Individual-level distance-independent-based growth and yield prediction models for long-term Japanese cedar (*Cryptomeria japonica*)

Keiko Fukumoto[a,*], Tomohiro Nishizono[b], Fumiaki Kitahara[b]

[a]*Shikoku Research Center, Forestry and Forest Products Research Institute, 2–915 Asakuranishi, Kochi, Kochi, 780-8077, Japan*

[b]*Forestry and Forest Products Research Institute, Forest Research and Management Organization, 1 Matsunosato, Tsukuba, Ibaraki 305-8687, Japan*

Keiko Fukumoto (kfukumoto@ffpri.affrc.go.jp)

Tomohiro Nishizono (nishizo@ffpri.affrc.go.jp)

Fumiaki Kitahara (bunsho@ffpri.affrc.go.jp)

*Corresponding author.

Keiko Fukumoto (kfukumoto@ffpri.affrc.go.jp)

Abstract

Yield prediction has been determined to be vital in sustainable forest management. Recently, research trends have shifted from stand-level to individual-level yield prediction. In this study, we examined the effectiveness of yield prediction models based on a distance-independent approach for Japanese cedar (*Cryptomeria japonica*) trees in western Japan. We further examined the accuracy of the models by reference to existing data collected long-term. First, we constructed distance-independent height, diameter growth, and survival models. Then, we simulated for approximately 50 years individual tree height, diameter at breast height (DBH), and volume growth using the test data. We then compared the predicted and observed values and calculated root mean square error (RMSE) and bias to evaluate the model accuracy. The models were noted to perform well when predicting mean height, DBH, and volume for Japanese cedar trees; in fact, they adequately predicted the diameter distribution. Our results suggest that distance-independent models could adequately predict long-term mean values and diameter distribution. However, RMSE and bias indicated that error propagation occurred over longer time spans. Thus, it is effective to conduct actual measurements at some point in the forest development phase and use the measurements as initial values for short- or medium-term predictions.

Keywords: Yield prediction, Distance-independent competition index, Simulation, Generalized linear mixed model, Japanese cedar.

1. Introduction

Yield prediction is crucial to sustainable forest management and planning, and various methods have been validated in countries targeting many species (e.g., Monserud and Sterba 1996; Fox et al. 2001; Böhm et al. 2011; Weiskittel et al. 2011; de-Miguel et al. 2013). Yield prediction methods follow either a stand- or individual-level approach, with the conventional method operating at stand level. Over time, there has been a shift toward individual-level approaches (Monserud and Sterba 1996; Hasenauer 2006).

Yield tables of major coniferous species in the national forests in Japan were published in 1933 (Hayao 1961). The tables cover each region under different site productivities and include data on stand mean height, diameter at breast height (DBH), and volume according to age. However, these yield tables did not account for various treatment scenarios such as initial planting density, thinning intensity, and thinning methods; they were compiled based on assumptions of growth under standard conditions. For this reason, several stand yield prediction systems, which consider growth under various treatment regimes, have been developed (Konohira 1995). For example, the Local Yield Construction System (LYCS) takes account of when and how thinning is conducted (Nakajima et al. 2010). LYCS can be adapted to three major coniferous species: Japanese cedar (*Cryptomeria japonica*), Japanese cypress (*Chamaecyparis obtusa*), and Japanese larch (*Larix kaempferi*). Moreover, LYCS provides yield growth predictions assuming low initial planting density (Shiraishi 2004) and long-rotation management (Nakajima and Shiraishi 2007). These factors have led to yield prediction at stand level being widely used in Japan.

The conventional yield prediction systems in Japan have a major issue, that is, the systems cannot select trees to remove for thinning treatment. Therefore, we could not understand the residual tree growth process. These systems are not suitable for selecting target trees for various thinning treatments and are insufficient to comprehend the specific residual trees growth. For this reason, yield prediction is required based on an individual-level approach in our country; however, yield prediction employing the approach for common Japanese conifer species has not yet been examined.

Some studies have tried yield prediction system using an individual-level approach; for example, Scolforo et al. (2019) constructed a growth and yield system for eucalypts. Seppänen and Mäkinen (2020) tried individual- and stand-level yield prediction systems for teak (*Tectona grandis*) plantations. Individual-level approaches are identified to be generally superior to stand-level approaches because they are flexible and better able to characterize growth response under various silvicultural practices (Weiskittel et al. 2011).

Competition indices are widely used for individual-level yield prediction, and these can be classified into distance-dependent and distance-independent (Canham et al. 2004). A distance-dependent competition index requires information on the distance between the subject tree and competition trees, whereas a distance-independent competition index does not. Some researchers developed tree growth model based on an individual-level distance-dependent approach (e.g., Coates et al. 2003; Alegria and Tomé 2013; Bose et al. 2015). For example, Alegria and Tomé (2013) constructed a distance-dependent individual tree growth and yield model for uneven aged maritime pine (*Pinus pinaster* Aiton) stands, and they suggested that the efficacy of distance-dependent competition indices was not clear compared with distance-independent competition indices. In general, distance-dependent competition indices are regarded as having higher accuracy as they are known to carry information on location and more reliably express local competition (Wimberly and Bare 1996; Miyamoto and Amano 2002; Contreras et al. 2011). However, some studies maintain that the accuracy of models based on the two indices is the same (Daniels et al. 1986; Biging and Dobbertin 1995; Kahriman et al. 2018; Kuehne et al. 2019) and that distance-independent competition indices may satisfactorily predict yield growth. For example, Palahí et al. (2003) developed individual-level distance-independent tree growth and mortality models for Scots pine (*Pinus sylvestris* L.). Sun et al. (2019) evaluated the six distance-independent indices for loblolly pine (*Pinus taeda* L.) diameter growth and survival models based on an individual approach. Their results indicated that the distance-independent tree growth and mortality models were well predicted actual tree growth and mortality. If the distance-independent models would predict stand growth and yield for Japanese common species well, it is easy and cost-effective to predict yield growth because the distance-independent competition indices do not require the information of the trees' positions in the stand. Our previous study indicated that a distance-independent diameter growth model offered accurate prediction of actual diameter growth in Japanese cedar trees (Fukumoto et al. 2020a). There is the possibility that a distance-independent based yield prediction model would predict actual yield growth well. To evaluate the effectiveness of yield prediction methods, we need to clarify model accuracy using test data. However, studies that have verified the accuracy between predicted and observed values using long-term data remain to be lacking.

Thus, this study aims to evaluate the effectiveness of long-term yield prediction based on a distance-independent individual tree approach for Japanese cedar trees in western Japan as a case study and to further validate our yield prediction model using long-term data available for two existing permanent plots.

2. Materials and Methods

2-1. Data collection

In this study, the dataset was collected from five study sites in the Shikoku region, western Japan, wherein the mean annual temperature is 16.2 °C and mean precipitation is 1322.5 mm. The study sites were in national forests located in Asagihara (A), Nishimata-higashimata (B), Nakanokawa-yama (C), Kudarukawa-yama (D) (Fig. 1, Table 1), and Ichinotani-yama (T) (Fig. 1, Table 2). The data from sites A–D were used as model training data, whereas the data from site T was used as test data. Sites A–D were originally established to evaluate the effect of initial planting density and thinning intensity on Japanese cedar growth. Japanese cedar was planted between 1950 and 1964 at each site. These sites had two to six study plots 0.035–0.227 ha in area. The first measurements were conducted when the plots were 11–28 years old. The site index (SI) ranged from 14.8 m to 27.7 m in each plot. SI was calculated as the upper mean height (250 trees/ha) at 40 years old. The upper mean height at 40 years old was estimated from the stand age–dominant height relationship using a smoothing spline because the measurement had not been conducted at 40 years old. The census intervals were approximately 5 years, and measurements were repeated 5 to 10 times. In total, data was collected from 5,130 trees.

The test site was located in Ichinotani-yama national forest (Fig. 1). This site had two study plots (Plot 1 and Plot 2) (Table 2), each 0.109 ha in area. In these plots, cleaning and thinning from below were conducted at age 31 and 36 years, respectively. The cleaning rates, based on the number of trees in the plots, were 20 % for Plot 1 and 18 % for Plot 2; the thinning rates were 44 % and 50 %, respectively; and the SIs were 22.1 and 18.0, respectively. Tree height and DBH in these plots were measured as for the other plots.

The DBH of each tree was measured at 1.2 m. The tree height was obtained by measuring approximately 30 trees selected based on diameter class. Unmeasured tree height was estimated using Näslund equation (Nigul et al. 2021). In field measurements, we recorded whether trees were dead or alive.

2-2. Individual-level growth and survival models

The individual-level Japanese cedar height growth, diameter growth, and survival rate prediction models were constructed based on a generalized linear mixed-effect model. The diameter growth model had been developed in a previous study (Fukumoto et al. 2020a), and the model parameters were re-estimated in this dataset. Annual individual height and diameter growth were defined, respectively, as follows:

$$\ln\left(h_{I,i,j+1}\right) = a_0 + a_1 H_{I,i,j} + a_2 H_{I,i,j}^2 + a_3 Age_{I,i,j} + a_4 SI_I + a_5 BAL_{I,i,j} + \varphi_{I,i}, \ (1)$$

$$\ln\left(d_{I,i,j+1}\right) = b_0 + b_1 DBH_{I,i,j} + b_2 DBH_{I,i,j}^2 + b_3 Age_{I,i,j} + b_4 Sr_{I,j} + \varphi_{I,i}, \ (2)$$

where $h_{I,i,j}$ and $d_{I,i,j}$ are the annual height and diameter growth, respectively, of the subject tree i in the I^{th} plot between the j^{th} measurement and the subsequent measurement. $H_{I,i,j}$ and $H_{I,i,j}^2$ are tree initial height and the height squared, respectively. $DBH_{I,i,j}$ and $DBH_{I,i,j}^2$ are DBH and DBH squared, respectively. $Age_{I,i,j}$ and SI_I are stand age and site index, respectively. $BAL_{I,i,j}$ and $Sr_{I,j}$ are competition indices, calculated as follows:

$$BAL_{I,i,j} = \sum \frac{\pi}{4} DBH_c^2, (3)$$

$$Sr_{I,j} = \frac{100^2}{\overline{H}_{I,j}\sqrt{N_{I,j}}}, (4)$$

where $BAL_{I,i,j}$ is the basal area of trees larger than the subject trees, and DBH_c is the DBH of competitor trees that have a larger diameter than the subject tree (Wykoff et al. 1982). $Sr_{I,j}$ is defined as the relative spacing index, and $\overline{H}_{I,j}$ is the mean height. $N_{I,j}$ is the number of trees per hectare. In this study, following pre-analysis, the relative spacing index was generated using mean height (i.e. mean height of all living trees in a plot) rather than upper mean height (i.e. mean height of 250 largest trees per hectare) (see Nagumo and Minowa 1990) as this increased model accuracy. In Eqs. 1 and 2, $a_0 - a_5$ and $b_0 - b_4$ are parameters, and $\varphi_{I,i}$ is the random effect with normal distribution for subject tree and plot. Here, measured trees were nested within plots and each tree was repeatedly measured over time. Thus, random effects were included at both the plot and tree level.

An individual-tree survival model was constructed with a logistic function to calculate the annual tree survival rate. Here, the "*Exposure*" method was used in the model because the data were collected with irregular measurement interval *t* (Shaffer 2004). The annual tree survival rate $S_{i,I,j}$ of subject tree *i* in the I^{th} plot at the j^{th} measurement is expressed as follows:

$$S_{i,I,j+1} = \left(\frac{1}{1+\exp(-c)}\right)^t, (5)$$

$$c = c_0 + c_1 DBH_{i,I,j} + c_2 SI_I + c_3 Sr_{I,j} + c_4\left(DBH_{i,I,j} * Sr_{I,j}\right) + \varphi_{i,I}, (6)$$

The interaction of terms *DBH* and *Sr* was used to express the effect of competition that is dependent on individual tree size. c_0 - c_4 are parameters, and $\varphi_{i,I}$ is the random parameter of subject tree *i* in the I^{th} plot. The lme4 package (Bates et al. 2015) in R version 4.0.4 (R Core Team 2021) was used to estimate the all parameters. Note that explanatory variables for each model were selected during preliminary analysis using a stepwise method referring to AIC values.

2-3. Model evaluation

To evaluate model performance, Marginal R^2, Conditional R^2, root mean square error (RMSE), and average bias (AB) were calculated for both height and diameter growth models following to Kozak and Kozak (2003). Then, Marginal R^2 and Conditional R^2 (Nakagawa and Schielzeth 2013) were calculated via the MuMIn package in the r.squaredGLMM function (Barto 2020). The area under the curve (AUC) was used to evaluate survival model performance (Godeau et al. 2020). AUC is calculated by drawing the receiver operating characteristic curve (Pencina et al. 2008). The AUC value ranges from 0 to 1, where a value of 1 indicates perfect distinction. Here, the AUC values was calculated by pROC package (Robin et al. 2011).

2-4. Simulation and model validation

The individual tree growth for two plots in Ichinotani-yama for 53 years were simulated. Our models (Eqs. 1, 2, and 5) were initialized with the first measurement data (tree height, DBH, stand age, competition index at 12-year old). SIs were set to the estimated values from the measurements data of the plots, assuming they could be predicted separately. Then, the models run forward until 65-year old to predict the individual tree height, diameter, and volume. The simulation interval was 1 year. The tree volume $v_{i,I,j}$ was calculated using the following equation:

$$v_{i,I,j} = d_0 + d_1 H_{i,I,j} + d_2 DBH^2_{i,I,j} + d_3\left(H_{i,I,j} * DBH^2_{i,I,j}\right) \quad (7)$$

where d_0-d_3 are parameters as defined for each diameter class (Table 3) (Hosoda et al. 2010). The thinning age and rate were adapted according to actual test data. Thinning trees were selected randomly by each diameter class, to clarify the contribution to the yield prediction system. The number of trees was calculated based on the actual thinning rate of each diameter class and predicted stand density. We defined that tree death occurs at a survival rate less than 50 %.

To validate model performance, the predicted and observed mean height, diameter, stand density, volume, and cumulative volume were compared in each plot. The predicted and observed diameter distribution at age 12, 22, 30, 46, and 65 years were also compared. Additionally, to validate the effectiveness of the prediction model, the RMSE and bias were calculated for individual height, DBH, and volume using the fixed effect only.

3. Results

3-1. Evaluation of growth and survival model

In each model, parameters estimation results shown in Table 4. The Marginal R^2 values for the height and diameter growth models were 0.23 and 0.52, respectively (Table 5). Meanwhile, the Conditional R^2 values for both models were 0.25 and 0.59, respectively. The accuracy of the height growth model was found to be low in comparison with the DBH model. The RMSE for height and diameter growth were 0.2048 and 0.2050, respectively. Average bias for both models were 0.057 and 0.048, respectively. AUC for the survival model was 0.84.

3-2. Yield predictions

In Plot 1, mean height was overestimated for trees over 20 years old, though DBH was showed little difference between predicted and observed values (Fig. 2a). Stand density was also showed little difference between predicted and observed values; however, there were no trees discerned with a survival rate under 50 %. Mean volume and cumulative stand volume were predicted well for trees up to 40 years old. In Plot 2, mean height, stand density, mean tree volume, and stand volume were predicted better than DBH (Fig. 2b). DBH was underestimated for trees over 40 years old.

3-3. Prediction of diameter distribution

In Plot 1, the diameter distribution between predicted and observed values was similar for trees up to 46 years old, beyond which the values tended to be slightly underestimated (Fig. 3a). The diameter distribution was fitted up to 36 years old in Plot 2, though diameters were underestimated beyond 41 years old (Fig. 3b). Interestingly, the tendency toward underestimation appeared after thinning treatment in both plots.

3-4. Predicted accuracy of height, DBH, and volume under time series

The RMSE under time series showed that the prediction accuracy worsened with increasing age (Fig. 4). The maximum RMSE values for height, DBH, and volume were 5.63 m, 11.8 cm, and 0.9 m^3, respectively. The bias of height in both plots showed that the predicted values were underestimated from 20 years old (Fig. 5a), with values ranging from −4.89 to 0.31 m. For DBH, the predicted values were overestimated from 35 years old, after which point the values tended to be underestimated (Fig. 5b). The bias for DBH ranged from −2.48 to 1.19 cm. The bias for volume showed underestimation from 30 years old, with values ranging from −0.36 to 0.02 m^3 (Fig. 5c).

4. Discussion

The Marginal R^2 and Conditional R^2 values for the height growth model were determined to be lower than the diameter growth model, thus indicating low model accuracy. In general, tree height measurement is susceptible to error (Larjavaara and Muller-Landau 2013). At our study site, the instrument used to measure tree height was changed from Blume-Leise to Vertex after 2000, and this may have introduced measurement error (Villasante and Fernandez 2014). In addition, only a proportion of the trees were explicitly measured at our study site; heights for the unmeasured trees were estimated using the relationship between DBH and tree height. The potential errors involved in height estimation may have affected accuracy of the height growth model in this study. On the other hand, mean height, DBH, and volume were predicted by our model with moderate accuracy, and diameter distribution up to 30 years of age was predicted well. Our results indicate that individual-level distance-independent models may adequately predict stand yield for a limited time and that such models can be useful in a yield prediction system. A characteristic of Japanese cedar is that it has very straight stems and stands are usually planted simultaneously, meaning that tree size is expected to be uniform. Therefore, our relatively simple models were well suited to growth predictions for Japanese cedar.

Most of the yield prediction models popular in Japan were built upon a stand-level framework (Konohira 1995; Nakajima et al. 2010). Because the models were developed for major species in each region, the system has shown practical application for local-level forest planning. However, the system only provides yield growth under standard treatment and cannot specifically select trees that should be removed for a thinning treatment; therefore, the system is not suitable for selecting target trees for a thinning exercise and is insufficient for evaluating tree growth under different treatment strategies. In this study, we extended individual-level yield prediction to address the problems of conventional yield prediction through the ability to select trees to be removed for a thinning treatment and to adequately express residual tree growth. Our model is ideal in a supporting role to improve forest management plans. Moreover, our model used distance-independent competition indices to express competition in a stand. These indices are more easily calculated than distance-dependent competition indices as they do not require location information data from a stand (Rivas et al. 2005). However, the distance-independent competition index has a limitation; Hasenauer (2006) implied that if the plot size increases, predictions may diverge from the real situation. Consequently, it would be advantageous to create models that incorporate distance-dependent competition indices. This would require trees' coordinate information, the collection of which, to date, has been costly in labor and time. Recently, terrestrial laser scanning had been employed to measure forest structure (Nishizono et al. 2020; Suematsu et al. 2020). Results indicate that it might, in the future, be feasible to obtain spatial information such as individual tree sizes and positions using this technique. It is relatively easy to calculate the distance-dependent competition index, and this permits realistic expression of tree growth. In a future study, we plan to incorporate both distance-dependent and distance-independent competition indices to flexibly predict yield growth under various forest management scenarios. We also aim to incorporate taper curves into our model for accurate prediction of timber production (Seppänen and Mäkinen 2020), as this could provide useful yield prediction data.

There are some limitations with individual-level models. Our models were developed based on the data of pure Japanese cedar plantations. Therefore, the models might not suitable for the mixed or un-even aged Japanese cedar plantation. In this study, prediction accuracy of mean values in Plot 1 was lower than that in Plot 2. One possible reason is that the standard deviation in Plot 1 was larger than in Plot 2. If the dispersion of data were large, the model may not be able to provide accurate predictions. The RMSE values increased with increasing tree age in both plots. Bias also showed that the values were not constant. The RMSE and bias values were high compared with other previous studies that was constructed yield prediction system for other species (e.g. Weiskittel et al. 2016; Scolforo et al. 2019); however, our models sufficiently predicted for short- and medium-term tree growth. In general, the individual-level model produces error propagation when tree growth predictions are made as a time series. Moreover, data for outliers (extremely large or small trees) might be difficult to predict well. To better model long-term individual tree growth, we need to incorporate data other than just initial values.

We validated our models by adapting the test data, which had been collected as a consequence of normal management. Recently, conifer plantations have matured in Japan, and it is now necessary to consider management of old trees (Miyamoto 2015). Moreover, we need to reduce management costs to improve revenue for forest owners (Fukumoto et al. 2017, 2020b, 2021; Sakai et al. 2019). While promising, our models do not yet address some of the problems currently experienced in the Japanese forestry industry, and further refinement is required to adapt the yield growth models for non-standard treatments. On the other hand, our models have the advantage of relative simplicity; to develop individual-level models would require huge datasets to estimate model parameters. This is the most important issue in yield prediction at individual level, since it is very challenging to collect long-term individual tree growth data. In this study, we examined yield prediction in limited areas and species; a useful next step would be to re-estimate the parameters to adapt the model for other regions and species. Parameter estimation calculated from minimal data would be a valuable topic for future study.

5. Conclusion

This study examined distance-independent individual-level yield prediction for Japanese cedar plantations in the Shikoku region, western Japan. We developed models employing three parameters, that is, height, DBH, and mortality, to predict yield. Results showed that our models predicted actual mean values for height, DBH, volume, and diameter distribution well, suggesting that individual-level models might be sufficient for yield prediction. One limitation was error propagation over extended time spans. Thus, it is useful to conduct actual measurements at some point in the forest development stage, and use the measurements as initial values for short- or medium-term predictions. Our intention is to improve the models for practical application for an individual-based yield production system in Japanese forestry, as such a tool would make a significant contribution to sustainable timber supply and forest management in Japan.

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Table 1. Summary of study sites at first and last measurement period

Site		Plot	Area (ha)	First measurement					Last measurement					SI*	Cumulative Thinning rate
				Age (years)	Density (trees/ha)	Mean height (m)	Mean DBH* (cm)	Sr* (%)	Age (years)	Density (trees/ha)	Mean height (m)	Mean DBH* (cm)	Sr* (%)		
A	Asagihara	1	0.227	12	1,308	3.6	3.9	78.2	60	1,185	15.3	19.9	19.0	15.7	-
		2	0.200	12	1,340	3.2	3.2	86.9	60	1,260	14.5	18.4	19.4	15.6	-
		3	0.116	12	5,147	3.4	3.6	42.1	60	4,509	12.6	13.1	11.8	14.8	-
		4	0.124	12	4,806	3.8	4.0	38.3	60	3,750	14.5	14.7	11.3	19.1	-
B	Nishimata-higashimata	5	0.203	10	3,286	7.4	9.6	23.5	66	1,187	26.9	31.9	10.8	23.5	0.20
		6	0.078	11	2,782	7.8	10.5	24.4	67	2,282	24.3	27.0	8.6	24.9	-
C	Nakanokawa-yama	7	0.089	28	2,337	17.4	22.0	11.9	54	1,663	24.5	29.4	10.0	22.6	-
		8	0.043	28	2,581	15.2	17.7	13.0	54	1,605	23.2	26.2	10.8	20.9	0.18
		9	0.055	28	3,364	17.5	18.2	9.9	54	1,982	26.2	28.0	8.6	23.3	-
		10	0.035	27	4,943	13.1	13.5	10.8	53	1,314	21.8	26.0	12.7	20.1	0.69
		11	0.036	27	3,306	12.3	14.8	14.1	53	1,750	21.0	23.2	11.4	18.3	0.32
		12	0.036	27	5,250	10.3	11.0	13.4	53	2,833	18.2	20.7	10.3	16.9	-
D	Kudarukawa-yama	13	0.116	14	2,509	11.3	14.5	17.7	61	707	33.3	40.8	11.3	27.5	0.44
		14	0.123	14	2,236	10.4	13.9	20.3	61	780	33.6	41.0	10.7	27.7	0.28
		15	0.106	14	2,189	11.3	15.6	18.9	61	868	33.4	40.6	10.2	27.4	0.26
		16	0.113	14	2,469	10.2	14.1	19.8	61	1,416	29.5	31.8	9.0	26.6	-

*DBH is diameter at breast height, and Sr is relative spacing index. SI is site index, which is calculated dominant height at 40 years old. Cumulative thinning rate (cumulative thinning volume/gross yield) is calculated between first and last measurements.

Table 2. Summary of the test data in Plot 1 and Plot 2 collected at Ichinotani-yama. Values in parentheses are standard deviations

		Age										Area (ha)	SI
		12	**17**	**22**	**30**	**36**	**41**	**46**	**56**	**62**	**65**		
(a) Plot 1	**Mean height (m)**	**7.6**	**9.9**	**11.7**	**13.7**	**17.4**	**19.3**	**20.6**	**21.6**	**22.1**	**22.5**	**0.109**	**22.1**
		(2.2)	(2.6)	(2.9)	(3.6)	(2.9)	(2.8)	(3.0)	(3.2)	(3.4)	(3.6)		
	Mean DBH (cm)	**9.9**	**13.0**	**15.3**	**17.3**	**21.2**	**25.8**	**27.2**	**30.3**	**31.6**	**33.1**		
		(3.5)	(4.7)	(5.7)	(7.1)	(6.2)	(6.2)	(6.8)	(7.8)	(8.5)	(9.5)		
	Mean volume (m^3)	**0.044**	**0.091**	**0.143**	**0.212**	**0.334**	**0.505**	**0.591**	**0.759**	**0.842**	**0.945**		
		(0.0)	(0.1)	(0.1)	(0.2)	(0.2)	(0.3)	(0.3)	(0.4)	(0.5)	(0.6)		
	Stand density (trees ha^{-1})	**1844**	**1844**	**1844**	**1477**	**835**	**826**	**826**	**826**	**807**	**807**		
(b) Plot 2	**Mean height (m)**	**6.0**	**8.1**	**9.6**	**10.9**	**13.4**	**15.1**	**16.0**	**17.4**	**18.4**	**19.3**	**0.109**	**18.0**
		(1.9)	(2.1)	(2.2)	(2.7)	(2.4)	(2.5)	(2.7)	(2.7)	(2.7)	(3.0)		
	Mean DBH (cm)	**7.7**	**10.5**	**12.6**	**13.9**	**16.6**	**20.7**	**21.9**	**25.5**	**27.1**	**28.7**		
		(3.0)	(3.8)	(4.4)	(5.3)	(5.2)	(5.8)	(6.2)	(7.4)	(8.3)	(8.5)		
	Mean volume (m^3)	**0.023**	**0.051**	**0.081**	**0.114**	**0.174**	**0.280**	**0.329**	**0.468**	**0.552**	**0.639**		
		(0.0)	(0.0)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.3)	(0.4)	(0.4)		
	Stand density (trees ha^{-1})	**2147**	**2147**	**2147**	**1771**	**881**	**872**	**872**	**872**	**853**	**853**		

Table 3. Parameters for the volume equation for Japanese cedar trees in Tosa regions according to Hosoda et al. (2010).

Diameter class (cm)	Intercept	H (m)	DBH^2 (m)	$H*DBH^2$
DBH <11	−0.00018	0.00006901	0.58810351	0.38337273
DBH <21	−0.01266	0.00177071	1.04476089	0.2964403
DBH <31	−0.03328	0.00442833	1.42509179	0.25603657
31 ≤ DBH	−0.51335	0.02464082	4.65164113	0.11705915

Table 4. Parameter estimation for the height and diameter growth models, and survival model

		Parameter	Description	Estimate
(1)	Height growth model	a_0	Intercept	-2.582
		a_1	Age	-0.002
		a_2	Height	0.002
		a_3	Height ˆ2	-0.001
		a_4	BAL	-0.078
		a_5	SI	0.089
(2)	Diameter growth model	b_0	Intercept	-1.971
		b_1	Age	-0.051
		b_2	DBH	0.126
		b_3	DBH ˆ 2	-0.001
		b_4	Sr	0.020
(3)	Survival model	c_0	Intercept	4.512
		c_1	DBH	0.008
		c_2	Sr	0.054
		c_3	SI	-0.159
		c_4	DBH * Sr	0.019

Table 5. Evaluation for the height, diameter and survival model.

	Marginal R^2	Conditional R^2	RMSE	AB	AUC
(1) Height growth model	0.23	0.25	0.2048	0.057	-
(2) Diameter growth model	0.52	0.59	0.2050	0.048	-
(3) Survival model	-	-	-	-	0.84

Figure captions

Figure1. Locations of the study site; (A) Asagihara, (B) Nishimata-higashimata, (C) Nakanokawa-yama, (D) Kudarukawa-yama, (T) Ichinotani-yama. The land area was provided by the Digital National Land Information (https://nlftp.mlit.go.jp/ksj/). The map projection and coordinate systems were used JGD2000 and UTM zone 53N, respectively.

Figure 2. Relationship between predicted and observed mean height, DBH, stand density, tree volume, and stand volume in test site (a) Plot 1 and (b) Plot 2

Figure 3 (a). Relationship between predicted and observed diameter distribution in Plot 1. The bars indicate actual values, the blue lines indicate predicted values

Figure 3 (b). The relationship between predicted and observed diameter distribution in Plot 2. The bars indicate actual values, the blue lines indicate predicted values

Figure 4. RMSE trend in Plot 1 and Plot 2 for (a) Height, (b) DBH, and (c) Volume

Figure 5. Bias trend in Plot 1 and Plot 2 for (a) Height, (b) DBH, and (c) Volume. Grey line indicates y= 0

Figure1.

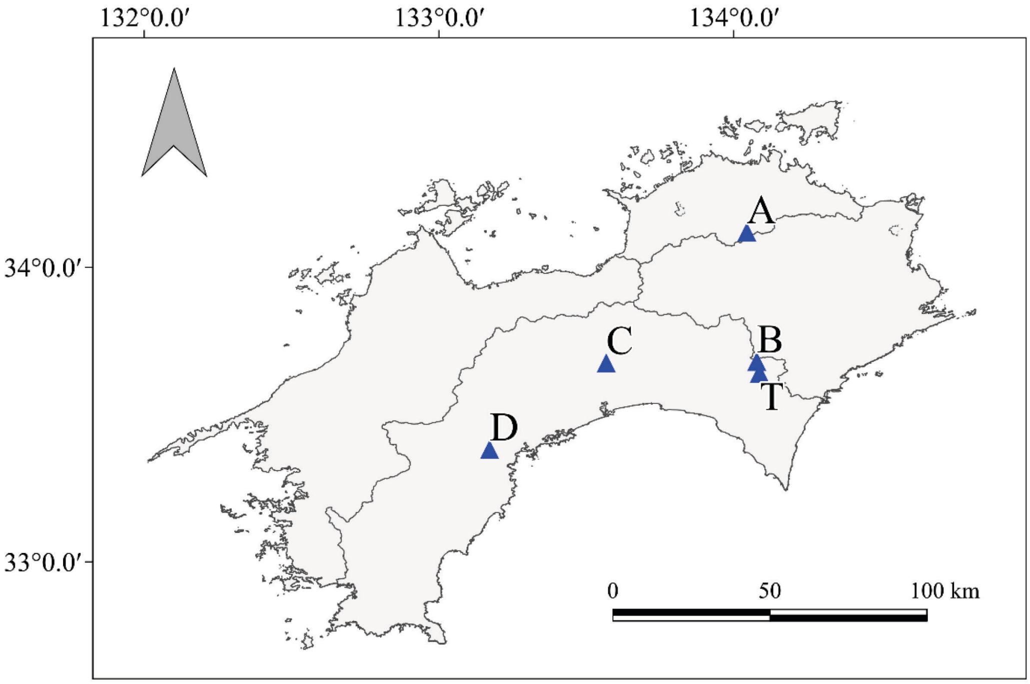
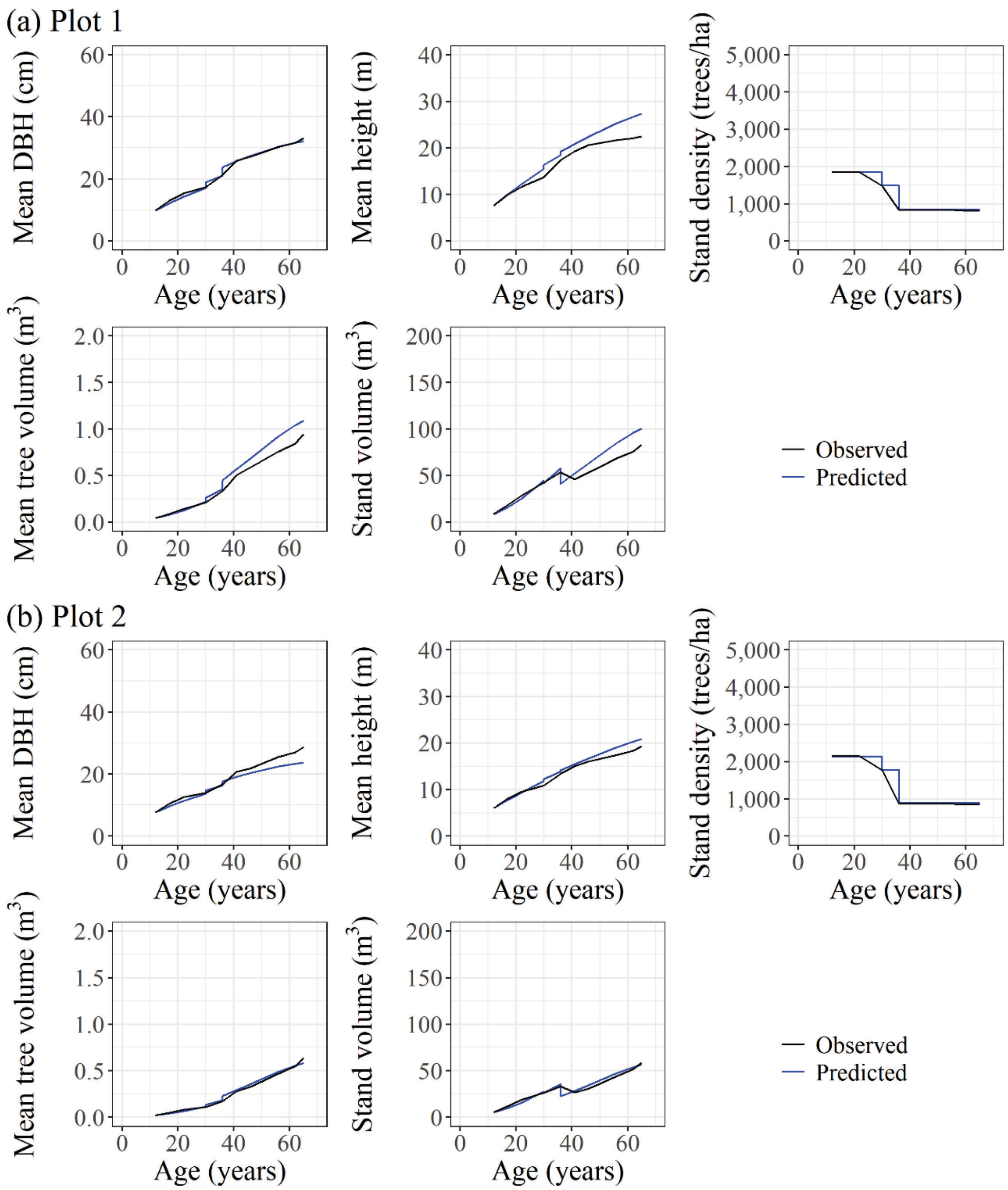
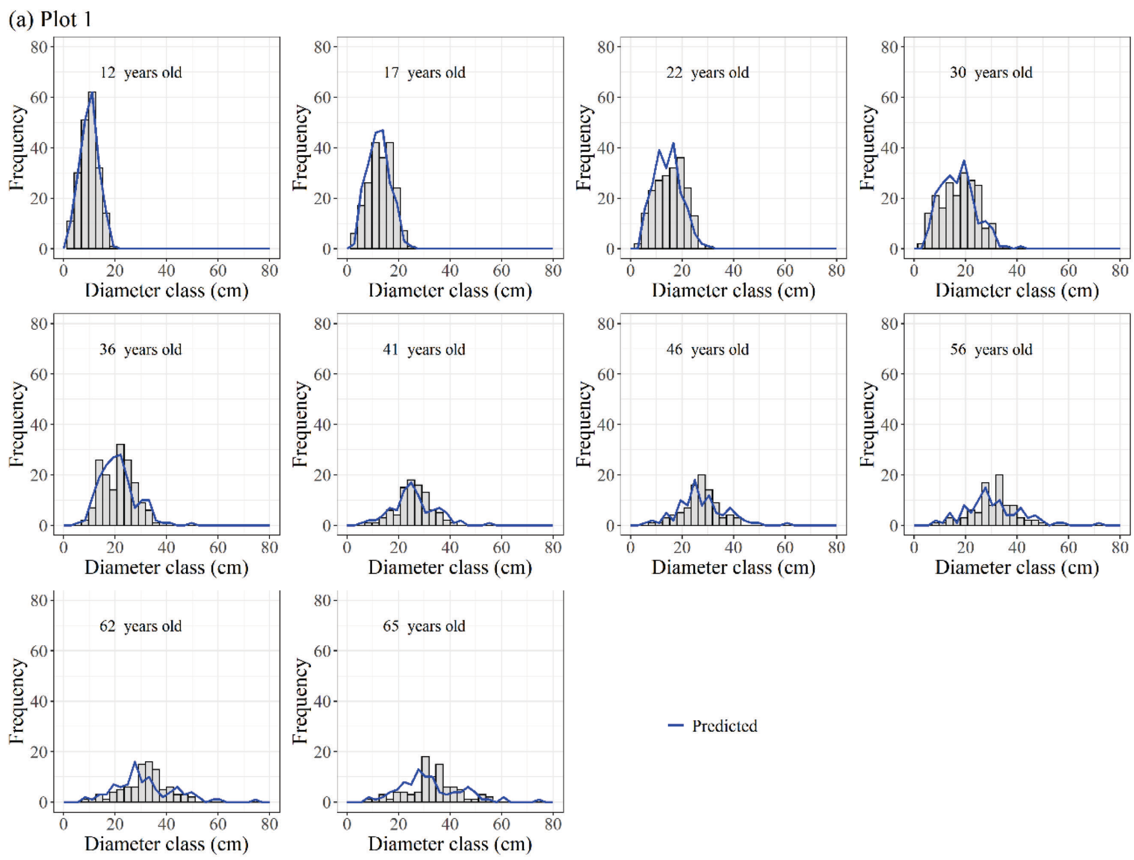


Figure 2.



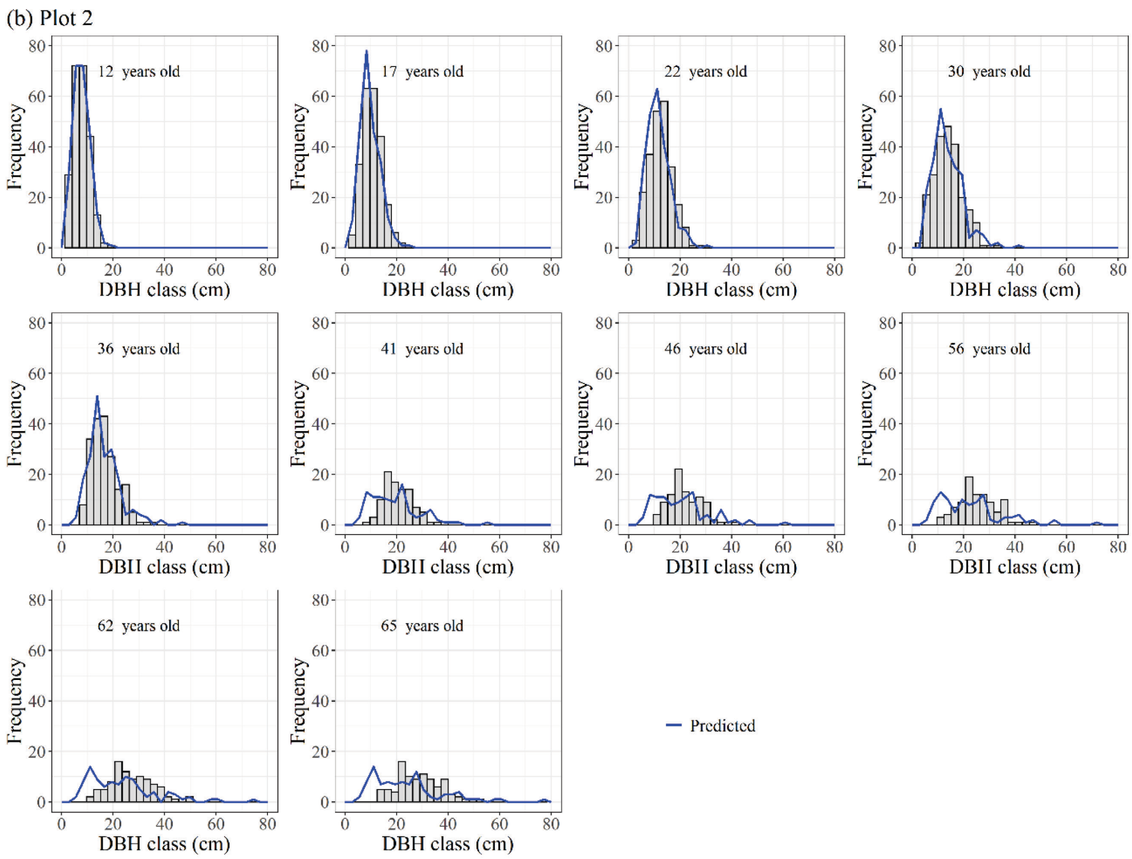
(a) Plot 1
Mean DBH (cm)
Mean height (m)
Stand density (trees/ha)
Mean tree volume (m3)
Stand volume (m3)
Age (years)
Observed
Predicted
(b) Plot 2

Figure 3 (a).



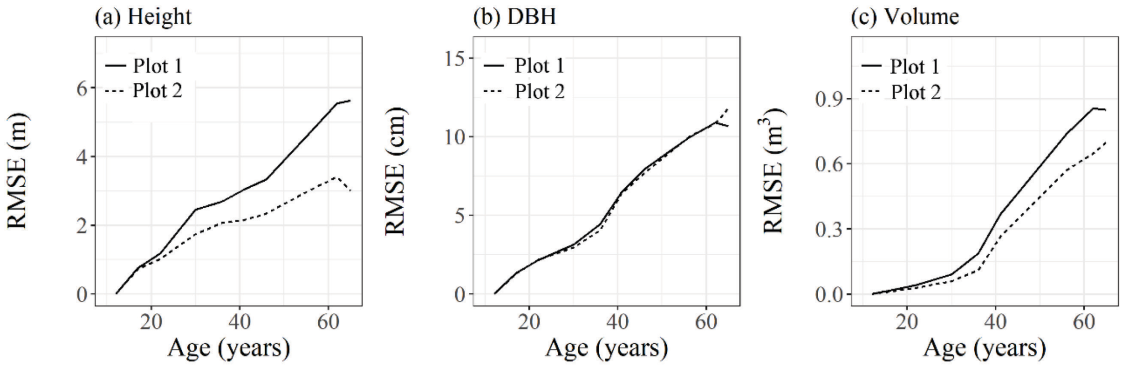
(a) Plot 1
12 years old
17 years old
22 years old
30 years old
36 years old
41 years old
46 years old
56 years old
62 years old
65 years old
Frequency
Diameter class (cm)
Predicted

563 Figure 3 (b).



564

565 Figure 4.



566

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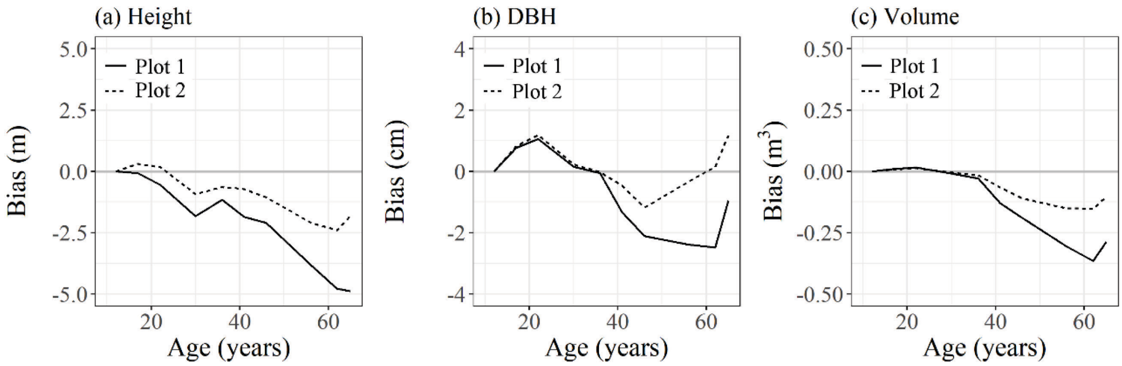
Figure 5.


(a) Height
Bias (m)
5.0
2.5
0.0
-2.5
-5.0
20
40
60
Age (years)
Plot 1
Plot 2
(b) DBH
Bias (cm)
4
2
0
-2
-4
20
40
60
Age (years)
Plot 1
Plot 2
(c) Volume
Bias (m3)
0.50
0.25
0.00
-0.25
-0.50
20
40
60
Age (years)
Plot 1
Plot 2