/																118.714
5	Thinning once	(15.0, 40.0)									22.373							126.539
5	Thinning twice	(10.0, 10.0, 12.0, 25.0)				3.277										22.344		135.183
6	No thinning	/																162.604
6	Thinning once	(15.0, 40.0)						30.901										171.799
6	Thinning twice	(10.0, 10.0, 5.0, 25.0)			1.903										28.904			183.551

Table A2. Cont.

Stand No.	Option	Thinning Regime	Thinning Time and Carbon Density																	C Goal Values
			2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030			
7	No thinning	/																	113.833	
7	Thinning once	(15.0, 40.0)										20.165							129.008	
7	Thinning twice	(10.0, 10.0, 25.0, 25.0)					5.707										27.173		143.760	
8	No thinning	/																	207.108	
8	Thinning once	(15.0, 40.0)										39.79							216.250	
8	Thinning twice	(10.0, 10.0, 2.0, 25.0)					0.992										36.119		232.155	
9	No thinning	/																	119.216	
9	Thinning once	(15.0, 40.0)									21.781								131.162	
9	Thinning twice	(10.0, 10.0, 25.0, 25.0)				6.408											26.604		142.718	
10	No thinning	/																	161.555	
10	Thinning once	(15.0, 40.0)						30.752											170.388	
10	Thinning twice	(10.0, 10.0, 3.0, 25.0)	1.139											28.318					182.144	
11	No thinning	/																	225.977	
11	Thinning once	(15.0, 40.0)									44.045								232.198	
11	Thinning twice	(10.0, 10.0, 10.0, 25.0)				5.577											40.632		333.476	
12	No thinning	/																	119.193	
12	Thinning once	(15.0, 40.0)						21.773											131.161	
12	Thinning twice	(10.0, 10.0, 25.0, 25.0)	6.404											26.61					142.825	
13	No thinning	/																	224.849	
13	Thinning once	(15.0, 40.0)									42.389								239.591	
13	Thinning twice	(10.0, 10.0, 11.0, 25.0)				5.693											41.982		255.939	
14	No thinning	/																	81.471	
14	Thinning once	(15.0, 40.0)								26.572									87.189	
14	Thinning twice	(10.0, 10.0, 14.0, 25.0)			2.602											15.651			93.243	
15	No thinning	/																	117.078	
15	Thinning once	(15.0, 40.0)								22.19									124.050	
15	Thinning twice	(10.0, 10.0, 7.0, 25.0)		1.908											21.13				132.474	
16	No thinning	/																	52.634	
16	Thinning once	(15.0, 40.0)								9.834									56.614	
16	Thinning twice	(10.0, 10.0, 17.0, 25.0)		2.02											10.439				60.674	
17	No thinning	/																	167.108	
17	Thinning once	(15.0, 40.0)							31.411										178.618	
17	Thinning twice	(10.0, 10.0, 13.0, 25.0)	4.969											31.799					190.947	
18	No thinning	/																	224.849	
18	Thinning once	(15.0, 40.0)								42.389									239.591	
18	Thinning twice	(10.0, 10.0, 12.0, 25.0)			6.21											42.307			255.939	
19	No thinning	/																	221.893	
19	Thinning once	(15.0, 40.0)							42.055										235.111	
19	Thinning twice	(10.0, 10.0, 7.0, 25.0)	3.616											40.048					251.078	
20	No thinning	/																	118.714	
20	Thinning once	(15.0, 40.0)								22.373									126.539	
20	Thinning twice	(10.0, 10.0, 12.0, 25.0)		3.277										22.344					135.183	

Notes: Thinning once (15.0, 40.0), thinning age is 15 years, and thinning intensity is 40%.

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