



# Carbon stock projection for four major forest plantation species in Japan

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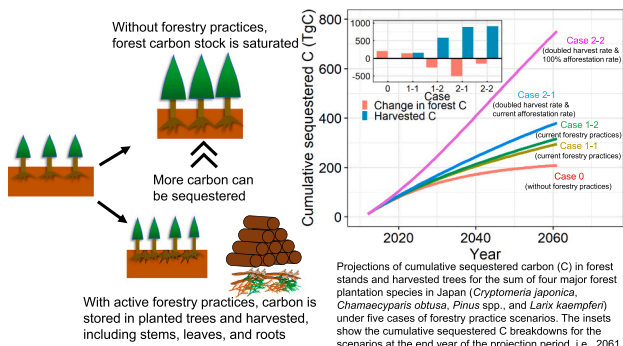
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## HIGHLIGHTS

- Four major forest plantation species in Japan were targeted.
- Latest forest age–carbon density functions for the species were presented.
- Past and future carbon sequestration by forests was predicted using the functions.
- Forest carbon stock is saturated in near future without forestry practices.
- Active forestry practices enhance carbon sequestration by Japanese forests.

## GRAPHICAL ABSTRACT



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## ABSTRACT

Carbon sequestration via afforestation and forest growth is effective for mitigating global warming. Accurate and robust information on forest growth characteristics by tree species, region, and large-scale land-use change is vital and future prediction of forest carbon stocks based on this information is of great significance. These predictions allow exploring forestry practices that maximize carbon sequestration by forests, including wood production. Forest inventories based on field measurements are considered the most accurate method for estimating forest carbon stocks. Japan's national forest inventories (NFIs) provide stand volumes for all Japanese forests, and estimates from direct field observations (m-NFIs) are the most reliable. Therefore, using the m-NFI from 2009 to 2013, we selected four major forest plantation species in Japan: *Cryptomeria japonica*, *Chamaecyparis obtusa*, *Pinus* spp., and *Larix kaempferi* and presented their forest age–carbon density function. We then estimated changes in forest carbon stocks from the past to the present using the functions. Next, we investigated the differences in the carbon sequestration potential of forests, including wood production, between five forestry practice scenarios with varying harvesting and afforestation rates, until 2061. Our results indicate that, for all four forest types, the estimates of growth rates and past forest carbon stocks in this study were higher than those considered until now. The predicted carbon sequestration from 2011 to 2061, assuming that 100 % of harvested carbon is retained for a long time, twice the rate of harvesting compared to the current rate, and a 100 % afforestation rate in harvested area, was three to four times higher than that in a scenario with no harvesting or

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replanting. Our results suggest that planted Japanese forests can exhibit a high carbon sequestration potential under the premise of active management, harvesting, afforestation, and prolonging the residence time of stored carbon in wood products with technology development.

## 1. Introduction

Forests absorb and accumulate large amounts of carbon (C) (Pan et al., 2011; Keenan and Williams, 2018; Harris et al., 2021). Temporal changes in forest C stocks can significantly impact future climate change (Booth et al., 2012; Bastin et al., 2019). Hence, we need to accurately predict the amount of C stock in future forests and adequately manage it to achieve the C sequestration potential.

Many previous studies have conducted predictions of future forest C stocks and optimizations of forest managements. The studies can be divided into two groups: (1) studies using complex process-based models, such as LPJ (Sitch et al., 2003), ORCHIDEE (Krinner et al., 2005), and SEIB-DGVM (Sato et al., 2007). Although these models require many computational resources, they can mechanistically express ecophysiological responses to future changes in environmental factors and make precise predictions on a theoretical basis (Eggers et al., 2008; Rabin et al., 2022; Yu et al., 2022). (2) Studies that express forest growth with increasing forest age using simple empirical models, such as EFFICIEN and CBM-CFS (Nabuurs et al., 2002; Chen et al., 2010; Túpek et al., 2010; Hu et al., 2015; Wear and Coulston, 2015; Zhu et al., 2018). While, these simple models cannot fully consider changes in environmental factors (e.g., de Vries et al., 2017), they require low computational power and are suitable for practical assessments of the effects of forest management and forestry practices, climate change, and pest and insect damage on forest growth (Karjalainen et al., 2003; López-Serrano et al., 2005; Schmid et al., 2006; Hennigar et al., 2008; Kurz et al., 2008; Foley et al., 2009; Sasaki et al., 2021).

The forest growth rate, that is, the C accumulation rate, which is the core information of simple empirical models, can change significantly over a long period owing to changes in environmental and social factors (e.g., Hember et al., 2012; Pretzsch et al., 2014). For example, air temperature and precipitation rates strongly regulate not only forest growth (Pan et al., 2013) but also mortality (Park Williams et al., 2013). Increased atmospheric CO<sub>2</sub> concentrations enhance forest growth (reviewed by Tharammal et al., 2019). The limitations of several factors such as nitrogen (Oren et al., 2001; Norby et al., 2010; Quinn Thomas et al., 2010) and phosphorus (Terrer et al., 2019) suppress the positive effects of CO<sub>2</sub>. The interactive effects of these environmental factors may vary among tree species (Maes et al., 2019). In addition, human activities, such as clear-cutting and thinning, have significant impacts on forest growth (Birdsey and Pan, 2015; Pugh et al., 2019).

In Japan, the C accumulation with increasing forest age is not fully understood. The main reason for this is that a national forest inventory (NFI) based on direct field measurements (m-NFI) has rarely been conducted in forests throughout Japan (two-thirds of the land area of approximately 25 million ha) (Egusa et al., 2020). Using the most reliable 2009–2013 m-NFI, Egusa et al. (2020) demonstrated that previous forest C stock estimates were significantly underestimated and strongly suggested that the forest C accumulation rate with increasing forest age has also been greatly underestimated. Fang et al. (2014) stated that the C accumulation rate with increasing forest age of representative Japanese forest plantation species (*Cryptomeria japonica*, *Chamaecyparis obtusa*, *Larix kaempferi*, *Pinus densiflora*, and *Pinus thunbergii*) increased between 1980 and 2005. However, they estimated forest C accumulation rates using NFI data based on predictions from yield tables (p-NFI), rather than m-NFI. To the best of our knowledge, no research has shown the C

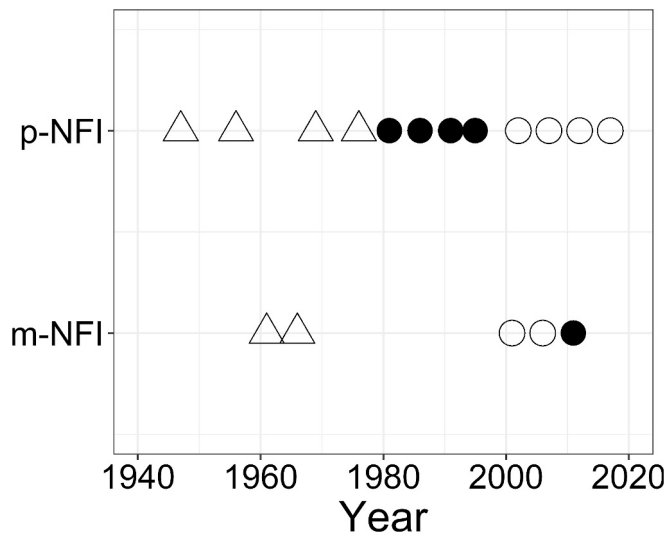
accumulation rate with increasing forest age in current Japanese forests using actual measurement data from forest resources throughout Japan. The four forest plantation species that Fang et al. (2014) targeted, *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi* occupied 4.5, 2.6, 0.8, and 1.0 million ha, respectively, in 2012. The total area of them is 86.9 % of Japan's planted forest area (10.3 million ha) and 35.6 % of Japan's forest area (25.1 million ha) (Japan Forestry Agency, 2016). Therefore, it is an urgent issue in Japan to clarify the C accumulation with increasing forest age of these tree species and to predict the amount of C sequestration in the future. Furthermore, while Japan has abundant forest resources, it relies on imports for the majority of domestic demand (Japan Forestry Agency, 2023). Therefore, clarifying the impact of forest management on the C accumulation of Japan's forests is expected to have ripple effects globally through the amount of wood supply.

The goal of this study is to accurately understand the C accumulation rate with increasing forest age in planted Japanese forests and to examine forest management and operation strategies that maximize future C sequestration. To achieve this, we targeted four major forest plantation species in Japan: *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*. Our specific objectives were to (i) obtain the functions between forest age ( $x$ ; years) and C density ( $C_d$ ; MgC ha<sup>-1</sup>) using the most reliable 2009–2013 m-NFI, (ii) estimate accurate changes in forest C stocks from past to present using the  $x - C_d$  functions and temporal changes in forest area by forest age, and (iii) investigate the effect of forest management scenarios on the C sequestration potential of forests, including wood production.

## 2. Material and methods

### 2.1. Data

We mainly used the 2009–2013 m-NFI based on direct field measurements to present the latest  $x - C_d$  functions and estimate past forest C stocks and future C sequestration potentials. Additionally, we used p-NFI, based on predictions from yield tables and used in previous studies, to calculate the forest growth rate and forest C stocks from past to present and compare them with those calculated from m-NFI. While the details of these data were presented by Egusa et al. (2020), valuable data selected from all datasets was additionally provided for completeness. The NFI is a national forest survey that uses multipoint observations over the country and has historically been aimed at estimating the entire country's timber productivity. It generally includes information on tree species composition and stand-scale or individual tree-scale stem and timber volumes in targeted forests. In Japan, two types of NFI exist (Fig. 1): (1) p-NFI, which is based on predictions from yield tables, which are empirical relationships between stand age and stand stem volume. Note that the yield tables for p-NFI are constructed using observational data obtained in the 1960s. Despite their general and broader use, p-NFI yield tables have not been revised for a long time. (2) m-NFI, which is based on direct field measurements. Using 10,000 survey plots, m-NFI surveys were conducted in 1961 and 1966 and then following a long gap in 1999 with revised sampling methods (Fig. 1). Using m-NFI data, our previous study (Egusa et al., 2020) validated and emphasized that p-NFI greatly underestimated the actual forest C stock derived from stem volume data, mainly because of the non-updated yield tables.



**Fig. 1.** Survey years of National Forest Inventory (NFI) in Japan. p-NFI and m-NFI denote NFI based on the predictions from yield tables and the direct field measurements, respectively. Triangles mean that the surveys were done with different methods to the current ones, circles. Solid circles represent the data used for the forest growth investigations in this study. Each m-NFI has a 5-year field measurement period; therefore, the 2009–2013 m-NFI is plotted at its central year, 2011.

For m-NFI data, this study used only published items, that is the stem volume per hectare ( $V_s$ ;  $m^3 \text{ ha}^{-1}$ ), name of the dominant tree species, and forest age for a given plot. While the m-NFI conducted in 1999–2003 was found to underestimate the actual stem volume, for the m-NFI in 2009–2013, experts checked the accuracy and surveyors underwent technical training, resulting in the most historically reliable NFI in Japan (see Fig. 1 and Egusa et al., 2020).

The p-NFI datasets since 1981 include data on the total stem volume, age class (ranked from 1 at 5-year intervals), forest area of a given tree species. In addition, we assumed that there might have been changes in the estimation process for forested areas after the 1995 p-NFI because we found a time-series imbalance between each age class's forest area. Thus, we computed the  $V_s$  for each species by dividing the p-NFI-estimated total stem volume by the forest area for each age class as the averaged values of 1981, 1986, 1991, and 1995 p-NFI (Fig. 1).

*Cr. japonica*, *Ch. obtusa*, and *Pinus* spp. are evergreen coniferous trees, while *L. kaempferi* is a deciduous, coniferous tree that grows in colder areas. The planted forests of these tree species are monoculture plantations. >90 % are even-aged forests, and the rest are unevenly-aged forests (Japan Forestry Agency, 2022). Although there may be some invasive trees, most of these forests are composed of a single tree species with a uniform age. 65 % of the planted forests are privately owned, and the national and local governments own the rest. All these tree species are widely used for such as construction, civil engineering, and pulp materials. The “standard rotation age”, which is not the recommended harvesting age, varies depending on the tree species and region and is generally between 40 and 60 years old.

We compared the forest C storage ability with forest age derived from the 2009–2013 m-NFI and the 1981–1995 p-NFI and further constructed the “state-of-the-art” forest age–C density functions ( $x$ – $C_d$  functions) with the 2009–2013 m-NFI. Here, we calculated  $C_d$  according to Fang et al. (2005).

$$C_d = V_s \times \text{BEF} \times 0.5, \quad (1)$$

in which

$$\text{BEF} = \max(a + b/V_s, 1.5), \quad (2)$$

where 0.5 is the C content ratio and  $a$  ( $\text{Mg m}^{-3}$ ) and  $b$  ( $\text{Mg ha}^{-1}$ ) are empirical parameters obtained for a given forest type. BEF is the biomass expansion factor ( $\text{Mg m}^{-3}$ ), which enables the conversion of  $V_s$  to stand-scale  $C_d$ , including branches, leaves, and roots. The term “ $\max(\cdot, \cdot)$ ” represents the maximum of the two factors and is used to avoid the unrealistically large values of BEF in the case of the extremely small values of  $V_s$ , where 1.5 was set referring to the results of Fang et al. (2005).

The time series of the total forest area for each species from the p-NFIs are shown in Fig. S1. Temporal changes in the forest area-age distribution for each species are shown in Fig. S2, according to the p-NFIs. Although the total forested area data in Fig. S1 are valid, we did not use the age-area distribution data in Fig. S2 for the C stock simulation owing to their uncertainty, particularly in the age class 1 domain. Thus, a combination of the 2009–2013 m-NFI and 1976–2012 p-NFIs was used to calculate future and past forest area distributions against age, as detailed later (Section 2.3).

## 2.2. Forest age–carbon density function

To eliminate aberrant  $C_d$  values among the estimations from the 2009–2013 m-NFI, outlier detection was conducted by identifying observational issues, mainly data entry mistakes, such as the case of a significantly higher  $C_d$  than expected, considering the forest age ( $x$ ; years). For each species, we assumed that a population of  $C_d$  samples in bins of  $x = 10$  would be distributed following the gamma distribution, with sample mean and standard deviation. Outliers over the upper one-tailed probability of 0.005 were removed and the mean and standard deviation were computed from the reduced sample. This procedure was repeated until the outliers were exhausted. If the sample size was less than six in each bin, the population was not used for subsequent examinations.

The Chapman-Richards equation (Richards, 1959; Pienaar and Turnbull, 1973) can effectively describe the increase in  $C_d$  with increasing  $x$  as follows:

$$C_d = C_{d,\max} \{1 - \exp(-kx)\}^{\frac{1}{1-m}}, \quad (3)$$

where  $C_{d,\max}$  is the maximum value of  $C_d$  and  $k$  and  $m$  ( $0 \leq m < 1$ ) are the fitting parameters. We used a hierarchical Bayesian framework to estimate the model parameters for the representation of the  $x$ – $C_d$  function for each species across the plots. According to the Japanese definition of administrative divisions, we identified the districts ( $j = 1-8$ ) throughout Japan which can be assumed to influence the air temperature ( $T$ ;  $^{\circ}\text{C}$ ) effect on the growth rate, breeds in each species, and forest planting and cultivation systems. If there was only a single plot in a given district for each species, we ignored the target data for the model estimation. In our hierarchical model,  $T$  at each plot would influence  $C_{d,\max}$ , which is generated from random variations in the districts, and  $k$  and  $m$  would be constant over the districts. To evaluate the effects of temperature on  $C_{d,\max}$ , we used the ground air temperature at a given plot  $i$  within district  $j$  from the 1981–2010 data from the Japan Meteorological Agency yearly 1-km gridded climate datasets, available at [https://nlfpt.mlit.go.jp/ksj/gml/datalist/KsjTmplt-G02-v3\\_0.html](https://nlfpt.mlit.go.jp/ksj/gml/datalist/KsjTmplt-G02-v3_0.html). Hence, we parameterized  $C_{d,\max}$  at  $i$  and  $j$  as a function of  $T$  using

$$C_{d,\max}(i, j) = \exp\{\theta(j)T(i, j) + \varepsilon\}, \quad (4)$$

in which

$$\theta(j) \sim N[\mu, \sigma^2], \quad (5)$$

where  $\theta(j)$  is the response factor to  $T$  at any plot  $i$  within the given district  $j$ , and  $\varepsilon$  is the species-specific constant over the plots.  $\theta$  was generated following the normal probability distribution with its parameters  $\mu$  and  $\sigma$  as the mean and standard deviation, respectively. Finally, we generated  $C_d$  at  $i$  and  $j$  from the gamma probability distribution with the mean  $E$  as

$C_d$  computed using Eq. (3), with the determined  $C_{d,max}$ ,  $k$ , and  $m$  values given by

$$C_d(i,j) \sim \text{Gamma}[\beta E(i,j), \beta], \tag{6}$$

where  $\beta E$  and  $\beta$  are the shape and rate parameters of the gamma distribution, respectively. We assumed a constant  $\beta$  over the districts.

In performing a Bayesian approach to determine the posterior distribution of the model parameters, i.e.,  $k, m, \mu, \sigma, \theta, \varepsilon$ , and  $\beta$ , we used the Hamiltonian Monte Carlo method with four chains, a sample size per chain of 5000, and a burn-in period of 1000. According to Gelman and Rubin's (1992) suggestion that Gelman–Rubin diagnostic  $R_c$  values  $>1.2$  for any parameter should indicate non-convergence, we adopted a more stringent rule of  $R_c < 1.1$  to declare convergence. Model parameterization was performed using the rstan software version 2.21.5 (<https://cran.r-project.org/web/packages/rstan/index.html>).

### 2.3. Backward and forward simulations of carbon stock

Valid future and past C stocks can be obtained as a product of the state-of-the-art  $x-C_d$  function and reasonable forest age ( $x$ )–forest area ( $A$ ; ha) distribution. Here, we used a first-order wave equation to describe the temporal changes in the  $x-A$  distribution (cf. Fig. S2) as follows:

$$\frac{\partial A(t,x)}{\partial t} = -\frac{\partial A(t,x)}{\partial x} - A_h(t,x), \tag{7}$$

where  $A(t,x)$  and  $A_h(t,x)$  are forest areas where trees are maintained and cut, respectively, at  $x$  in the  $x-A$  distribution at time  $t$  (A.D. years).  $A(t,1)$  is equal to  $A_p(t)$ , which denotes the afforested area at  $t$ .

We estimated the  $x-A$  distribution for each species in 2011, that is,  $A(2011,x)$ , from the product of the  $x$ –the number of surveyed plot distributions for each species in the 2009–2013 m-NFI and each species' forest area per plot (1625.59, 1598.30, 1200.53, and 1875.64 ha plot<sup>-1</sup> for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively), which were derived by dividing the forest area of each species in the 2012 p-NFI (see Fig. S1), based on the total number of surveyed plots in the 2009–2013 m-NFI.  $A(2011,x)$  was used as the initial condition for Eq. (7) to calculate the past and future  $x-A$  distributions.

The past (1976–2010)  $x-A$  distributions for each species were computed by solving Eq. (7) backwards over time. The horizontal movement of the 1–35 years domain in the  $x-A$  distribution in 2012 for all species backward to  $A$  at 1–5 years old in 1981 (Fig. S2) indicated that we could deduce:

$$A(2011,x) = A(2012-x,1) = A_p(2012-x), \text{ for } 2 \leq x \leq 36. \tag{8}$$

Temporal changes in total forest area,  $\sum_x A(t,x)$ , for each species (Fig. S1) and the estimated  $A_p(t)$  using Eq. (8) allowed us to infer the time course of the forest area where trees were cut using the following balance equation:

$$\sum_{l=1}^q \sum_x A_h(t-l+1,x) = \sum_{l=1}^q A_p(t-l+1) - \left\{ \sum_x A(t,x) - \sum_x A(t-q,x) \right\}, \tag{9}$$

where  $q$  is the interval between the p-NFIs: four for 1991–1995, seven for 1995–2002, and five otherwise. Computing Eq. (9) with  $t = 1981-2011$  and dividing the solutions by  $q$  yields  $\sum_x A_h(t,x)$  every year in 1977–2011. For *Cr. japonica*, *Ch. obtusa*, and *L. kaempferi* forests, the forest area was reduced only at its rotation age, mainly because of the harvest, resulting in the almost parallel movement of the  $x-A$  distributions with changing time (Fig. S2a, b, d). On the other hand, a reduction in the *Pinus* spp. forest area might have occurred over the forest age, partly because of pine wilt disease (Mamiya, 1988), decreasing the peak of the  $x-A$  distribution with time (Fig. S2c). Hence, we assumed that the trees were cut 20 % each at  $x = 10, 20, 30, 40$ , and 50 for the *Pinus* spp.

and 100 % at  $x = 50$  for the other species. Note that we included the effects of other disturbances in this operation.

For the projection of the future (2011–2061)  $x-A$  distributions using Eq. (7), the boundary condition was set as

$$A_p(t) = R_p \times \sum_x A_h(t,x) = A(t,1), \tag{10}$$

where  $R_p$  is the afforestation rate.  $\sum_x A_h(t,x)$  denotes the total forest area at  $t$  where trees are cut. Assuming that trees are cut in proportion to the present forest area at each forest age and only at a rotation age  $x \geq 40$ , we defined  $A_h(t,x)$  as

$$A_h(t,x) = \begin{cases} R_h \times A(t,x) & \text{for } x \geq 40 \\ 0 & \text{for } x < 40 \end{cases}, \tag{11}$$

where  $R_h$  is the harvest rate.

To examine how the central forestry practice, that is, harvesting and afforestation, impacts the long-term forest C stock, including wood production, we conducted five numerical experiments with the alteration of the harvest ( $R_h$  in Eq. (11)) and afforestation ( $R_p$  in Eq. (10)), as summarized in Table 1. Case 0 was the control scenario, in which there was no harvest or afforestation and forest C stock increased simply with forest age.

Cases 1–1 and 1–2 assume the current forestry practice status derived from the 2007 and 2012 p-NFIs and the FY2016 Forest and Forestry Statistics Catalogue (Japan Forestry Agency, 2016), respectively. Accordingly, the harvest rate in Case 1–1 was calculated as  $R_h = \sum_{x \geq 41} \{A(2012,x) - A(2007,x)\} / \{5 \sum_{x \geq 41} A(2012,x)\}$  for each species, resulting in a reduced forest area per year of 10,144, 1058, 5825, and 2724 ha year<sup>-1</sup> for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively. The total reduced forest area of 19,751 ha year<sup>-1</sup>, based on the p-NFI, was much less than the total afforestation area of 28,130 ha year<sup>-1</sup> reported by the Forest and Forestry Statistics Catalogue from 2007 to 2012; and thus, we assumed the afforestation rate in Case 1–1 to be 100 %. The harvest rate for all the species in Case 1–2 was calculated by dividing the annual mean total preparatory cutting area in 2007–2012, 76,378 ha year<sup>-1</sup>, by the total forest area at  $x \geq 41$ , 5.91 Mha, which was the average value between 2007 and 2012. Also, the afforestation rate for all the species in Case 1–2 was obtained by dividing the total afforestation area (28,130 ha year<sup>-1</sup>) by 5.91 Mha. Note that we calculated Case 1–2 harvest and afforestation rates according to the Forest and Forestry Statistics Catalogue, which does not classify the data by species.

Cases 2–1 and 2–2 examine future changes in C stock in response to different forestry practices from the current ones. The harvest rate for all the species in both Cases 2–1 and 2–2 was 2.5 %, almost double the value in Case 1–2. The afforestation rate in Case 2–1 was set to be 36.8 % for

**Table 1**  
Forestry practice parameters for all scenarios.<sup>a</sup>

Scenario	Parameter	<i>Cr. japonica</i>	<i>Ch. obtusa</i>	<i>Pinus</i> spp.	<i>L. kaempferi</i>
Case 0	Harvest rate (%)	0	0	0	0
	Afforestation rate (%)	0	0	0	0
Case 1-1	Harvest rate (%)	0.316	0.0728	0.841	0.355
	Afforestation rate (%)	100	100	100	100
Case 1-2	Harvest rate (%)	1.29	1.29	1.29	1.29
	Afforestation rate (%)	36.8	36.8	36.8	36.8
Case 2-1	Harvest rate (%)	2.50	2.50	2.50	2.50
	Afforestation rate (%)	36.8	36.8	36.8	36.8
Case 2-2	Harvest rate (%)	2.50	2.50	2.50	2.50
	Afforestation rate (%)	100	100	100	100

<sup>a</sup> See main text and Eqs. (10) and (11).

all the species, following virtually the same afforestation activity as in Case 1–2. In Case 2–2, assuming the aggressive afforestation activity, the species' afforestation rate was 100 %.

### 3. Results

#### 3.1. Comparison of the functions of forest stand carbon growth rate against forest age between p-NFI and m-NFI

In the m-NFI from 2009 to 2013,  $C_d$  increased until about 50 years of age for all tree species and after that the rate of increase slowed (Fig. 2). We note considerable variation in  $C_d$  in each forest age.  $C_d$  values were highest for *Cr. japonica*, followed by *Ch. obtusa*, *L. kaempferi*, and *Pinus* spp. The state-of-the-art  $x - C_d$  function expressed by the Chapman-Richards equation (Eq. (3)) and parameterized by the m-NFI data roughly passed the median  $C_d$  values per 10 years of age for all tree species (Fig. 2; Table S1). The uncertainty of the estimated  $x - C_d$  functions decreased with increasing sample size and was the smallest for *Cr. japonica* and largest for *L. kaempferi*.

The  $C_d$  values calculated from the p-NFI data for 1981, 1986, 1991, and 1995 were similar. This indicates that only a minimal update to the yield table was performed during this period. Therefore, we used the average  $C_d$  values of p-NFI in 1981, 1986, 1991, and 1995 to establish the p-NFI-based  $x - C_d$  function.

According to the forest age-C accumulation rate relationship obtained by differentiating the state-of-the-art  $x - C_d$  function for forest age, the maximum C accumulation rates were 5.0 (4.6–5.4 as 95 % credible interval)  $\text{MgC ha}^{-1} \text{ year}^{-1}$  at seven years old, 4.7 (4.1–5.3)  $\text{MgC ha}^{-1} \text{ year}^{-1}$  at seven years old, 3.5 (2.6–4.4)  $\text{MgC ha}^{-1} \text{ year}^{-1}$  at four years old, and 3.1 (2.3–4.0)  $\text{MgC ha}^{-1} \text{ year}^{-1}$  at four years old for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively (Fig. 3).

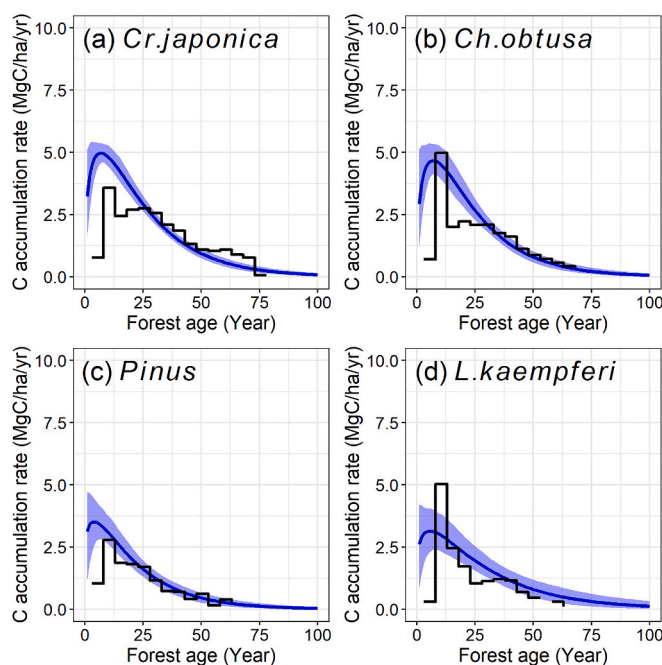


Fig. 3. Relationships between forest age and forest stand carbon (C) accumulation rate for (a) *Cryptomeria japonica*, (b) *Chamaecyparis obtusa*, (c) *Pinus* spp., and (d) *Larix kaempferi*. The solid curves and the stairstep graphs represent the relationships modeled with a derivative of Eq. (3) and the 2009–2013 m-NFI data and estimated as forest age-mean values of 1981, 1986, 1991, and 1995 p-NFI data, respectively. The shaded areas indicate 95 % credible intervals.

We then obtained the p-NFI-based forest age-C accumulation rate relationship by taking the difference in  $C_d$  at five-year intervals (= one age class) and compared the relationships. The p-NFI-based relationship between forest age and the C accumulation rate fluctuated greatly with forest age. Considering this, the m-NFI-based C accumulation rate was higher than the p-NFI-based C accumulation rate for all tree species in the young stands aged 25–30 years or younger and almost the same in older stands. However, the mNFI-based C accumulation rate of *Cr. japonica* was much higher than that of the p-NFI-based in the young stands and was slightly lower in the old stands.

#### 3.2. Historical forest stand carbon stock estimated using p-NFI and m-NFI

From 1976 to 2010, the m-NFI-based C stock estimates greatly exceeded the p-NFI-based estimates for all tree species (Fig. 4). The difference between the two increased slightly over time for *Ch. obtusa*, remained unchanged or decreased slightly for *Cr. japonica* and *L. kaempferi*, and largely decreased for *Pinus* spp. The differences between the average m-NFI-based and p-NFI-based estimates in 1981 were 197.3, 79.9, 34.8, and 27.4 TgC for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively, whereas those in 2007 were 188.7, 106.1, 15.5, and 20.6 TgC, respectively.

We compared C stocks by forest age for the m-NFI- and p-NFI-based estimations in 1981 and 2007, respectively (Fig. 4). In 1981, the m-NFI-based C stocks were larger than the p-NFI-based C stocks up to 50 years of age for *Cr. japonica*, *Ch. obtusa*, and *Pinus* spp., and after 50 years of age, both were almost equal. For *L. kaempferi*, the m-NFI- and p-NFI-based C stocks were similar at 20 years of age or younger; however, the m-NFI-based C stocks were much higher than the p-NFI-based C stocks at 25 years of age or older. In 2007, the m-NFI-based C stocks were larger than the p-NFI-based ones throughout all forest ages for *Cr. japonica* and *Ch. obtusa*, particularly at 40–50 years old. For *Pinus* spp. and *L. kaempferi*, the p-NFI-based C stocks were similar to or larger at 40 years of age or younger, whereas the m-NFI-based stocks were larger at 50

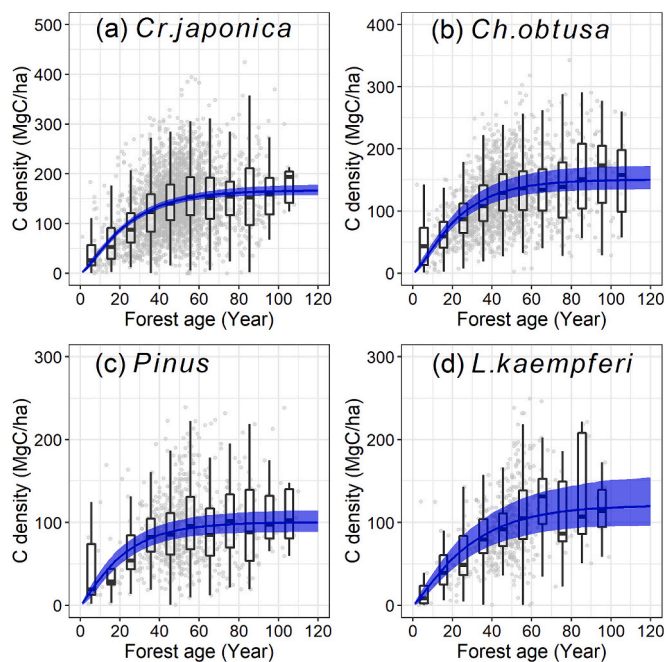
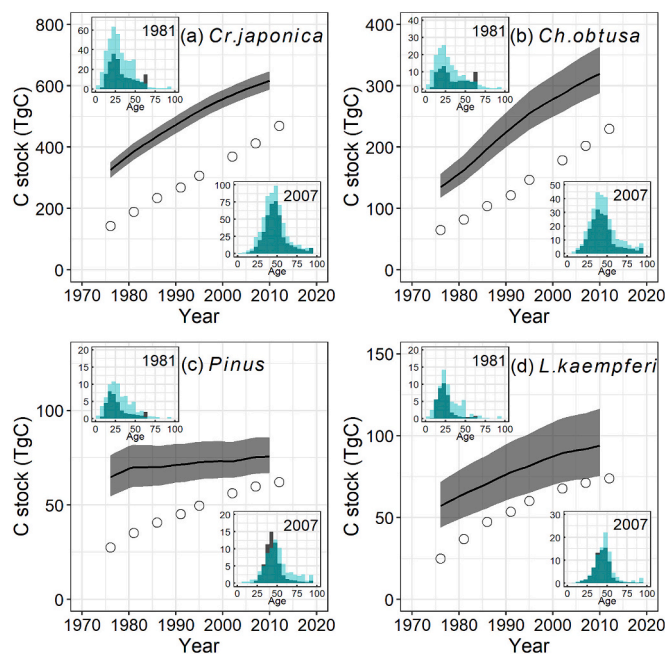


Fig. 2. Relationships between forest age and forest stand carbon (C) density for (a) *Cryptomeria japonica*, (b) *Chamaecyparis obtusa*, (c) *Pinus* spp., and (d) *Larix kaempferi*, investigated using the 2009–2013 m-NFI data (grey dots). The box-and-whisker plot in each 10-year bin represents the interquartile range (box), the median value (horizontal bar within the box), and the minimum value larger than  $1Q - 1.5 IQR$  or the maximum value smaller than  $3Q + 1.5 IQR$  (where  $1Q$ ,  $3Q$ , and  $IQR$  are the first and third quartiles and the interquartile range, respectively) (whisker). Solid curves represent the relationships between forest age and C density modeled with Eq. (3). The shaded areas indicate 95 % credible intervals.



**Fig. 4.** Historical forest carbon (C) stock for (a) *Cryptomeria japonica*, (b) *Chamaecyparis obtusa*, (c) *Pinus* spp., and (d) *Larix kaempferi*. Solid lines represent the C stock time courses by the m-NFI-based model with Eq. (3) (see Fig. 1) and Eq. (7) (see main text). The shaded areas indicate the 95 % credible intervals. Open circles represent the estimated C stock time courses from the p-NFI dataset. The insets show the forest age-C stock distributions in the specific year, 1981 or 2007, in which sky blue and cyan blue bars denote estimations from the m-NFI-based model and the p-NFI data, respectively, and black bars mean the parts where cyan blue bars surpass sky blue ones.

years of age or older. The peak forest age of C stocks in all tree species shifted from ~25 years in 1981 to ~50 years in 2007 and 26 years later (Fig. 4), reflecting inactive forest harvesting.

### 3.3. Future projections of carbon stock as forest stands and harvested trees

The scenarios used in the numerical experiments are listed in Table 1. When forestry practices were not implemented at all (Case 0), although the accumulation rate gradually slowed, the forest C stocks continued to increase. The changes in forest C stocks from 2011 to 2061 were from 622 to 735, 323 to 386, 76 to 85, and 95 to 117 TgC for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively (Fig. 5). Cases 1–1 and 1–2 assumed the current state of harvesting and afforestation; however, the former and latter rely on p-NFI data and the FY2016 Forest and Forestry Statistics Catalogue, respectively. As a result, there were large discrepancies between the results for Cases 1–1 and 1–2. In Case 1–1, several patterns were observed with almost no difference from Case 0 (*Ch. obtusa*; Fig. 5b). The increase was similar to Case 0, but with a slightly smaller C stock in 2061 (*Cr. japonica*; Fig. 5a, *L. kaempferi*; Fig. 5d) and almost unchanged C stocks from 2011 to 2061 (*Pinus* spp.; Fig. 5c). In Case 1–2, forest C stocks for all tree species linearly decreased from 2011 to 2061, from 622 to 470, 323 to 250, 76 to 54, and 95 to 74 Tg C for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively (Fig. 5). We referred to the FY2016 Forest and Forestry Statistics Catalogue and assumed the conditions of Case 1–2 as the premises for Cases 2–1 and 2–2.

When the harvesting rate was doubled compared to the current level and the same level of afforestation was carried out (Case 2–1), forest C stocks decreased from 2011 to 2061 most among all scenarios, with 622–337, 323–180, 76–39, and 95–52 TgC for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi* (Fig. 5). When the harvesting rate was

doubled to the current level and the harvested area was always re-planted (Case 2–2), forest C stocks reached their lowest value around 2030, increased slightly, and then became constant for all tree species. The changes of forest C stock from 2011 to 2061 were from 622 to 533, 323 to 283, 76 to 64, and 95 to 82 TgC, for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi* (Fig. 5).

The insets in Fig. 5 show the relationship between forest age and forest area in 2061 for each scenario. In 2011, the newly planted area was small and the peak of the forest area was ~50 y. Therefore, in 2061, the forest area against forest age showed a mountain shape with a peak at ~100 y and edges at ~50 and ~150 y for all tree species and all scenarios. In addition, the forest area peak was more prominent in descending order of harvesting. By adding a mountain shape with a peak at approximately 30 years of age and edges at approximately 0 and 50 years of age, a double mountain-type relationship between forest area and forest age was formed for all tree species. In Case 2–2, compared to the other scenarios, the peak at ~30 years of age and tail at ~0 years of age were large, which is thought to contribute to the slight increase in C stocks around 2060. Therefore, for Case 2–2, further C accumulation can be expected if the numerical experimental period is extended.

Fig. 6 shows the amount of C stored in forest stands and in harvested trees, that is, the total C sequestration of the forest from 2011 to 2061. It should be noted that the total amount of sequestered C contributes to the reduction of CO<sub>2</sub> concentrations in the atmosphere, depending on how long the lifespan of C in the harvested trees is extended. The results for Case 0 show only the amount of C accumulated in the forest stands from 2011 to 2061. The differences in the sequestered C between Cases 1–2 and 2–1 were 36, 19, 5, and 4 TgC for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively. That is, even if the harvesting rate was doubled to the current level and only the same level of re-planting was carried out (Case 2–1), the total amount of sequestered C over 50 years increased from the current situation (Case 1–2) (Fig. 6). This is because the decrease in accumulated C in forest stands was compensated for more by the increase in harvested C in Case 2–1 than in Case 1–2. In Case 2–2, although the amount of harvesting was the same as in Case 2–1, all of the harvested area was re-planted; therefore, Case 2–2 had a much larger total C sequestration than Case 2–1 by 207, 108, 26, and 31 TgC for *Cr. japonica*, *Ch. obtusa*, *Pinus* spp., and *L. kaempferi*, respectively (Fig. 6). This is because a large amount of C was fixed in the forest stands in Case 2–2.

## 4. Discussion and conclusions

### 4.1. Forest stand carbon growth rate

We presented the latest  $x-C_d$  functions for four major forest plantation species in Japan using the 2009–2013 m-NFI based on direct field measurements. We then compared them with that obtained from p-NFI, which is based on yield tables made from observed values in the 1960s, and confirmed that the forest C growth rate in Japan was greater than previously thought. Egusa et al. (2020) demonstrated that forest C stocks and C accumulation rates, that is, growth rates, across Japan estimated based on m-NFI were 1.7 times and 2.4 times those estimated based on p-NFI, respectively. They considered that possible reasons for this are an underestimation of the growth of old forests, an increase in growth rate due to changes in environmental factors, and inactive forest management compared to the assumptions in the yield tables. Our analysis gave clues to narrowing down its causes, which might lead to elucidating the forest growth characteristics of Japan's forests and contributing to future predictions.

Among the three factors, it became clear that at least the underestimation of the growth in old forests did not lead to an underestimation of current yield tables (i.e., the difference between p-NFI and m-NFI). The highest forest C accumulation rate estimated in this study and forest C accumulation rate at a most frequent forest age in 2012 were 5.0 MgC ha<sup>-1</sup> year<sup>-1</sup> at seven years old and 0.9 MgC ha<sup>-1</sup> year<sup>-1</sup> at 50 years old,

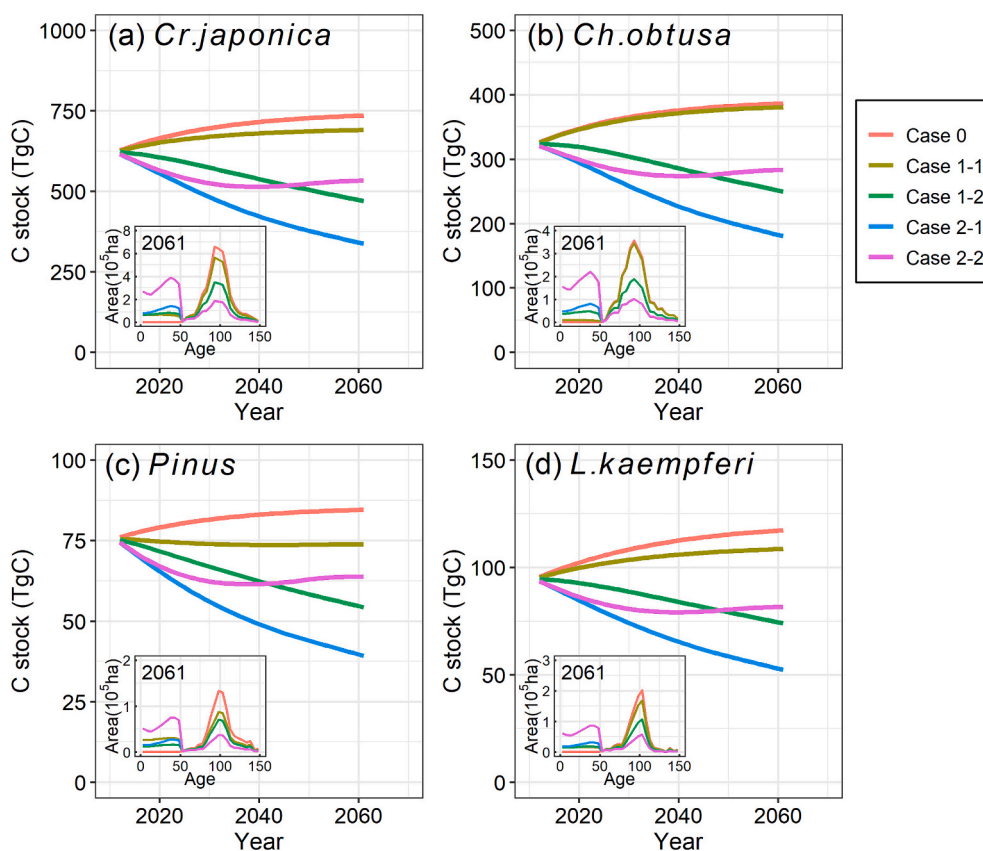


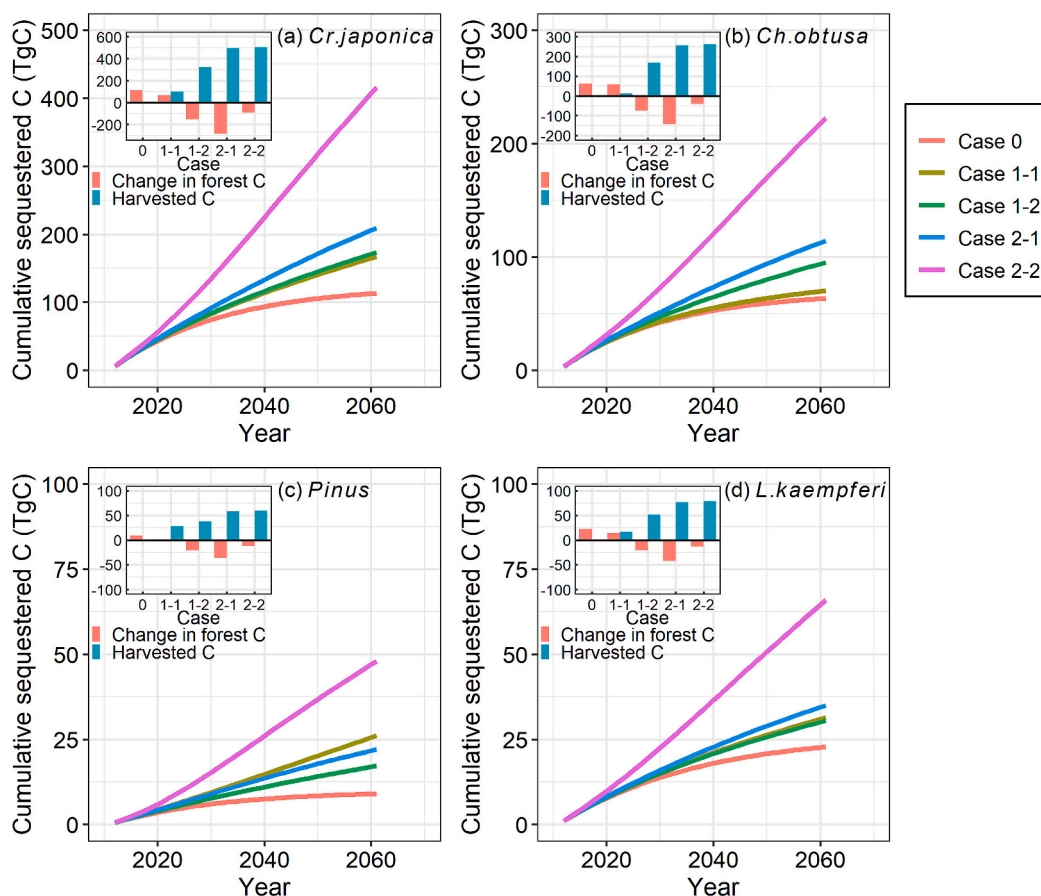
Fig. 5. Forest-stand carbon (C) stock projection for (a) *Cryptomeria japonica*, (b) *Chamaecyparis obtusa*, (c) *Pinus* spp., and (d) *Larix kaempferi*, under 5-type forestry practice scenarios (see main text and Table 1). The insets show the forest age-area distributions for the scenarios in the end year of the projection period, i.e., 2061.

respectively, for *Cr. japonica*, and similar tendencies were observed for the other tree species (Figs. 3 and S2). The m-NFI-based C accumulation rate was almost the same as the p-NFI-based C accumulation rate in forests aged 30 years or older for all tree species. Therefore, young, planted forests in Japan have the potential to raise the national average forest C accumulation rate ( $\sim 1.8 \text{ MgC ha}^{-1} \text{ year}^{-1}$ ; Egusa et al., 2020). While, the currently planted forests, which have an average forest age of around 50, lower the average forest C accumulation rate. However, it should be noted that there is little data on m-NFI in forests over 80 years old and that old forests in m-NFI could be affected by forestry practices such as selective logging. Recent studies have demonstrated that the growth of old forests has been underestimated, although there has been much debate about the degree of growth (Luyssaert et al., 2008; Stephenson et al., 2014; Gundersen et al., 2021). In several regions, the growth of old forests has been intensively examined (Begović et al., 2022; Barnett et al., 2023). In the future, we should collect forest C stock data in Japan's old forests that have achieved the maximum growth rate for their age by continuing appropriate forest management over a long period, such as in university forests and forestry research institutes (e.g., Hiroshima et al., 2020), and create a more accurate forest age-C density function that considers older age.

Changes in environmental conditions can significantly increase forest growth rates in Japan. Egusa et al. (2020) showed that the rate of increase in carbon stocks in Japan's forests from 1976 to 2012 was much greater than before. The rapid increase in forest C stocks of the major planted tree species in Japan since 1976 (Fig. 4) suggests an acceleration of forest growth rates. To date, only a few studies have examined how stand-level forest C accumulation rates have accelerated or been restricted over long periods and across wide areas, and these studies were limited to North America and Europe (McMahon et al., 2010; Hember et al., 2012; Vayreda et al., 2012; Pretzsch et al., 2014). Egusa et al. (2020) and the present study demonstrate, using long-term and

wide-area data, that forest C accumulation rates at the stand-level in the temperate forests of East Asia have been accelerating. Specifically, the following changes in environmental conditions are conceivable. An increase in atmospheric  $\text{CO}_2$  concentration might fertilize the growth rate of forests in Japan (Ueyama et al., 2020). In Japan, nitrogen deposition has increased since the late 1980s (Morino et al., 2011). Therefore, the effect of  $\text{CO}_2$  fertilization is not restricted by nitrogen (Oren et al., 2001). In addition, as summarized by Fang et al. (2014), from 1980 to 2005, the average annual temperature in Japan was around  $14^\circ \text{C}$  and on an upward trend, while the annual precipitation was not significantly changed and was slightly  $< 2000 \text{ mm}$ . Warming under such moist conditions may have optimized forest growth in Japan.

Changes in forest management can increase the forest C growth in forests. Fang et al. (2014) compared the C accumulation rates of four major plantation tree species obtained from past and present p-NFIs and argued that there was an increasing trend in C accumulation rates between 1980 and 2005. They assumed that the effects of forest management were negligible because the increase in the C accumulation rate was small in forests below 40 years of age. However, our results, calculated using m-NFI, showed significant increases in C accumulation rates in young forests. Forest growth rates estimated from p-NFI and m-NFI were almost the same in the older forests, whereas there was a large difference in the young forests (Fig. 3). In Japan, timber prices peaked around 1980 and then declined by up to half (Japan Forestry Agency, 2023). In addition, since the gradual liberalization of timber imports around 1970, the proportion of imported timber has increased, meeting more than half of the domestic demand (Japan Forestry Agency, 2023). This social background has significantly lowered motivation for forestry management and practice in Japan. Previous studies have shown that timber volume and forest C stocks are sometimes several tens of percent higher in unthinned forests than in thinned ones (Hoover and Stout, 2007; Lin et al., 2018; Jørgensen et al., 2021). Therefore, it is possible



**Fig. 6.** Projections of cumulative sequestered carbon (C) in forest stands and the harvested trees for (a) *Cryptomeria japonica*, (b) *Chamaecyparis obtusa*, (c) *Pinus* spp., and (d) *Larix kaempferi*, under 5-type forestry practice scenarios (see main text and Table 1). The insets show the cumulative sequestered C breakdowns for the scenarios in the end year of the projection period, i.e., 2061.

that the current increase in forest growth rates in Japan and the resulting inability of the yield tables in the p-NFI to reflect current forest growth rates are due to inactive forestry practices. In the future, we should attempt to elucidate the effects of long-term, wide-area environmental changes and forest management on forest growth in more detail using single-tree-scale data.

#### 4.2. Implications of forestry practices to climate mitigation

Ciais et al. (2008) found a large difference between the C stocks of current and old forests, that is, potential C stocks, in Europe, indicating that European forests may continue to sequester C in the future. In addition, it has been reported that a small number of large and old trees can absorb and store as much C as smaller trees (Stephenson et al., 2014). On the other hand, in the United States, because the growth rate decreases with forest age, it has been calculated that current forests have already accumulated C up to nearly 80 % of the amount of C stocks predicted in 2080 (Zhu et al., 2018). Another study reported that the growth of young trees accounts for most of the recent global increase in forest C stocks (Pugh et al., 2019). In Japan's planted forests, forestry practices have been inactive over the past several decades regardless of their ownership type (Kuboyama, 2015); therefore, forest age has continued to rise, and forests over 50 years old account for more than half of the entire forests (Fig. S2). Under such aging conditions, the amount of C stocks in planted forests in Japan is expected to saturate in the near future without any forestry practices (Case 0 in Fig. 5) or decrease gradually without any change in the current forestry practices (Cases 1–2 in Fig. 5). Thus, it will be difficult for planted forests in Japan to act as large C sinks.

Here, it should be noted that our calculation results include significant uncertainty. As written in Section 4.1, the growth rate of old forests is still not fully clarified. Additionally, future climate change could have a major impact on forests. The expected increase in atmospheric CO<sub>2</sub> concentrations and air temperatures in the future will continue to increase forest growth. However, at the same time, excessive increases in air temperature, associated increases in VPD, and drought also increase forest mortality globally (Allen et al., 2010; Hartmann et al., 2022; McDowell et al., 2022). This increase in mortality is expected to continue in the future (McDowell et al., 2016; Adams et al., 2017). Increases in pests, diseases, and wildfires are also a concern (review by Anderegg et al., 2020). That is, these negative factors may offset the increase in forest growth, and our calculation results of forest C accumulation could increase or decrease. Even though the growth of old forests is greater than we thought, and even if rising atmospheric CO<sub>2</sub> concentrations and air temperatures promote forest growth, continuing to accumulate C only in forests, as in Case 0 of our calculations, would be risky, considering rising mortality and other factors. Storing C as wood products would diversify the risk among forests and urban areas.

This study predicted that the amount of C stock in Japan's planted forests would temporarily decrease owing to active harvesting and afforestation; however, it would stabilize and then increase slightly in approximately ten years (Case 2–2 in Fig. 5). Active harvesting, accompanied by active afforestation, has also been suggested to be effective in terms of forest conservation. Furthermore, if harvested trees can be stored for an extended period in the form of wood products, active harvesting and afforestation are irreplaceably effective methods for forest C sequestration (Case 2–2 in Fig. 6). Note that this calculation shows the maximum possible amount, assuming a 100 % yield rate.



When we assume that the proportion of trunks to all trees is 60 % and the proportion that can be used as wood products is 70 % (Saito et al., 2021), only 40 % of all trees can be used as wood products. In such a case, the total amount of sequestered C by four tree species in 2061 is calculated as 208.5, 200.9, and 208.5 TgC for Case 0, 1–1, and 2–2, respectively. Therefore, it is essential to increase C sequestration by increasing the amount of C stored in harvested and utilized trees.

Here, several pathways exist to increase C storage in harvested and utilized trees. The first is to devise ways to utilize wood efficiently and extend the life of wood products. There are some doubts over the C neutrality of the use of wood for bioenergy (Birdsey et al., 2018; DeCicco and Schlesinger, 2018; Favero et al., 2020) and, while it still has significance, further investigation is needed. C storage through the promotion of high- and medium-rise wooden buildings is one of the most promising methods to reduce atmospheric CO<sub>2</sub> concentrations for climate mitigation (Churkina et al., 2020; Mishra et al., 2022). Churkina et al. (2020) explored the potential to suppress C emissions through C storage in wooden buildings and the disuse of mineral-based materials such as concrete and steel. They particularly emphasized the promotion of highly functional bio-based materials such as cross-laminated timber (CLT). The growing interest in high-performance wood products, such as CLT, has led to the consecutive construction of high-rise wooden buildings in Japan, partly because of the change in regulations on fire-resistant structures in 2019. The proportion of wooden houses in Japan shows a decreasing trend, with 55.6 % of newly built houses in 2022 (Statistics Bureau of Japan, 2022). Considering Japan's potential high timber supply capacity, it is possible to increase this proportion in the future. Furthermore, the half-life of wooden buildings extended from 38 years in 1964 to 63 years from 1997 to 2010 (Kayo and Tonosaki, 2022). Thus, in the future, wooden buildings will play a dominant role in long-term C sequestration in Japan.

The second is to reduce C loss during the various stages of utilizing harvested trees. For example, previous studies have shown that harvested and re-planted forests could be a C source because of increased CO<sub>2</sub> emissions from residues left in the forest after harvesting and soil and roots (e.g., Amiro et al., 2010; Aguilos et al., 2014). Additionally, a lot of sawdust is produced during the processing of wood into timber, and scrap wood also contains a large amount of C. Knowing exactly how much C is lost in each stage is an important challenge (Kilpeläinen et al., 2011; Braun et al., 2016; Piccardo and Gustavsson, 2021). It is necessary to reduce C loss and store as much C in wood products as possible through utilization. Creating cellulose nanomaterials from foliage, sawdust, and scrap wood is an ongoing innovation (reviewed by Nagarajan et al., 2021). In the future, it would be possible for the materials to be used as building materials and preserved for a long time. Furthermore, achieving long-term C isolation is becoming less of a pipe dream. Isolating trees underground or in the ocean is considered possible with current technology (Zeng and Hausmann, 2022) and is in the pilot phase (Sidik, 2023). Combining these methods and increasing the amount of C stored in harvested and utilized trees is the pathway we should take in the future.

Although our calculation results show the potential of Japan's planted forests, it is an entirely achievable future. As forest harvesting was inactive for a long period, Japan's forestry industry declined, and the number of forestry workers decreased from 126,000 in 1985 to 44,000 in 2020 (Japan Forestry Agency, 2023). However, in recent years, the proportion of young people has increased. Additionally, the Forestry Agency promotes cost reduction and improved competitiveness by developing high-performance forestry machinery and labor-saving measures for afforestation and cultivation. Furthermore, considering that the thinning area reached 370,000 ha in 2021 (Japan Forestry Agency, 2023), it would be entirely possible to double the current harvesting area (approximately 220,000 ha for four tree species with a harvesting rate of 2.5 %). Of course, when planting trees, it is necessary to consider the environmental factors at each location, select appropriate tree species, and understand their influence on a wide range of

ecosystem services (See discussion in Kirschbaum et al., 2024). Japan aims to achieve carbon neutrality in 2050. Japan's greenhouse gas emissions in 2021 are 1.17 billion tons of CO<sub>2</sub> (equivalent to 319 TgC) (Japan Ministry of the Environment, 2023). The annual average C sequestration rate of the four tree species calculated in our case 2–2 is 15.0 TgC yr<sup>-1</sup>, which can potentially offset 4.7 % of the emissions. Furthermore, the active use of wood in Japan will have an impact globally. Although Japan's self-sufficiency rate of wood has been improving in recent years, it is still around 40 %. Japan relies on imports from Southeast Asia, North America, Europe, etc., to meet its wood demands (Japan Forestry Agency, 2023). The wood market is globally connected, and changes in supply and demand in one country or region will affect the entire world (Kallio et al., 2018). Therefore, increasing Japan's domestic wood supply and reducing imports will also reduce the amount of harvested trees in other countries. Forests are expected to achieve climate change mitigation through land-use optimization, such as reducing deforestation and protecting forests (Grassi et al., 2017). It is important that we fully bring out the potential of forests by promoting technology development.

### CRedit authorship contribution statement

**Tomohiro Egusa:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Ryo Nakahata:** Writing – review & editing, Formal analysis, Data curation. **Mathias Neumann:** Writing – review & editing, Conceptualization. **Tomo'omi Kumagai:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

### Declaration of competing interest

The authors have no conflicts of interest associated with this work.

### Data availability

Data will be made available on request.

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2024.172241>.

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