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ARTICLE

RESEARCH ARTICLE

Evaluation of the impact of forest information on regional harvest planning and land productivity based on mixed-integer programming

Evaluación del impacto de la información forestal en la planificación regional de cosecha y la productividad del suelo mediante programación entera mixta

Tohru Nakajima
Forest Management Laboratory, Graduate School of Agricultural and Life Sciences,
University of Tokyo. 113-8657, Tokyo Japan
Corresponding author: nakajima@fr.a.u-tokyo.ac.jp, https://orcid.org/0000-0002-9834-2206

Kazuma Mukai
Forest Management Laboratory, Graduate School of Agricultural and Life Sciences,
University of Tokyo. 113-8657, Tokyo Japan
https://orcid.org/0009-0004-3222-6909

Hayato Kamei
Forest Management Laboratory, Graduate School of Agricultural and Life Sciences,
University of Tokyo. 113-8657, Tokyo Japan
https://orcid.org/0009-0008-2747-4050

Satoshi Tatsuhara
Forest Management Laboratory, Graduate School of Agricultural and Life Sciences,
University of Tokyo. 113-8657, Tokyo Japan
https://orcid.org/0000-0002-8841-232X

Abstract: *Aim of study*: To investigate the impact of site class information on forest operation and harvest planning using mixed-integer programming, silviculture regimes, and forest planning. *Area of study:* A privately owned Japanese cedar "sugi" (*Cryptomeria japonica*) plantation managed by a forestry association in a cool temperate mountain forest in Japan. *Material and methods*: Income and timber volume were estimated for each position, forest age, and stem diameter. Age-class distribution, harvest volume, required labor, profit, and other relevant metrics were compared over the forecast period using two optimized harvest plans incorporating status considerations, i.e., with or without site indices. Data were validated based on the premise and assumption that concentrating labor in well-positioned forest management units augments timber yield and improves profits by optimizing timber quality, reducing the proportion of biomass timber, and increasing the proportion of Grade-A timber. *Main results*: Accounting for status notably increased the total harvested volume by 5.7% over 24 quarters, with a significant 10.8% increase in revenue. Integrating site-class information facilitates efficient and sustainable forest management practices. Stand units with a favorable status may be prioritized for relatively shorter logging operations owing to declining labor availability. Thinning is less affected by a favorable status than clear-cutting, as thinning is financially subsidized, considerably reducing its economic impact. Conversely, logging in areas with poorer status poses risks because a slight decline in timber prices can negatively affect income and expenses. *Research highlights*: Incorporating site class information helps avoid unprofitable locations and improves harvest plans under constraints, such as labor requirements.

Keywords: clear-Cutting; forest management; harvest; labor requirements; land productivity; rotation periods.

Resumen: *Objetivo del estudio*: Investigar el impacto de la información sobre la clase de sitio en las operaciones forestales y la planificación de la cosecha mediante programación entera mixta, considerando regímenes silvícolas y planificación forestal. *Área de estudio*: Una plantación privada de cedro japonés “sugi” (*Cryptomeria japonica*) gestionada por una cooperativa forestal en un bosque montañoso templado frío en Japón. *Material y métodos*: Se estimaron los ingresos y el volumen de madera para cada localización, edad del rodal y diámetro del fuste. La distribución por clases de edad, el volumen de cosecha, los requerimientos de mano de obra, los beneficios y otros indicadores relevantes se compararon durante el período de planificación utilizando dos planes de cosecha optimizados: uno considerando la clase de sitio y otro sin considerarla. Los datos se validaron bajo el supuesto de que concentrar la mano de obra en unidades forestales con condiciones favorables aumenta el rendimiento de la madera y mejora los beneficios mediante la optimización de la calidad, la reducción de madera de biomasa y el incremento de madera de alta calidad. *Resultados principales*: La consideración de la clase de sitio incrementó el volumen total de cosecha en un 5,7 % durante 24 periodos, con un aumento significativo del 10,8 % en los ingresos. La integración de la información de la clase de sitio facilita prácticas de gestión forestal más eficientes y sostenibles. Las unidades con mejores condiciones pueden priorizarse para operaciones de corta más cortas debido a la disminución de la disponibilidad de mano de obra. El aclareo se ve menos afectado que la corta final debido a subsidios, mientras que la explotación en áreas de baja calidad presenta riesgos económicos. *Aspectos destacados de la investigació*n: La incorporación de información sobre la clase de sitio permite evitar áreas no rentables y mejorar la planificación de la cosecha bajo restricciones de mano de obra.

Palabras clave: corta rasa; cosecha; gestión forestal; periodos de rotación; productividad del suelo; requerimientos de mano de obra

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Supplementary information ↓

1. INTRODUCTION

Forests serve myriad functions and provide essential ecosystem services, including biodiversity preservation, carbon sequestration for climate regulation, water source replenishment, and timber yield (Science Council of Japan, 2001; Martynova et al., 2021). However, managing forests to optimize these services poses challenges owing to inherent tradeoffs (Triviño et al., 2017).

The adoption of the Sustainable Development Goals (SDGs) in 2015 spurred research across diverse sectors, including forestry, exploring the nexus between public interest functions included in multi-objective functions, such as carbon stocks, biodiversity, recreation, and SDGs, while developing evaluation methodologies (Timko et al., 2018). Maintaining a balanced approach to these functions requires the development of management strategies that incorporate more rational forest practices, such as logging and reforestation, over the long term. Accurate inventories of current forest conditions support future projections required for effective logging planning. Aerial light detection and ranging (LiDAR) data, which enhance the accuracy of site indices and have been increasingly utilized globally, promote sustainable forest management (Wulder et al., 2008).

Aircraft LiDAR-derived data have facilitated diverse applications, including tree height estimation (Andersen et al., 2006), site class determination (Watt et al., 2015), diameter measurement (Salas et al., 2010), crown delineation (Paris & Bruzzone, 2014), enhancing density estimation accuracy (Fassnacht et al., 2017), growth prediction from crown data (Nakajima et al., 2011), volume prediction, and ground data-based volume comparisons (Leboeuf et al., 2022). Some studies have examined variations in profit and harvest in preconceived plans, correcting for errors in basal area and tree height measurements using aircraft LiDAR (Eid, 2000; Islam et al., 2009; Rodrigues et al., 2021).

Additionally, investigations have explored factors influencing tree growth by incorporating topographic data, such as digital elevation models, to estimate site indices, revealing the significant impacts of factors such as solar radiation and soil moisture content (Mitsuda et al., 2007). The variations in the site class significantly affected the predictions of the optimal rotation lengths. Forests with better site classes tend to reach their optimum rotation ages sooner than those with poorer classes across different regions and tree species (Kronrad & Huang, 2002; Mabvurira & Pukkala, 2002; Pasalodos-Tato & Pukkala, 2007).

Site class refers to the classification of forestland based on its ability to produce successive crops of industrial wood. This classification relies on the maximum mean annual increment, measured in cubic feet per acre, of natural, well-stocked, and even-aged stands of species suitable for local sites (Clutter et al., 1983). Hence, site class significantly contributes to harvested timber volume and income over time, with sites with improved productivity correlating with increased harvests and revenues across all tree species (Rørstad et al., 2010; Paudel & Dwivedi, 2021). This approach has been applied to devise sustainable forest plans tailored to regional contexts. Prediction tools that use diverse topographic features, site classes and stand ages may help optimize forest management practices (Nakajima et al., 2009; Watanabe & Tatsuhara, 2013). Moreover, profitability enhancement strategies have integrated adjacent sub-compartments and synchronized harvesting schedules for small sub-compartment areas (Nakajima et al., 2017; Suzuki et al., 2018).

Although previous studies have highlighted variations in harvest yield and income based on site class distinctions, few studies have comprehensively addressed the effective implementation of sustainable forest management. Specifically, additional research is needed to visually illustrate the benefits of afforestation, logging, and various forest activities. These benefits can be elucidated relatively more effectively through improved forest state inventories supported by advanced remote sensing technologies. Accordingly, substantial global investments have been made to refine forest information using remote-sensing methods, including aircraft LiDAR and drone technology. Therefore, to evaluate the cost-effectiveness of these endeavors, it is imperative to elucidate how enhanced assessment, which improves the accuracy of site quality information, positively impacts forest management planning and regional sustainability benefits.

The primary aim of this study was to quantitatively elucidate the positive impacts of recent advancements in forest condition inventories on forest management planning. In particular, the site class, recognized for its significant impact on profitability in forest management (Nakajima et al., 2017), was assessed among the various site characteristics estimated from remotely sensed data. Specifically, harvesting plans were optimized, encompassing afforestation, nursery operations, thinning, and final cutting at the landscape level under two scenarios. In the first scenario, each forest area designated for harvesting and afforestation was equipped with accurate site class information; however, in the second scenario, accurate site class information was not available for these forest areas.

2. MATERIAL AND METHODS

The overall methodological framework of this study is illustrated in Fig. 1.

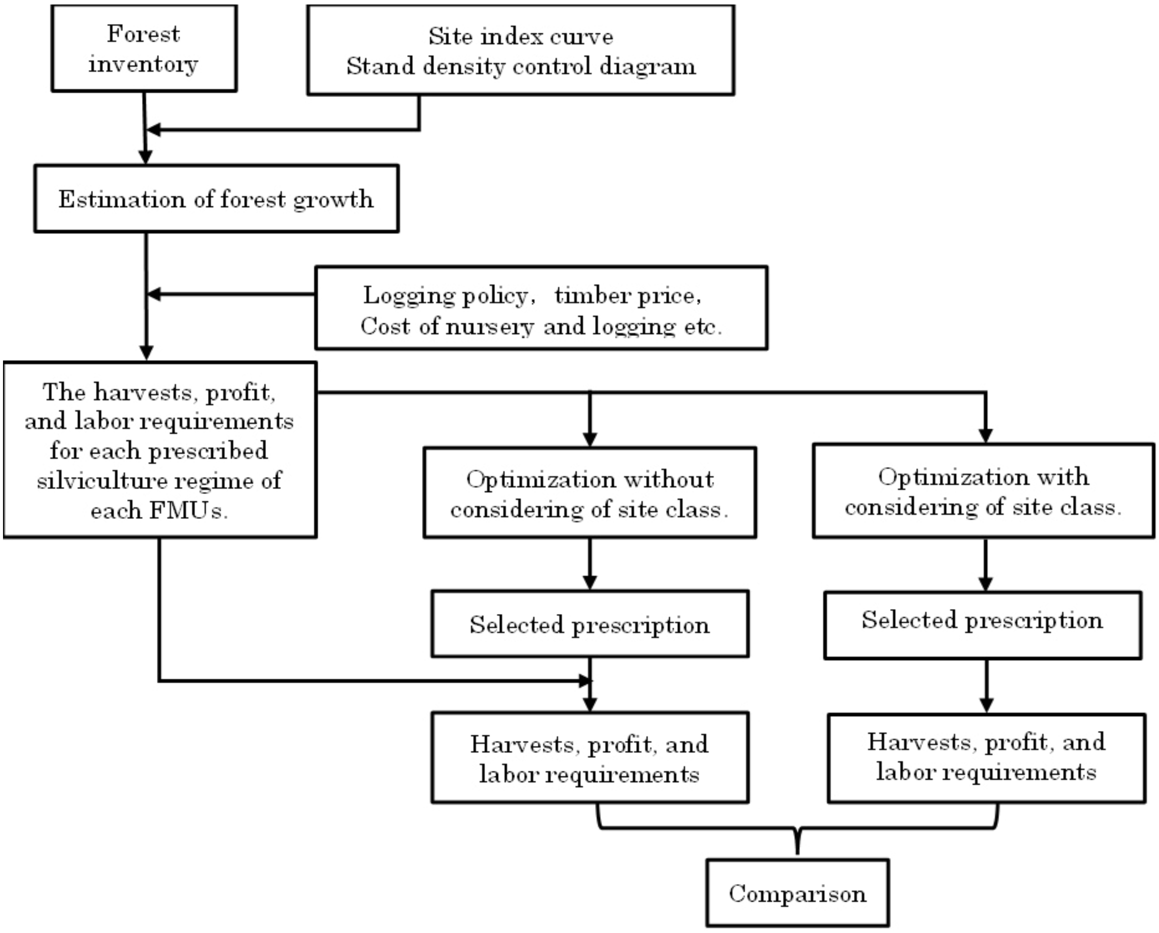

Figure 1. Overview of the methodology used in this study. FMU, forest management unit.

2.1. Methodology overview

Harvests, profits, and labor requirements for each prescribed silviculture regime (hereafter, prescription) in each forest management unit (FMU) were calculated. A silvicultural regime (prescription) is a set of timber thinnings, clearcuts, and final cuts applicable to an FMU and is named based on the final cut year. Prescriptions were created by optimizing total harvests with or without considering site classes, and were assigned to each FMU. The site classes varied between 1 and 5, and 1 represented the most optimal site class. In this process, one harvest schedule and 16 prescriptions (Table 1) were simulated for each FMU. Moreover, harvests, profits, and labor requirements during the planning horizon were calculated while considering the site classes. When site classes were not considered, a harvest schedule was created assuming that the site classes of all FMUs fell in the middle class, and the actual harvests, profits, and labor requirements were calculated based on this harvest schedule. Variable harvest time and volume were calculated for the harvest of each FMU. Finally, the harvests, profits, and labor requirements were compared for the two cases.

Table 1. Distance in metres to the nearest forest road for each prescription (rotation age) in the Atsumi District sugi plantation, Tsuruoka City, Yamagata Prefecture, Japan with the site class considered (a) and not considered (b)

a) Site class considered

Prescription	50 yr	55 yr	60 yr	65 yr	70 yr	75 yr	80 yr	85 yr
Average	-	-	61.7	100.8	37.0	90.6	64.1	40.6
Standard deviation	-	-	38.3	117.6	26.9	120.2	104.0	116.9
Prescription	**90 yr**	**95 yr**	**100 yr**	**105 yr**	**110 yr**	**115 yr**	**120 yr**	**No clear-cutting**
Average	43.8	287.9	108.2	117.9	60.5	62.4	84.4	116.9
Standard deviation	141.4	186.6	130.9	141.0	113.1	97.0	162.2	168.3

b) Site class not considered

Prescription	50 yr	55 yr	60 yr	65 yr	70 yr	75 yr	80 yr	85 yr
Average	-	-	78.1	91.7	-	166.5	23.9	27.8
Standard deviation	-	-	34.3	91.9	-	181.5	48.3	96.5
Prescription	**90 yr**	**95 yr**	**100 yr**	**105 yr**	**110 yr**	**115 yr**	**120 yr**	**No clear-cutting**
Average	52.2	132.8	66.4	40.7	44.2	61.6	60.3	231.1
Standard deviation	154.2	152.5	70.1	55.1	106.9	81.2	123.6	179.3

The middle class was applied because of a lack of information on site index classes. To avoid this limitation, the Japanese government must organize forest inventory data by assuming an average status for all forests. As noted above, site class 4 was the most frequently occurring class within the study area. Accordingly, we designated site class 4 as representative of the middle class in our analysis.

2.2. Study site

The study site was a privately owned sugi (*Cryptomeria japonica* D. Don) planted forest managed by the Atsumi Forest Owners' Cooperative in the former Atsumi District, Tsuruoka City, Yamagata Prefecture, Japan. The former Atsumi district is located on the Japan Sea side of Yamagata Prefecture, bordering Niigata Prefecture. In 2008, it merged with surrounding areas to become a part of the city. The Atsumi Forest Owners' Cooperative has focused on establishing a low-cost logging system since 2012. It currently produces approximately 21,000 m3 of timber per year by conducting commercial thinning through the aggregation of stands using a high-density road network and high-performance forestry machinery. The cooperative reduces the number of log types to be bucked, ensuring a steady supply of large timber volumes at low prices. All B-grade logs were utilized at the short-lamina sawmill of the cooperative, whereas root bends and treetops were sold as biomass materials to a woody biomass power plant in Tsuruoka City.

2.3. Data analyses

Specific analyses were performed based on the data from the study site (Supplementary material, Appendix A). The detailed forest inventory and stand information used in this study are provided in Suppl. Table S1. Additional information on operations performed, simulation parameters, harvest scheduling results, labor requirements, profit calculations, and spatial analyses are summarized in Suppl. Tables S2–S8. As reported by Nakajima et al. (2017), small-area operations of less than 1 ha are disadvantageous in terms of profitability. This issue was addressed by applying the methodology of Suzuki et al. (2018) to establish an FMU that integrated multiple small groups.

A case that considered the site class was established. First, the FMU site class was calculated based on each sub-compartment listed in the forest inventory. The FMU site class was used to select the optimal combination of prescriptions leading to the highest-yielding schedule. However, when site class was not considered, the harvest schedule was optimized by setting the site classes of all target FMUs to class 4, which represented the majority among the site classes in the target area, and then a prescription was assigned to each FMU. Thus, this modeling approach did not completely exclude the site index class. All prescriptions essentially consisted of thinning operations, as shown in Suppl. Table S2.

Specifically, the age class, harvests, labor requirements, and profits for each FMU-assigned site class were considered real values and were combined with the selected prescription without considering the site class. Subsequently, the transition period for the entire forecast period was calculated. The transition period refers to the initial phase in harvest planning for even-aged plantations with a bell-shaped age-class distribution, during which harvest volumes and labor requirements tend to increase sharply. Until this period passes, these variables remain unstable, making it challenging to satisfy the optimization constraints described later in the study. Therefore, the constraints were temporarily relaxed during this phase to account for such variability. The fluctuations in age class, harvests, labor requirements, and profits for each FMU-assigned site class were calculated for the entire forecast period. The same calculations were conducted for the selected forestry systems when considering the site class. Predictions for age-class distribution, harvests, labor requirements, and profits were generated for the entire forecast period and compared for the two selected prescriptions, with and without the site class. The selected FMUs were the same for both scenarios.

Although the target site was a privately owned C. japonica forest, specific stands were excluded (Suzuki et al., 2018). Forests designated for landslide protection and erosion control were excluded to preserve functions of public interest. Site classes 1 and 2 were excluded because the covered area was negligible. Stands with a forest age ≥ 150 years were excluded because of the difficulties in predicting growth. The exclusion of these stands resulted in a total forest area of 6,445 ha.

As small-area operations are disadvantageous from a profitability standpoint, the ESRI ArcGIS software was employed to integrate the sub-compartments. Next, square tile polygons with an area of 8 ha were overlaid on the entire target forest, and each sub-compartment, with its center of gravity within the same tile polygon, was integrated. Sub-compartments smaller than 3 ha after integration were excluded, resulting in a total area of 5,169 ha for the analyzed target FMUs.

A 10 m slope angle layer was created, and FMUs with an average slope of more than 30° were excluded because of the difficulties in performing work on steep slopes using a vehicle-based system. Although international literature often cites a slope of 12° as the operational limit for mechanized forestry, this standard does not necessarily apply to Japan, where steep terrain is common. In this study, we assumed a slope threshold of 30° based on field interviews and practical considerations in domestic forestry operations. Even on such steep slopes, it is feasible to conduct forestry work by constructing forest roads with appropriate cut-and-fill techniques. The final total area of the FMUs was 3,643 ha, and the age-class composition was unimodal (Fig. 2).

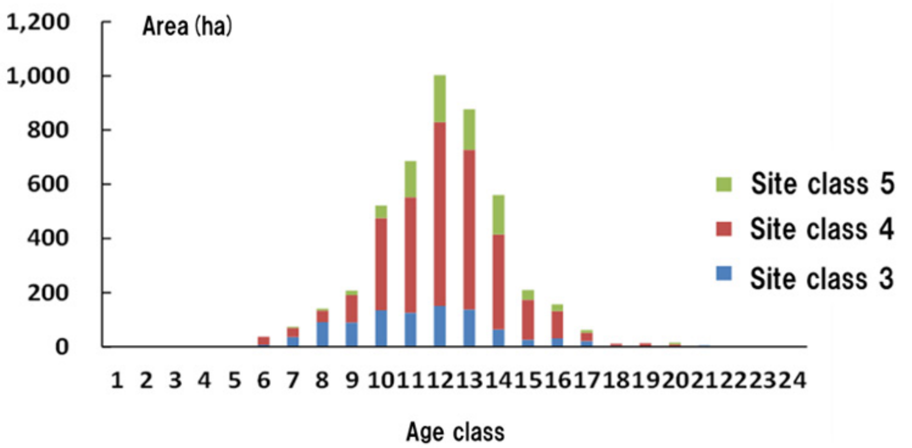

Figure 2. Initial age-class distribution of forest management units (FMUs) in the study area in Tsuruoka City, Yamagata Prefecture, Japan.

A single FMU contained multiple sub-compartments of different forest ages. Thus, the area-weighted average forest age of each sub-compartment was used as the average forest age for that FMU. If a young sub-compartment that had not reached the rotation age was included, the age of the youngest sub-compartment was determined, and the average age of the FMU when that sub-compartment reached 50 years was used as the base age (Suzuki et al., 2018). As logging is not permitted until an average FMU touches its base age, in this study, logging was not allowed until all the sub-compartments of FMUs were more than 50 years old. According to the United Nations (UN) Report for Global Forest Resources Assessment (1997), the rotational age is the planned number of years between the establishment or regeneration of a tree crop or stand and its final cutting at a specified stage of maturity (UN, 1997).

Final cutting can only be performed for stand age ≥ 50 years. The FMUs that reached the rotation age were treated uniformly based on the average forest age. However, when the FMU subjected to final cutting contained sub-compartments with a stand age of <50 years, the calculations in this study were performed assuming that such sub-compartments were not harvested until they reached a stand age of 50 years. The strategies for obtaining the attribute information and spatial distribution of the FMU site classes are presented in Table 1 and Fig. 3, respectively.

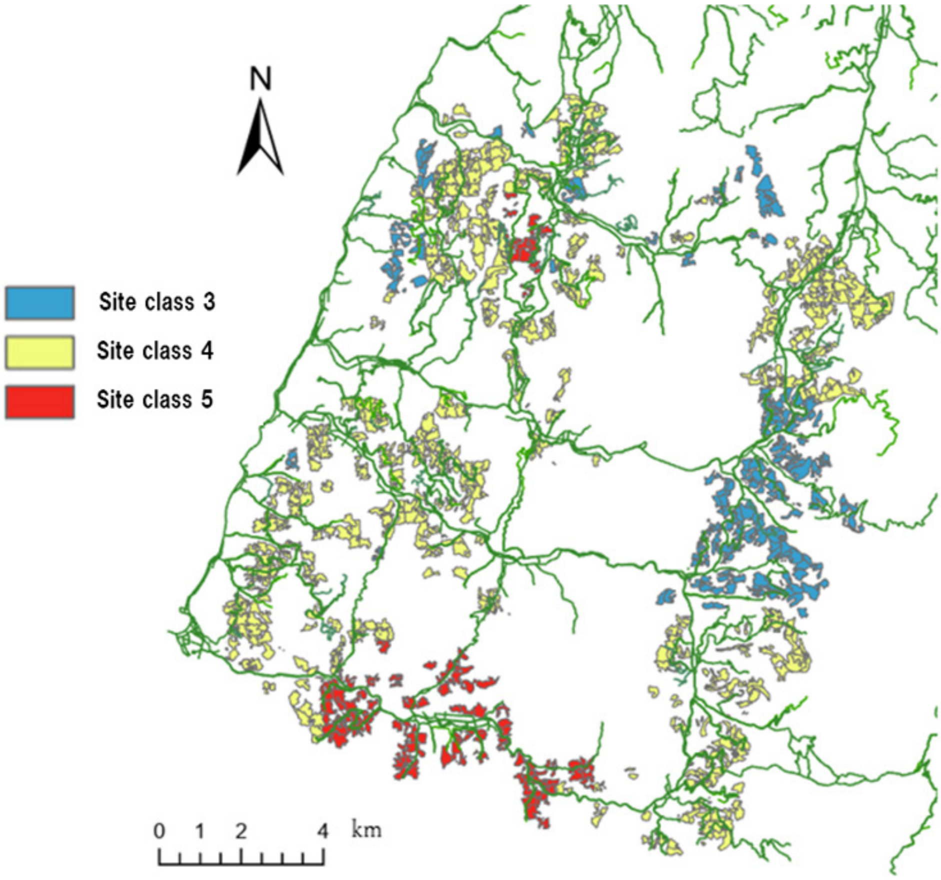

Figure 3. Spatial distribution of the forest management unit (FMU) site classes. The FMUs are the forestry fields that will be target areas for activities, including thinning, clear-cutting, and replanting during the planning horizon (Suzuki et al., 2018).

The prescriptions in this study correspond to the rotation age. A total of 16 prescriptions were established. Prescriptions 1 to 15 were established at 5-year intervals from 50- to 120-year rotation age (45 + 15 × 5 = 120), and prescription 16 did not include harvesting. However, an FMU adopts a prescription only if its profits are positive. Hence, the total number of simulations was 16 possible prescriptions that were profitable.

Profits were calculated based on age class using the single-stand simulation method with the inclusion of the FMU attribute information. Labor requirements for silvicultural practices, final cutting, and thinning were calculated for each age class. The harvests for final cutting and thinning were determined for each age class. As shown in the Appendix, thinning costs varied depending on the tree size and volume harvested.

For each prescription, age-class transition figures were developed to show how the age class would shift during the planning period if each FMU adopted that prescription (Suzuki et al., 2018). However, if an FMU could not adopt a prescription owing to the limitations of standard forest age, the age class would shift in the same manner as if no final cutting occurred. Based on this age-class transition table, the profit, labor requirements, and harvest values were determined for each FMU based on the prescription and planning periods.

A harvest schedule was created using mixed-integer programming as an optimization problem with IBM ILOG CPLEX Optimization Studio ver12.5.1. In CPLEX, the branch-and-bound method was used. In the case of objective function maximization, the linear relaxation problem of mixed integer programming was used as an upper bound for the optimal solution, and the search for a solution was terminated when the gap with the lower bound became zero. In this case, the gap was set to 0.3% to obtain the solution. The values obtained for each FMU based on the prescription and planning periods were used as inputs for CPLEX to solve the optimization problem. Profits were calculated using approximate numbers up to the thousandth place to simplify the calculations. An objective function was used to maximize the total harvest volume to solve the optimization problem as follows:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} V_{i,j,t} x_{i,j}$$

The stability of labor requirements (employment) and harvests is considered a requirement for stable forestry operations. However, with the current unimodal age structure, the timber volume near the peak of the age structure increased significantly in the first half of the planning horizon. It was postulated that certain labor requirements would be insufficient to cope with this increase. In this study, the planning horizon was determined to be 120 years, the same as the maximum rotation age based on previous research (Suzuki et al., 2018). Consequently, many forests were not expected to be harvested by the maximum rotation age (120 years) and were left unattended. Therefore, in this study, the unimodal age-class structure was addressed by allowing some variation in the first half of the plan and focusing on high stability in the second half.

The planning horizon was divided into the first 10 planning periods (transition periods) and the second 14 planning periods (stable periods). Each transition period was 50 years (Suzuki et al., 2018). Considering that the age-class distribution of planted forests in Japan differs markedly from that of normal forests (Fig. 4), the 50-year transition period shifted the current age-class distribution closer to that of normal forests. Additionally, the limitations of stabilized timber production were overcome during this period. The upper bound of the fluctuation during the transition periods was set at +30% of the level, while the fluctuation tolerance during the stable period was set at ±10%. This level is the standard for maintaining the value of each planning period within a certain fluctuation tolerance. For labor requirements, the level was set at 27,000 person-days per planning period, based on the assumption that the current workforce of the Atsumi Forest Owners' Cooperative is nearly 14 people. The workforce would be 14,000 person-days per planning period (5 years), assuming 200 operating days annually. However, securing more than twice the amount of work would be challenging. The values for each parameter are presented in Table 2.

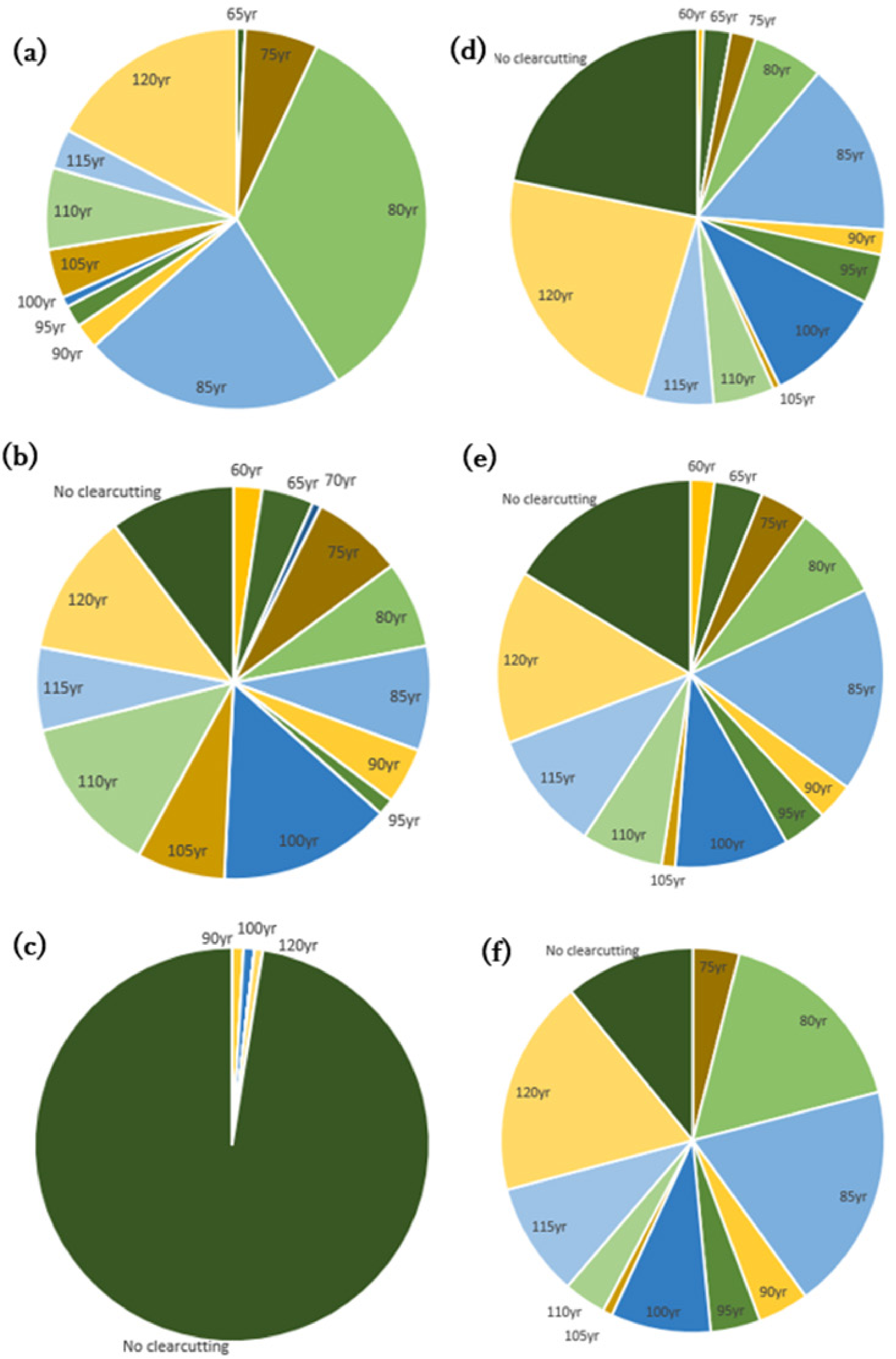

Figure 4. Area percentages of selected prescriptions. (a–c) Site classes considered. (d–f) site classes not considered. (a and d) site class 3 considered and not considered, respectively. (b and e) site class 4 considered and not considered, respectively. and (c and f) site class 5 considered and not considered, respectively. The “no clear-cutting” prescription did not involve clear-cutting. however, thinning was performed in the same manner as in other prescriptions (Suzuki et al., 2018).

Table 2. Attribute information used to define forest management units (FMUs) in the study area in Tsuruoka City, Yamagata Prefecture, Japan

Attribute	Method of acquisition
Area	Obtained from GIS
Site class	Area-weighted average of sub-compartments
Average age	Area-weighted average of sub-compartments
Base age	Average age when the smallest age of the sub-compartments it belongs to is 50.
Distance to road	Obtained from GIS
Average gathering distance	Obtained from GIS
Average slope angle	Obtained from GIS

GIS, Geographical Information System

Additional supplementary tables provide detailed information on the simulation inputs and results.

Specifically, Supplementary Tables S3–S8 summarize the parameters used in the simulation, the results of harvest scheduling, labor requirements, profit calculations, and additional scenario analyses.

The following equations define the labor and harvest constrains applied during the transition: Transitional labor requirements constraints

$$\sum_{i=1}^{I}\sum_{j=1}^{J} L_{i,j,t}x_{i,j} \leq (1+r_{trans})LStandard \qquad \forall t \in \{1,\cdots,t_s\}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} L_{i,j,t}x_{i,j} \geq LStart \qquad \forall t \in \{1,\cdots,t_s\}$$

Transitional harvest volume constraints:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} V_{i,j,t}x_{i,j} \leq (1+r_{trans})VStandard \qquad \forall t \in \{1,\cdots,t_s\}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} V_{i,j,t}x_{i,j} \geq VStart \qquad \forall t \in \{1,\cdots,t_s\}$$

Stable labor requirement constraints:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} L_{i,j,t}x_{i,j} \leq (1+r_{stable})LStandard \qquad \forall t \in \{t_s,\cdots,T\}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} L_{i,j,t}x_{i,j} \geq (1-r_{stable})LStandard \qquad \forall t \in \{t_s,\cdots,T\}$$

Stable harvest volume constraints:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} V_{i,j,t}x_{i,j} \leq (1+r_{stable})VStandard \qquad \forall t \in \{t_s,\cdots,T\}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} V_{i,j,t}x_{i,j} \geq (1-r_{stable})VStandard \qquad \forall t \in \{t_s,\cdots,T\}$$

Uniqueness of the prescription:

Each FMU must always select a prescription:

$$\sum_{j=1}^{J} x_{i,j} = 1 \qquad \forall i$$

Adoptable prescriptions:

$$y_{i,j} \geq x_{i,j} \qquad \forall i,j$$

Binary variable conditions. The decision variable takes 0 or 1:

$$x_{i,j}, y_{i,j} \in \{0,1\} \qquad \forall i,j$$

Where *LStandard* and *VStandard* represent the sustainable labor requirement and sustainable harvest levels, respectively, *LStart* and *VStart* represent the labor requirements and harvests, respectively, at the beginning of the planning period. Moreover, *VStandard* was calculated automatically during the optimization process while satisfying the other constraints (Suzuki et al., 2018). i: FMU number; I: Total number of FMUs; j: Prescription number; J: Total number of prescriptions; t: Planning period; T: Total number of planning periods; $P_{i,j,t}$: Profit in planning period t when FMU i adopts prescription j; $L_{i,j,t}$: Labour requirement in planning period t when FMU i adopts prescription j; $V_{i,j,t}$: Harvest volume during planning period t when FMU i adopts prescription j; $x_{i,j}$: 1 if FMU i adopts prescription j, and 0 otherwise; $y_{i,j}$: 1 if FMU i can adopt prescription j, and 0 otherwise; r_{trans}: tolerance rate during the transition period; and r_{stable}: tolerance rate during the stable period.

3. RESULTS

In cases where the site class was or was not considered, 50 years (Prescription 1) and 55 years (Prescription 2) were not selected (Fig. 4). The area of FMUs subjected to harvest was 2,919.88 and 3,032.24 ha in the scenarios that considered and did not consider site class, respectively (number of FMUs: 534 and 557, respectively), whereas the overlapping area of FMUs in both scenarios was 2,588.74 ha (number of FMUs: 478) (Fig. 4).

Approximately 63% of FMUs selected a rotation age of ≤ 85 years for site class 3. Among the specific prescriptions, the rotation ages of 80 years (prescription 7) and 85 years (prescription 8) were chosen by 34 and 22% of FMUs, respectively (Fig. 4a). A small number of FMUs also selected no clear-cutting (prescription 16). In site class 4, 31% of FMUs chose a rotation age of ≤85 years; however, overall selections varied widely, extending up to 120 years (Fig. 4b). Notably, 10% of FMUs opted against clear-cutting. For site class 5, 98% of selected FMUs did not opt for any clear-cutting (Fig. 4c), indicating a strong preference for continuous cover approaches in the relatively low-productivity sites. When the site classes were not considered, 22% of FMUs with site class 3 received no clear-cutting, whereas 24% were selected in 120 years (prescription 15) (Fig. 4d), a larger proportion than that of FMUs with site classes 4 and 5. In site class 5, 89% of the trees were clear-cut (Fig. 4f), indicating that a certain percentage of each prescription was selected for each site.

The total harvest over the planning horizon was 2,472,739 m^3 when the site class was not considered and 2,613,228 m^3 when the site class was considered, representing a 5.7% increase. The largest difference was in the sixth planning period, with a 28.9% increase of 29,099 m^3 when site class was considered. Conversely, during the 16th planning period, the volume decreased by 13.9% (16,307 m^3) (Fig. 5). Moreover, Fig. 5 shows that when the site index was not considered (Scenario 2), the upper volume constraint was exceeded in period 16, even with a 110,000 m^3 (VStart × 1.1) constraint. When the optimization stage was performed without considering the site index class, assuming that the site index class of all FMUs was four, the constraint was satisfied. The standard deviation was small across all seasons when site class was not considered and relatively smaller when site class was considered only for stable periods (Table 3).

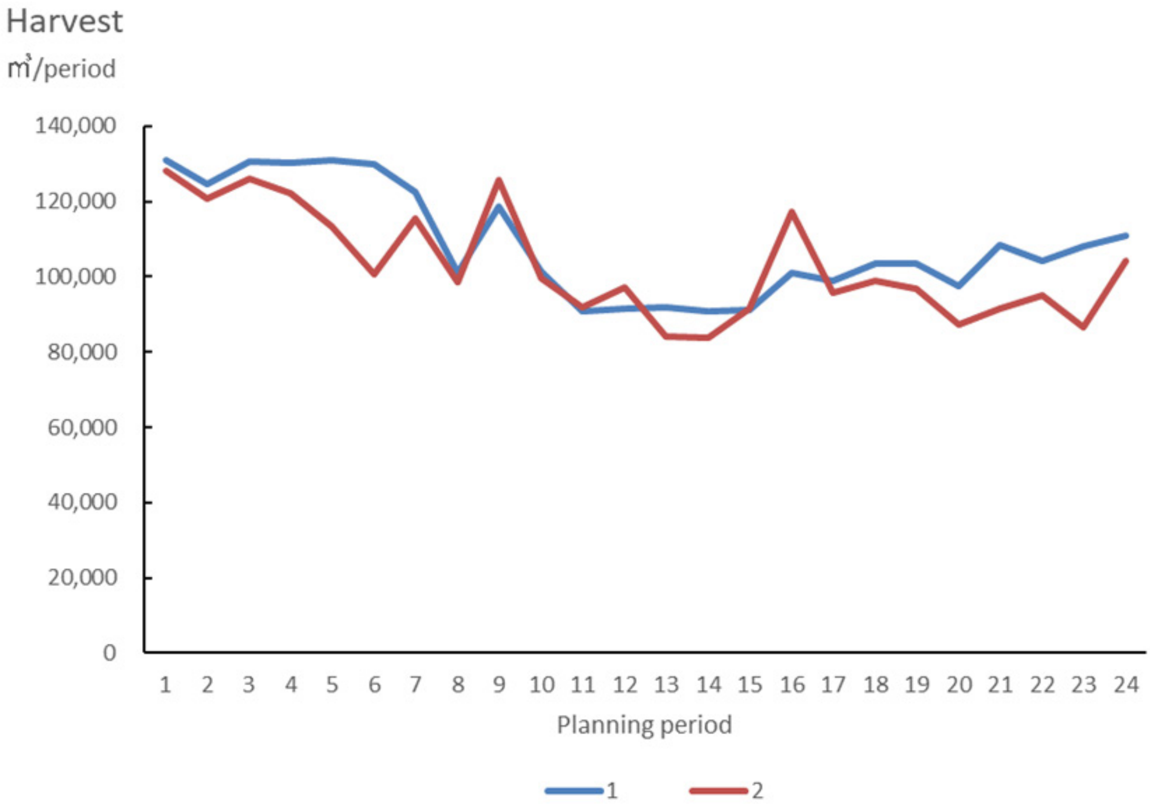

Figure 5. Changes in harvests in each planning period when site classes (1) were considered and (2) were not considered.

Table 3. Parameter values used in the mixed-integer programming model for harvest scheduling in the study area

Parameter	Value
LStart (person-days)	10,000
LStandard (person-days)	27,000
VStart (m^3)	100,000
I	657
J	16
T	24
rtrans	0.3
rstable	0.1

The total profit over the planning horizon was Japanese yen (JPY) 8,364 million when the site class was not considered and JPY 9,267 million when the site class was considered. The variability in profits during the planning horizon is summarized in Table 4. A mounting to an increase of 10.8%. The highest difference was in the sixth planning period, wherein the total profits increased by 55.3% (171 million yen) when site class was considered. Conversely, during the 16th planning period, it decreased by 20.5% (93 million JPY; Fig. 6).

Table 4. Standard deviation and total values of profit across planning periods under scenarios with and without site class information

	Standard deviation over the planning horizon	Standard deviation during the stable period[1]	Total harvest volume (m^3) [2]
Site class considered	14,346	7,040	2,613,228
Site class not considered	13,980	8,472	2,472,739

[1] After the 11th planning period.

[2] The duration of each planning horizon was 24 planning periods.

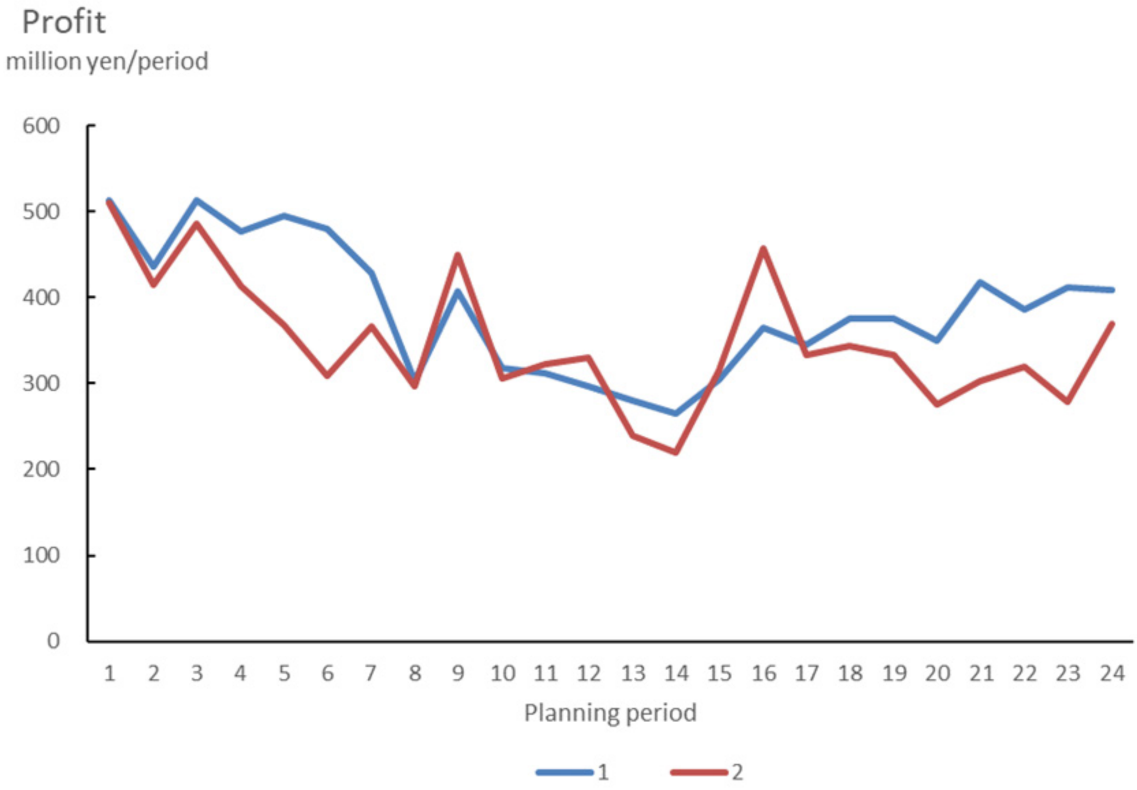

Figure 6. Changes in the profits for the planning periods when site classes (1) were considered and (2) were not considered.

As with the harvest, the standard deviation over the planning horizon was small when site class was not considered; however, it was relatively smaller during the stable period when site class was considered (Table 5). The total labor requirement over the planning horizon was 746,385 person-days when the site class was considered and 738,899 person-days when the site class was not considered, with a difference of approximately 1% (Fig. 7). The total harvests over the 24 planning horizons for A-, B-, and C-grade logs were 573,115 m^3 (21.9%), 1,282,388 m^3 (49.1%), and 757,381 m^3 (29.0%), respectively, when the site class was considered (Suppl. Fig. S1a), and 548,020 m^3 (22.1%), 1,168,061 m^3 (47.1%), and 761,708 m^3 (30.7%), respectively, when the site class was not considered (Suppl. Fig. S1b).

Table 5. Standard deviation and total harvest volume across planning periods under scenarios with and without site class information

	Standard deviation over the planning horizon	Standard deviation during the stable period[1]	Total profits (yen)
Site class considered	73,557,682	48,492,846	9,266,918,254
Site class not considered	72,844,747	55,436,727	8,364,039,125

[1] After the 11th planning period.

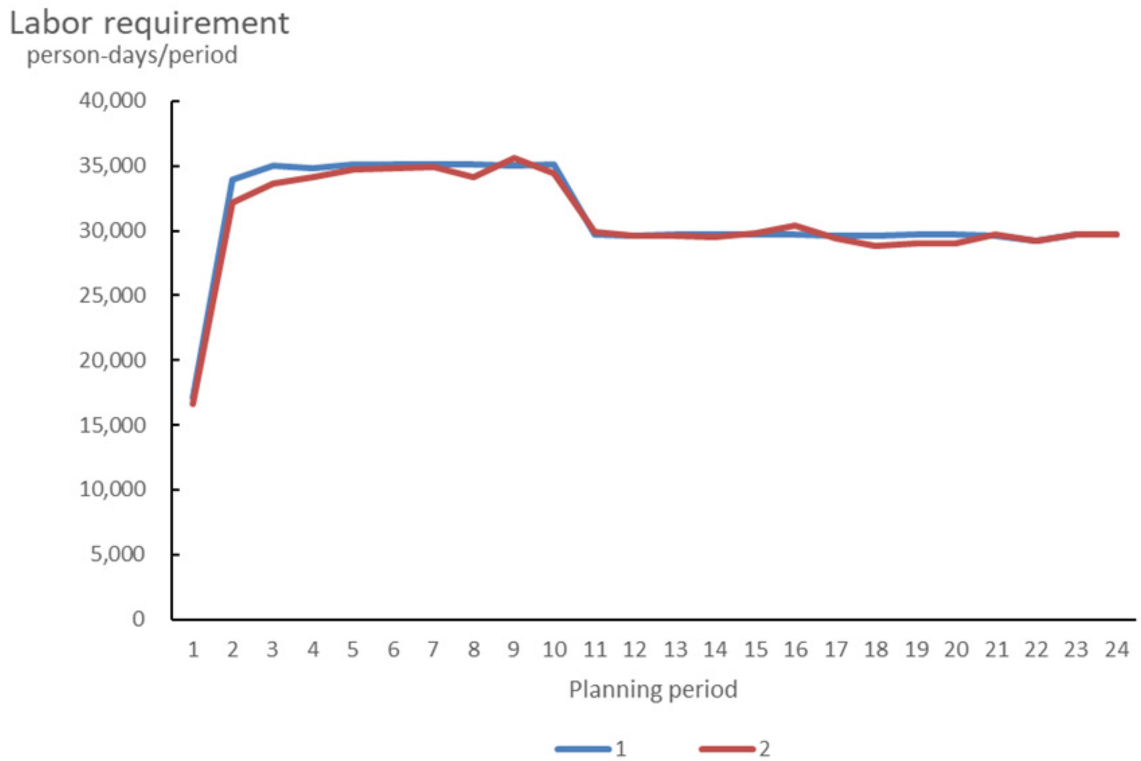

Figure 7. Changes in labor requirements for the planning periods when site classes (1) were considered and (2) were not considered.

The total harvests of A- and B-grade logs increased by 4.6% and 9.8%, respectively, owing to the addition of site class information. However, the total harvest of C-grade logs decreased by 0.6%. When the site class was considered, the labor requirements were 232,865 days (31.2%), 510,899 days (68.4%), and 2,621 days (0.4%) in the FMUs of site classes 3, 4, and 5, respectively (Suppl. Fig. S2a). When the site class was not considered, 152,015 person-days (20.6%), 495,185 person-days (67.0%), and 91,699 person-days (12.4%) were recorded in the FMU with site classes 3, 4, and 5, respectively (Supplementary material Fig. S2b). The addition of site class information increased the labor requirement applied to FMUs with site class 3 by 53.2% and site class 4 by 3.2%. However, it decreased the labor requirement for site class 5 by 97.1%.

Approximately 946,868 m^3 (36.2%), 1,660,281 m^3 (63.6%), and 6,079 m^3 (0.2%) of timber volumes were harvested from FMUs with site classes 3, 4, and 5, respectively, when site class was considered. Moreover, the harvest obtained from FMUs with site class 3 was particularly large in the 5th and 6th planning periods and 21st to 23rd planning periods (Suppl. Fig. S3a). When the site class was not considered, 641,212 m^3 (25.9%) was harvested from FMUs with site class 3; 1,608,352 m^3 (65.0%) from FMUs with site class 4; and 223,175 m^3 (9.0%) from FMUs with site class 5 (Supplementary material Fig. S3b).

Adding site class information also increased the harvest from FMUs with site class 3 by 47.7% and from FMUs with site class 4 by 3.2%. However, adding site class information decreased the harvest rate of FMUs with site class 5 by 97.3%. The total harvest across the site classes increased by 5.7%.

When considering site classes, FMUs with site classes 3, 4, and 5 earned profits of 3,766 million yen (40.6%), 5,488 million yen (59.2%), and 11 million yen (0.1%), respectively. (Suppl. Fig. S4a). When the site class was not considered, the FMUs with site classes 3, 4, and 5 earned profits of 2,634 million yen (31.5%), 5,305 million yen (63.4%), and 424 million yen (5.1%), respectively (Suppl. Fig. S4b). Adding site class information increases profits by 43.0% for FMUs with site class 3 and 3.4% for FMUs with site class 4. Moreover, the profit gained from the FMUs with site class 5 decreased by 97.2%. The total profit of the site classes increased by 10.8%.

The spatial distribution of harvests per hectare during each planning period with and without considering the site class revealed that the FMUs selected for timber harvesting differed depending on whether the site class was considered (Suppl. Fig S5). The spatial distribution of cumulative harvests was determined by summing the harvests per hectare from the first planning period to each planning period. The frequently harvested parts were visually assessed. In the latter half of the year, such as during the 24th planning period, areas with large harvests were concentrated when the site class was considered. Cumulative harvests were large and small in the eastern and southern regions, where site classes 3 and 5, respectively, were concentrated. However, when site class was not considered, FMUs with high and low cumulative harvests remained scattered. When site productivity was not considered, the stands selected for harvesting were not concentrated in areas with high-productivity clusters. On the contrary, the harvest stands were more randomly distributed across both high- and low-productivity areas when site productivity was ignored than in the scenario where site productivity was taken into consideration. As left shown in Suppl. Fig. S5(g), incorporating site productivity into the selection process led to a relatively more spatially dispersed pattern of harvest stands.

When the site class was considered, the cumulative harvest was lower in the southern region; correspondingly, no clear-cutting (prescription 16) was often selected in the same area (Suppl. Fig. S6a). However, when site class was not considered, the selected prescriptions were relatively scattered (Suppl, Fig. S6b).

The mean and standard deviation values of the distance to the road were calculated for each prescription (Table 1). Excluding the 75-year and 90-year prescriptions, the standard deviations were smaller when site class was not considered, and the impact of the distance to the road was larger. Furthermore, when the site class was not considered, the FMUs with prescriptions for no clear-cutting exhibited a larger average distance to the road than exhibited by those with prescriptions for clear-cutting, indicating that FMUs far from the road were often assigned no clear-cutting. Owing to the temporal and spatial selection of prescriptions, the age-class distribution of the entire study area changed.

When considering the site classes (Suppl. Fig. S7), the FMUs with better site classes 3 and 4 were selectively subjected to final cutting and were then reforested, whereas those with a poorer site class 5 were left unharvested. In the 20th and 24th planning periods, the second final cutting was primarily conducted on FMUs with site class 3, whereas more than half of the FMUs belonging to the 1st to 3rd age classes in the 24th planning period belonged to site class 3 (Suppl, Fig. S7f). If the site class was not considered (Suppl. Fig. S8), no such selection occurred, and FMUs with site class 3 were mixed with FMUs that were left unharvested. Conversely, the FMUs in site class 5 were repeatedly cut and reforested during each planning period.

4. DISCUSSION

When site class was considered, all FMUs with better site class 3 were assigned to the final cutting, whereas 98% of the FMUs with poor site class 5 were assigned to no final cutting, indicating that site class information significantly impacted prescription selection. The optimization formula presented in the “Material and methods” section and the software used to apply this formula allowed us to make these observations on the results for the final cutting concentrated around site class 3. However, when site class was not considered, a prescription was selected based on limited information, such as the distance to the road. From a spatial perspective, adding site class information helps concentrate on forest operations in areas with improved site classes. This selection and concentration resulted in a 5.7% increase in the harvest with the same labor requirements. Moreover, the harvests of A- and B-grade logs increased by 4.6% and 9.8%, respectively, while profits increased by 10.8%. This resulted from concentrating on the limited labor needs of FMUs with poorer site classes and those with better site classes, resulting in increased growth and the ability to utilize wood at higher prices.

Although optimization did not affect timber grade, interview surveys indicated that prioritizing the clearing of areas with good site quality led to larger tree sizes, resulting in a generally greater quantity of grade A and B timber. Therefore, the relatively high quality of A- and B-grade logs, considering their accurate site index classes, may not only be a byproduct but rather reflect across all landscapes.

Furthermore, changes in age distribution revealed that FMUs with better site classes tended to undergo final cutting within a relatively short period, whereas those with poorer site classes were not subjected to final cutting and were not reforested. Japan's population is continuously declining and is predicted to reach approximately 87 million by 2070 (Statistics Bureau, Ministry of Internal Affairs and Communications Japan, 2023), whereas the current workforce is relatively restricted. These findings indicate that site class information is required for efficient and sustainable forest management.

Furthermore, when the site class was considered, fluctuations in harvests and profits during the planning period became smaller and more stable than when the site class was not considered. Specifically, elucidating the site class enables relatively accurate predictions of harvests and profits from each FMU, thereby minimizing fluctuations in actual harvests and profits during the planning period. Furthermore, harvesting forests with poor site classes may lead to a small decline in timber prices, resulting in untenable income and expenses. Knowing site class information can help avoid harvesting forests that may become unprofitable; hence, incorporating site class information improves stability. Site class exerts a significant impact on cutting age, harvest, and profit (Nakajima et al., 2017; Paudel & Dwivedi, 2021). However, no studies have reported how the presence or absence of site-class information impacts long-term forest plans at the local level. In this study, we quantitatively demonstrate the positive impact of advanced site-class information on forest management plans.

The complex and steep topography of Japan's forests, compared with those in other countries (Laamrani et al., 2015; Ørka et al., 2018; González-Rodríguez et al., 2020), results in relatively large fluctuations in growth owing to differences in site classes. In Japan's forests, if prescriptions are selected for each FMU without considering their site class, a marked difference in growth arises between FMUs within the same region, potentially reducing harvests and profits in that region.

The method used in this study had several limitations. First, owing to the many sub-compartments in the study area, we created an FMU by merging adjacent sub-compartments to ensure profitability. Consequently, the FMU contained sub-compartments with varying site classes and forest ages, which were co-treated using an area-weighted average. This may have led to deviations from reality. Second, as the harvest was scheduled for a long term with a 120-year horizon, restrictions on labor requirements and fluctuations in various costs and material prices occurred over time. Thus, the optimal management plan may have changed because of these fluctuations. This can be addressed by setting several patterns for dynamic factors, such as timber prices, and optimizing each pattern. In this study, we assume that trees will be replanted after the final cut and do not consider abandoning reforestation. Considering the current situation, wherein the reforestation rate in Japan remains low, including prescriptions that do not involve reforestation after the final cutting could lead to a plan that is relatively more aligned with reality.

Third, the site class information used in this study was obtained from a forest inventory, which is less accurate than data estimated using LiDAR (Watt et al., 2015). As the available forest inventory groups indicate that FMUs with the same site classes are grouped together, which may not reflect accurate microtopography, it is expected that a relatively more appropriate prescription will be determined when site classes are assessed using LiDAR data. The present study and that of Suzuki et al. (2018) share a similar methodological foundation, including the use of basic GIS data, forest inventory information, and predictive models designed to optimize management decisions based on specific objective functions. However, a key distinction lies in the treatment of site class information. In this study, a scenario was constructed wherein site class data were intentionally excluded from the input variables. This approach enabled an examination of how forest management decisions may proceed in areas lacking reliable site class data. The results demonstrated the potential of incorporating remote sensing technologies, such as airborne LiDAR, to accurately estimate topography and tree height, thereby allowing site class information to be inferred or corrected where it is absent or uncertain. Therefore, although the input data, models, and optimization techniques used in the present study are largely aligned with those of Suzuki et al. (2018), the assumptions regarding data availability and the derived implications differ. The present study thus offers distinct insights into the role of data quality in forest planning while highlighting the value of improving input accuracy through advanced remote sensing technologies. Finally, although, we focused on timber production and estimated the optimal conditions required to maximize harvesting volume under labor constraints, forests also serve many other functions. The development of a management plan that incorporates these factors is a direction for future research.

5. CONCLUSIONS

In this study, we evaluated land productivity using forest data, optimized prescriptions at the landscape scale with/ without considering their site classes, and then compared the resulting prescriptions, harvests, and profits in both scenarios. We provide quantitative evidence indicating that incorporating site class information facilitates the selection of more suitable prescriptions and intensifies operations in FMUs with superior site classes. This increased the harvest yield, profits, and overall stability.

Globally, remote sensing technologies, such as LiDAR, are increasingly used for comprehensive forest inventories on scales surpassing watershed dimensions. Forest management endeavors are frequently funded through public channels such as local governmental subsidies, with Japan exhibiting a notably higher subsidy ratio than other nations. Our study highlights the potential of augmenting harvest yields and profits by effectively leveraging site-class information. Moreover, integrating site class data enhances forecast accuracy, potentially mitigating discrepancies between the planning and implementation phases while averting stagnation in forest management practices.

Furthermore, the harvest schedule delineated in this study holds promise for enhancing the practicability of executing forest management plans, offering temporal and spatial specificity crucial for ongoing municipal forest management plan preparation at the local level.

Supplementary information ↑

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Supplementary material

(Appendix A, Tables S1–S8 and Figures S1-S8) accompanies this paper on the *Forest Systems* website.

Data availability

Data will be available on request from the corresponding author.

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Authorship contribution statement

Tohru Nakajima: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Kazuma Mukai: Data curation, Formal analysis, Validation, Visualization.

Hayato Kamei: Writing – review & editing.

Satoshi Tatsuhara: Conceptualization, Writing – review & editing.

Competing interests

The authors have declared that no competing interests exist.

Statement on the use of Artificial Intelligence

The authors used ChatGPT (OpenAI, GPT-5, 2026) for language editing and for translating the title, abstract and keywords into Spanish. The authors reviewed and edited the output and take full responsibility for the final content of the manuscript.

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