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Predicting *Tectona grandis* Suitability to Evaluate Potential Plantation Areas under Future Climate on Java, Indonesia

Eko PRASETYO[1,2], Fajar SETIAWAN[3], WIDIYATNO[4], Mohammad NA'IEM[4], Haruka OHASHI[5], Yoshihiko TSUMURA[6], Ikutaro TSUYAMA[7] and Tetsuya MATSUI[6,8]*

[1] Vocational College, Universitas Gadjah Mada, Sekip Unit II, Yogyakarta, Indonesia
[2] Graduate School of Life and Environmental Sciences, University of Tsukuba, Tsukuba, Japan
[3] Research Center for Limnology and Water Resources, National Research and Innovation Agency (BRIN), Bogor, Indonesia
[4] Faculty of Forestry, Universitas Gadjah Mada, Bulaksumur, Yogyakarta, Indonesia
[5] Department of Wildlife Biology, Forestry and Forest Products Research Institute, Forest Research and Management Organization, Tsukuba, Japan
[6] Faculty of Life and Environmental Sciences, University of Tsukuba, Tsukuba, Japan
[7] Hokkaido Research Center, Forestry and Forest Product Research Institute, Forest Research and Management Organization, Sapporo, Japan
[8] Center for Biodiversity and Climate Change, Forestry and Forest Products Research Institute, Forest Research and Management Organization, Tsukuba, Japan

Abstract

Indonesia, mainly Java, is home to the second largest area of *Tectona grandis* (teak) plantations globally; however, despite their importance, little is known about the impact of climate change on this tree species. Here, species distribution models were developed using estimated site index values of *T. grandis* on Java as the response variable, with seven bioclimatic variables and three soil characteristics as predictor variables. Three statistical approaches—generalized linear, general additive, and random forest models—were examined. Two global climate models with two representative concentration pathways (2.6 and 8.5) and time periods (the 2050s and 2070s) were also used to compare the effect of predicted future changes in the site index. Of the three models, random forest model showed the best fit, with precipitation as the important predictor of *T. grandis* growth followed by temperature. The model predicted that 12.6% of Java Island would experience an increase in climatic suitability, with northeast of Banten Province, northeast and northwest of Central Java Province, and northwest of East Java Province becoming the most suitable for *T. grandis* growth in both the 2050s and 2070s. These findings suggest that certain areas should be prioritized for the development of future *T. grandis* plantations on Java.

Discipline: Forestry
Additional key words: bioclimatic variables, climate change, random forest, site index, species distribution model

Introduction

Climate change represents a change in either mean climatic variables or variability of the climate system over several decades or longer (Adedeji et al. 2014). Presently, these changes are strongly correlated with increasing temperatures. For example, 2010-2019 represented the warmest decade globally since 1850 in terms of average surface temperature (National Academy of Science & The Royal Society 2020). In Indonesia, the effect of climate change has increased temperature by 0.06°C per year since 1950 (Indonesian Ministry of Environment and Forestry 2017). Meanwhile, annual rainfall has decreased by 2%-3% since 1990 (Avia 2019), and the number of days with rainfall has fallen (Siswanto et al. 2016).

Climate change is expected to lead to a reduction in the geographic range of plants, vertebrates, and insects (Warren et al. 2018). For instance, vascular plants are more greatly impacted by habitat loss than are animals

*Corresponding author: tematsui@affrc.go.jp
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(Ohashi et al. 2019). Moreover, climate change has a direct impact on plant growth (Austin 2002). For example, potential habitats of *Pinus merkusii* in Thailand and Cambodia were found to be vulnerable due to climate change (van Zonneveld et al. 2009). In India, 30% of natural teak (*Tectona grandis* Linn. F., Lamiaceae) habitats are vulnerable to future climatic scenarios (Gopalakrishnan et al. 2011). Likewise, *T. grandis* plantations in Bangladesh also face increasing future climate stress (Deb et al. 2017).

Tectona grandis is one of the important commercial tree species in Indonesia. Most *T. grandis* plantations in Indonesia are located on the island of Java, home to the second largest area of *T. grandis* plantations in the world after India (Midgley et al. 2015). *T. grandis* was naturalized in Indonesia approximately 600 years ago (Pandey & Brown 2000) and grew naturally in areas with annual rainfall ranging from 800 to 2,500 mm (Palanisamy et al. 2009). *T. grandis* is a deciduous tree. This species sheds its leaves during the dry season and grows new leaves in the early rainy season (Palanisamy et al. 2009). For the excellent quality of wood, *T. grandis* required a periodic dry period (< 40 mm precipitation per month) of 3-6 months (Palanisamy et al. 2009, Tanaka et al. 1998). Limestone areas are generally suitable for growing *T. grandis* because these areas have adequate soil drainage (Tanaka et al. 1998). The recent logging and export ban of *T. grandis* in Myanmar has provided an opportunity for other countries, such as Indonesia, to enter the global market (FAO 2015). *T. grandis* is a well-known high-quality tropical hardwood (Pandey & Brown 2000). Note that the wood from mature commercial *T. grandis* plantations in Indonesia is comparable with native *T. grandis* and fetches high prices (Kollert & Kleine 2017).

Commercial plantation management incorporating climate change adaptation and mitigation strategies has become an important challenge in recent years (Millar et al. 2007). The magnitude of response of plantation forests to climate change can be predicted using species distribution models (SDMs). These numerical tools combine observations of species occurrence with environmental conditions (Elith & Leathwick 2009). These tools are used not only for the development of conservation and mitigation strategies (Araujo 2009) but also for the planned management of future forest plantations (Deb et al. 2017). Thus, SDMs with different climate change scenarios could be used to understand the magnitude and direction of possible future responses to climate change (Millar et al. 2007).

Research into tree growth using SDMs, especially in commercial plantations, is extremely limited in Indonesia (Saputra & Lee 2021). Not surprisingly, the impacts of climate change on *T. grandis* plantations in Java remain unknown. However, such information is vital for maintaining the sustainability of wood production on *T. grandis* plantations in the future. In subtropical and tropical regions, the physiological processes required for plant growth include a favorable water balance and high temperatures (Seynave 2008). The seasonal response of *T. grandis* planted on Java is similar to that in their native habitat. Dry season rainfall before the growing season is correlated with radial growth (Jacoby 1989), and ring width during the dry season (June to November) is an important indicator of annual *T. grandis* growth on Java (D'Arrigo et al. 2006). Climate change may negatively impact global commercial forestry via decreases in yield due to rising temperatures and prolonged periods of drought (Brzostek et al. 2014). Regarding Indonesia, where *T. grandis* are planted over > 1 million ha (Midgley et al. 2015), climate change can probably affect the sustainability of teak plantations in Java. Thus, our hypotheses are as follows: i) the variable on precipitation explains the variation of *T. grandis* growth on Java more strongly compared with that on temperature, and ii) the suitable site of *T. grandis* growth is distributed in the high precipitation area. Based on this, the objectives of this study were to elucidate suitable environmental conditions for *T. grandis* growth on Java and project potentially suitable sites for *T. grandis* plantations under future climate in the region.

Materials and methods

1. Study site

This study was conducted on the island of Java, Indonesia. The island comprises six provinces: Jakarta, Banten, Yogyakarta, West Java, Central Java, and East Java (Fig. 1). Most *T. grandis* stands on Java are state-owned and located in lowland forests (Pandey & Brown 2000, Hardiwinoto et al. 2021).

Primary and secondary forests are not dominant types of land cover in Java, and most are located in mountainous regions (Fig. 1). Concurrently, East and West Java comprise huge areas of plantation forest, particularly on the border between the two but also in patches across West Java Province. Java has 3.3 million ha of paddy fields, representing approximately 25.7% of the entire island (Indonesian Statistic 2015). Based on a map from the Indonesian Ministry of Forestry (2012), most of these fields are located in lowland areas of northern Java, whereas dryland agriculture is located at higher altitudes.

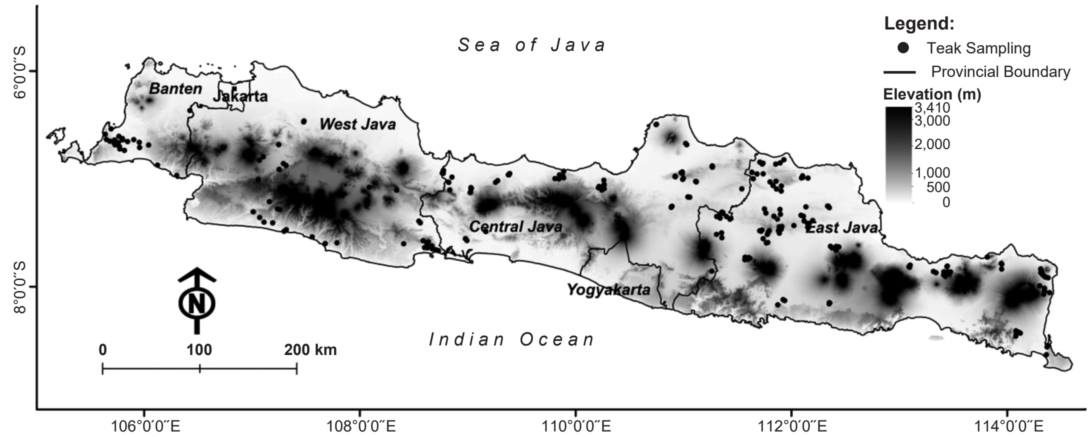


Fig. 1. Sampling sites and elevations on Java

2. Site index calculations

Figure 2 shows a flowchart of the study design. An initial field survey was carried out at 282 sites. At each site, the height from the base of the tree to the highest twig of each tree was measured using a Haga altimeter (Haga GmbH & Co. KG, Nuremberg, Germany) within a 100 m × 100 m area (i.e., 1.0 ha). Then, 100 highest trees evenly distributed at each site were selected, and the age of the plantation site was obtained from the forest managers. Both sets of data were used to calculate the site index (SI), which represents the dominant height at a specific age and is used to determine the

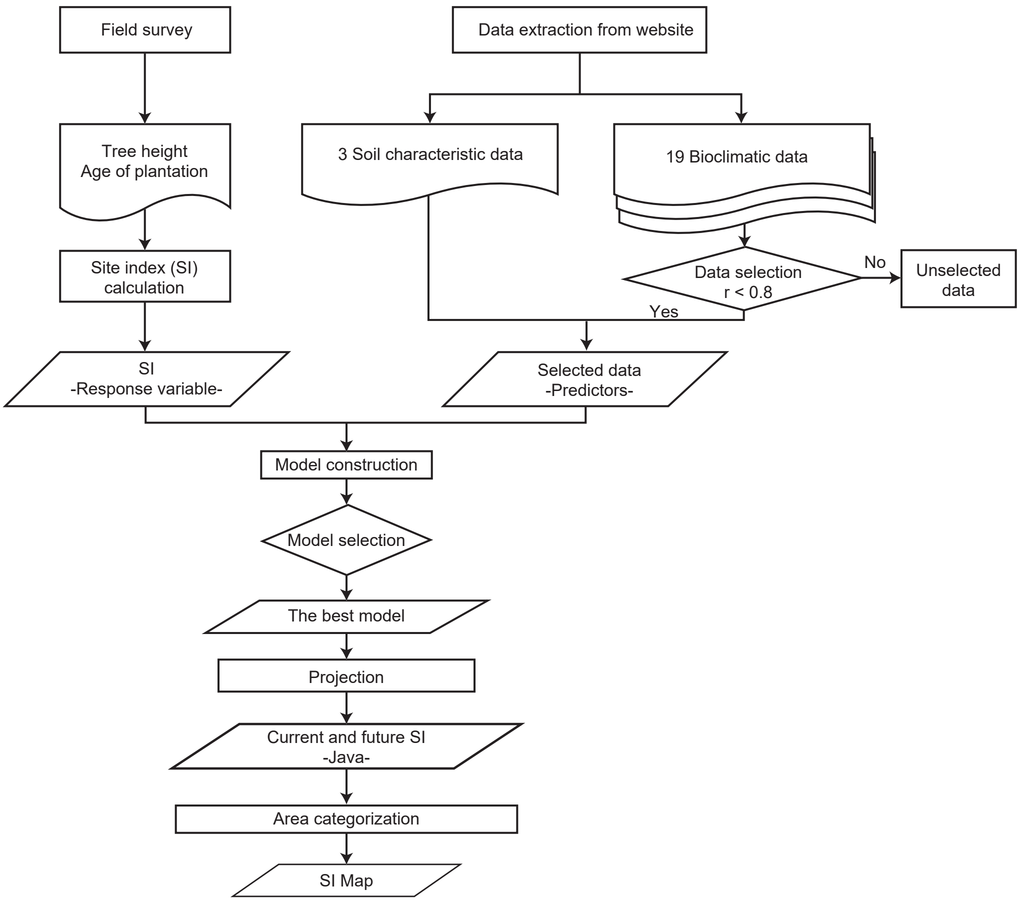
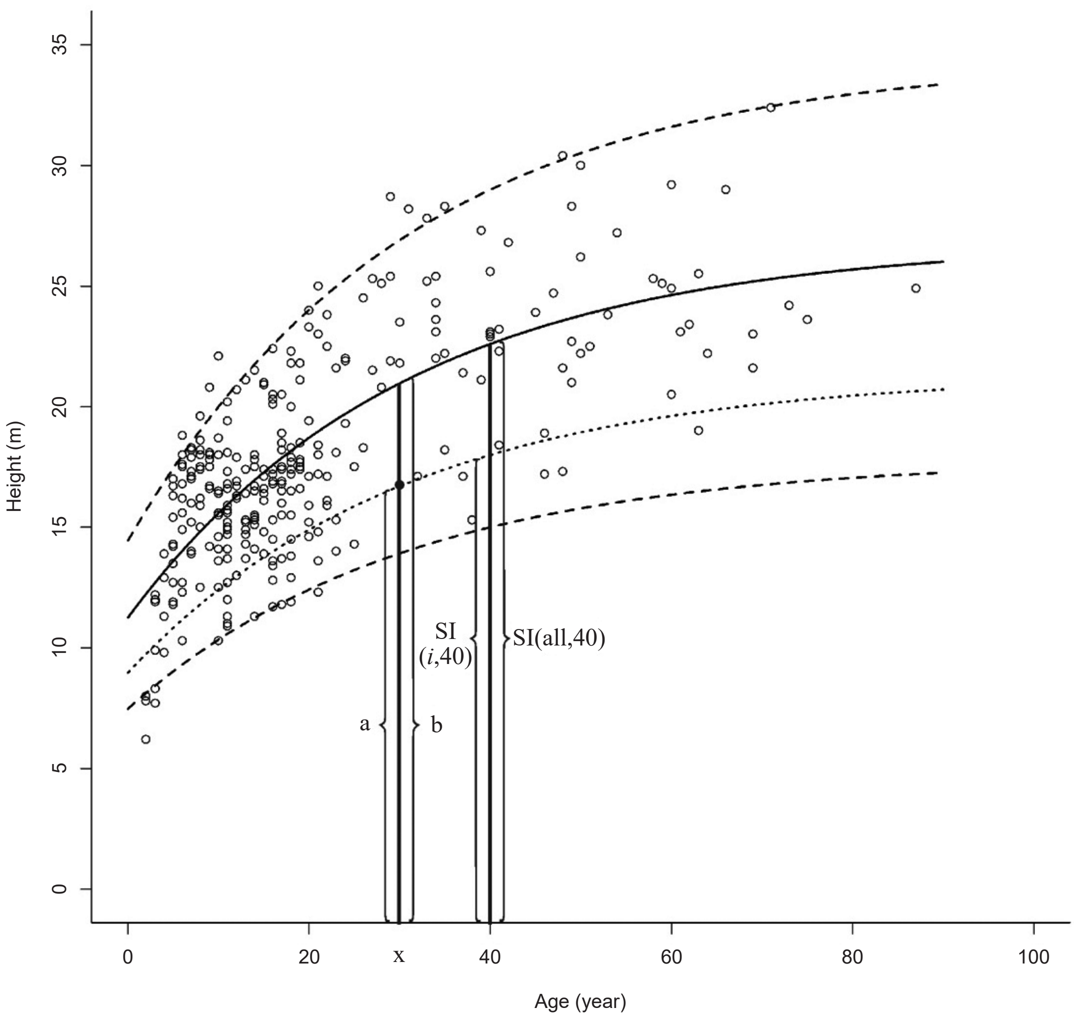


Fig. 2. Flowchart of the study design
r: Pearson's correlation

productivity of a site as a forest plantation (Clutter et al. 1983). Some of the highest trees in an area are used to measure SI because it is not influenced by variation in the stand or thinning (Krisnawati et al. 2010).

SI values were calculated using the Mitscherilich equation based on Leibig's law of the minimum (Harmsen 2000). This equation describes the response to an increase in the main factor that is limiting growth. In the present study, values were calculated on the basis of a reference age of 40 years because this is the shortest rotation period of *T. grandis* harvesting. Three steps were used to calculate the SI at each sampling location. First, the SI equation was calculated from 282 observation data points (Fig. 1) using the "nls2" (Grothendieck 2015) and "optimx" (Nash 2014) packages in R ver. 3.6.3 (R Core Team 2020). The first package was used to determine the nonlinear least-squares fitting of a nonlinear model, and the second package was used for optimization and to allow several tools to use the same front-end (Nash 2014). Second, the expected height in year "x" for site "*i*" (the original age; see Fig. 3) was calculated using the SI equation. Third, the SI of site *i* in year 40 was calculated by comparing the observation height and expected height at year x and multiplying by



——	= Modelled growth curve for *T. grandis* in Java (n=282 sites)
------	= Lowest and highest growth curve
……..	= Expected growth curve for site *i* (black circle)
a	= Observed tree height in site *i* (at age x)
b	= Expected tree height in site *i* (at age x)
SI (all,40)	= Expected tree height at age 40
SI (*i*,40)	= Predicted tree height at age 40 in site *i*
SI (*i*,40)	= a / b × SI (all,40)

Fig. 3. Site index (SI) regression lines and calculation methods at each site

the SI in year 40 (Fig. 3). In this way, SI values were calculated for all sample sites and used as the response variable for subsequent SDM analyses.

3. Predictors—climate and soil data

Nineteen bioclimatic datasets (Bio 1-19) in the study area from 1950 to 2000 were extracted from the WorldClim database (Hijmans et al. 2005) using the "point sampling" tool in open source QGIS 3.4.4 (QGIS Development Team 2019). Pearson's correlation was used to identify highly correlated bioclimatic variables. Correlation coefficients > 0.8 were categorized as strong correlations (Chan 2003), and under this condition, only one of the variables was chosen for model construction. The selected bioclimatic dataset was extracted at a spatial resolution of 1 km^2 in 145,802 grid cells throughout Java. In the present study, the effect of CO_2 concentration was not considered.

Soil characteristics were derived from SoilGrids250m (Hengl et al. 2017). Three variables—the type of soil, cation exchange capacity (CEC), and soil pH—were used as predictor variables. CEC and soil pH values were extracted from SoilGrids250m to a depth of 30 cm (ISRIC 2017). These soil predictors were selected on the basis of a literature search. For example, Wehr et al. (2017) reported that *T. grandis* is tolerant to low pH and Ca-poor soil in tropical Northern Australia. In the present study, we assumed that these soil characteristics would not change in the future.

Two global climate models (GCMs), namely, HadGEM2-ES (Jones et al. 2011) and CCSM4 (Gent et al. 2011), were used to create SDMs of future climate change. Both are plausible models for Southeast Asia (McSweeney et al. 2015). For each GCM, we analyzed climate change scenarios using representative concentration pathways (RCPs), which include a radiative forcing target level for the year 2100. These RCPs range from very low (RCP 2.6) to medium (RCP 4.5 and 6.0) and very high (RCP 8.5) emission scenarios (Moss et al. 2010). In the present study, the models were projected under two pathways: RCP 2.6 as a mitigation scenario and RCP 8.5 as a business-as-usual scenario because of the different climate mitigation strategies. RCP 8.5 scenario does not include any climate mitigation programs (Riahi et al. 2011). The model was also projected with time periods: the 2050s (the average for 2041-2060) and 2070s (the average for 2061-2080). Table 1 shows the summary of each scenario. Accordingly, a total of nine prediction maps were constructed, one current and eight future maps (two GCMs × two RCPs × two time periods).

4. SDM analysis—model construction and evaluation

The selected bioclimatic and soil variables were used as predictors in the models, with SI as a response variable. A generalized linear model (GLM), generalized additive model (GAM), and random forest model (RF) were constructed using R ver. 3.6.3 (R Core Team 2020). For GLM and GAM, the "MuMIn" package (Burnham & Anderson 2002) was used to select the predictors. All combinations of selected predictor variables were compared using the "degree" command. Then, the second order of the Akaike information criterion (AICc) value was applied to fit the best combination of predictors. The model with the lowest AICc in each GLM and GAM calculation was chosen. The RFs were constructed using all 10 predictors, with the default number of decision trees (500). The importance of the predictors in the RF model was calculated using the "importance" command. Model comparisons were

Table 1. Summary of climate change scenario on Java Island

GCM [a]	RCP [b]	Time period	Annual Temperature (°C)	Annual Precipitation (mm)
Current			24.8 (2.7)	2,547 (703)
HadGEM2-ES	2.6	2050s	26.4 (2.7)	2,114 (544)
CCSM4	2.6	2050s	25.9 (2.7)	2,521 (701)
HadGEM2-ES	8.5	2050s	27.3 (2.7)	2,262 (563)
CCSM4	8.5	2050s	26.7 (2.7)	2,661 (717)
HadGEM2-ES	2.6	2070s	26.4 (2.7)	2,031 (510)
CCSM4	2.6	2070s	25.8 (2.7)	2,675 (748)
HadGEM2-ES	8.5	2070s	28.4 (2.7)	2,091 (508)
CCSM4	8.5	2070s	27.4 (2.7)	2,778 (767)

[a] GCM: global climate model
[b] RCP: representative concentration pathway
( ): standard deviation

performed to select the best model by plotting the observed SI and predicted SI of each model. In the present study, only the best model was selected for further analyses as well as used to map the current and future SI for Java.

5. Mapping of current and future SI values

Potential SI maps of *T. grandis* under current climatic conditions and predicted conditions in the 2050s and 2070s were projected using the best fit model. The projected SI maps were compared by calculating the gains and losses in SI for each grid square. Gains were defined as an increase in SI under future climate change, whereas losses were defined as a decrease. In this study, "steady" was defined as no change in SI value beyond a range of 0.2 m (i.e., $-0.1 < SI < 0.1$ m). The results were categorized into five types: high increase, low increase, steady, low decrease, and high decrease (Table 2). Lastly, the final map was resulted to show the "certain increase," "uncertain," and "certain decrease." High increase in all scenarios defines as a "certain increase" and vice versa. If one area that had low increase, steady and low decrease was categorized as "uncertain." This final excludes the inappropriate land use for plantation, i.e., natural forest and settlement area.

Results

1. Site index calculations

Overall, the mean tree height was 17.9 m, with a minimum of 6.2 m and maximum of 32.8 m. The age of the *T. grandis* plantations varied from 1 to 87 years (Fig. 3). We obtained SI values by using the following Mitscherlich equation, the coefficient of which was statistically significant.

$$SI = 26.833 \times (1 - 0.580 \times \exp[-0.033 \times Age]) \quad \text{(i)}$$

The SI value, namely, the height at 40 years, was 22.6 m, according to the above equation. Next, we applied the equation as a guide curve and calculated SI values for every sampling point. Accordingly, the mean SI was 18.0 m, with a standard deviation of 3.3. This value was used to compare the three SDMs (GLM, GAM, and RF).

2. Model construction

The four and seven predictors used in GLM and GAM, respectively, are the best combination of predictors based on the AICc value. The best GLM and GAM were compared with the RF model constructed using all predictors. Model comparisons based on the coefficient of determination showed that the RF model was highly correlated with the actual observations (Fig. 4). Both GAM and GLM showed a low capacity in terms of explaining and predicting SI. Based on Figure 4, the RF model has uncertainty particularly of the lowest and highest SI because the data were concentrated in the middle SI. However, the gradation or trend in the RF model is acceptable, and then, the RF model was used to predict and map the current and future SI on Java.

Precipitations (bio18, bio13) and temperature (bio4) were the most important three predictor in RF model, and all three soil predictors were much less important compared with the climatic parameters (Table 3). The response curve of predictors in RF showed how each predictor affected the SI of *T. grandis*. SI peaked when the bio18, bio19, and bio13 values decreased to approximately < 200 mm, and when the bio9 values decreased to < 22°C, which is a relatively low temperature in the driest month (Fig. 5).

Table 2. Five categories used for integrated site index (SI) evaluation under various scenarios

Category	HadGEM2-ES	CCSM4
High increase	+	+
Low increase	+	0
Low increase	0	+
Steady	+	−
Steady	0	0
Steady	−	+
Low decrease	−	0
Low decrease	0	−
High decrease	−	−

+: gains, 0: stable, −: losses

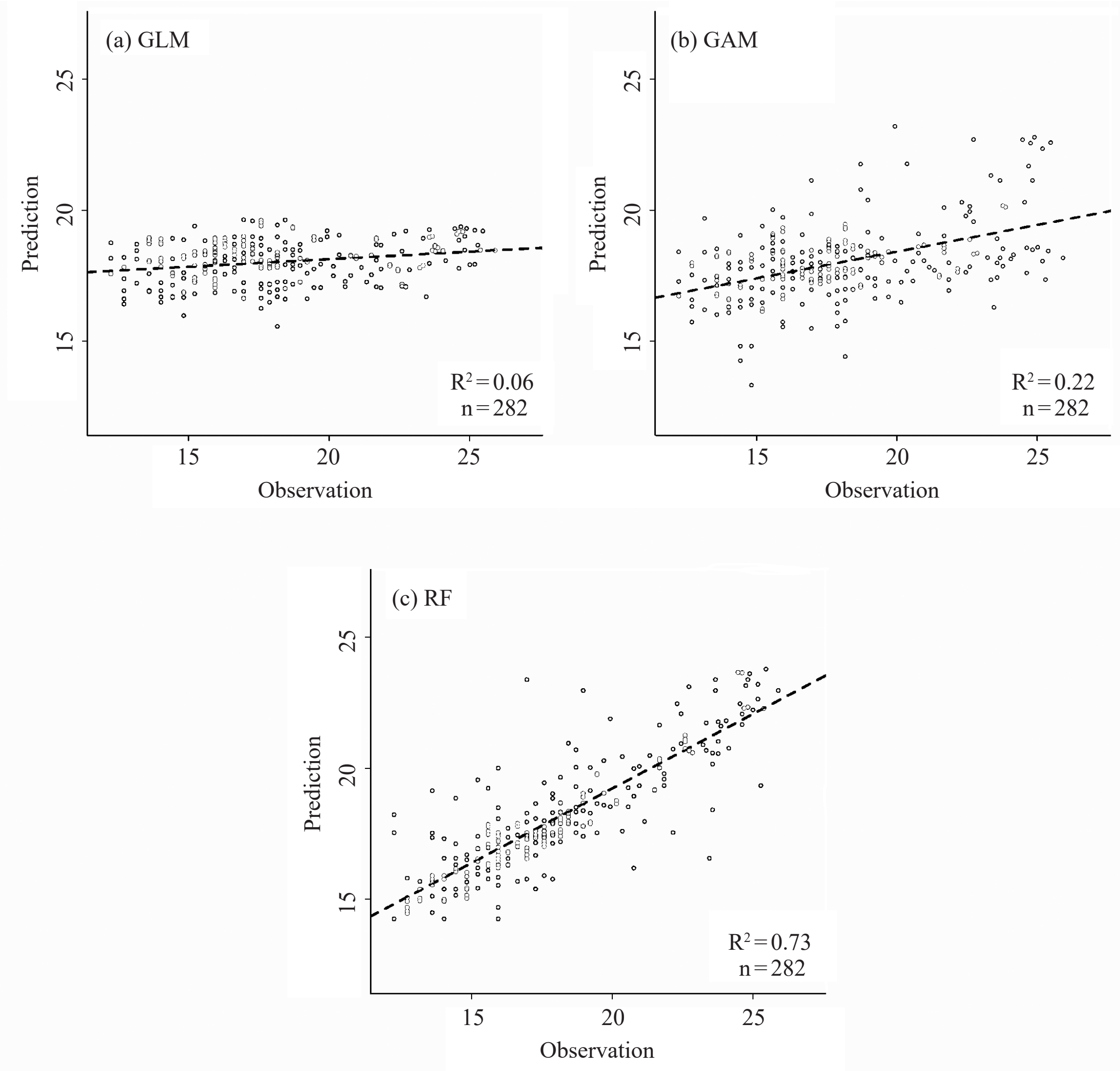


Fig. 4. Correlations between observed and predicted site index (SI) values under each model type
(a) Generalized linear model (GLM), (b) general additive model (GAM), and (c) random forest model (RF)

Table 3. Ten predictor variables and their values

Variable	Predictor	Contribution to the RF model (%)	Sample sites (Min, Max)	Java Island (Min, Max)
bio18	Precipitation in the warmest quarter (mm)	13.7	148 - 1,317	50 - 1,794
bio13	Precipitation in the wettest month (mm)	12.9	215 - 632	206 - 849
bio4	Temperature seasonality	12.8	272 - 1,025	197 - 1,067
bio19	Precipitation in the coldest quarter (mm)	12.0	70 - 1,504	52 - 2,296
bio9	Mean temperature in the driest quarter (°C)	11.3	20 - 27	5 - 28
bio5	Maximum temperature in the warmest month (°C)	10.3	27 - 34	11 - 35
bio2	Mean diurnal range (°C)	10.2	7.6 - 12.3	7.4 - 12.9
CEC	Cation exchange capacity (cmol + /kg)	9.7	8 - 34	3 - 70
Soil pH	Soil pH (H_2O)	5.6	4.9 - 5.5	4.8 - 6.8
TAXUSDA	Soil type based on USDA soil classification	1.5	4 orders	10 orders

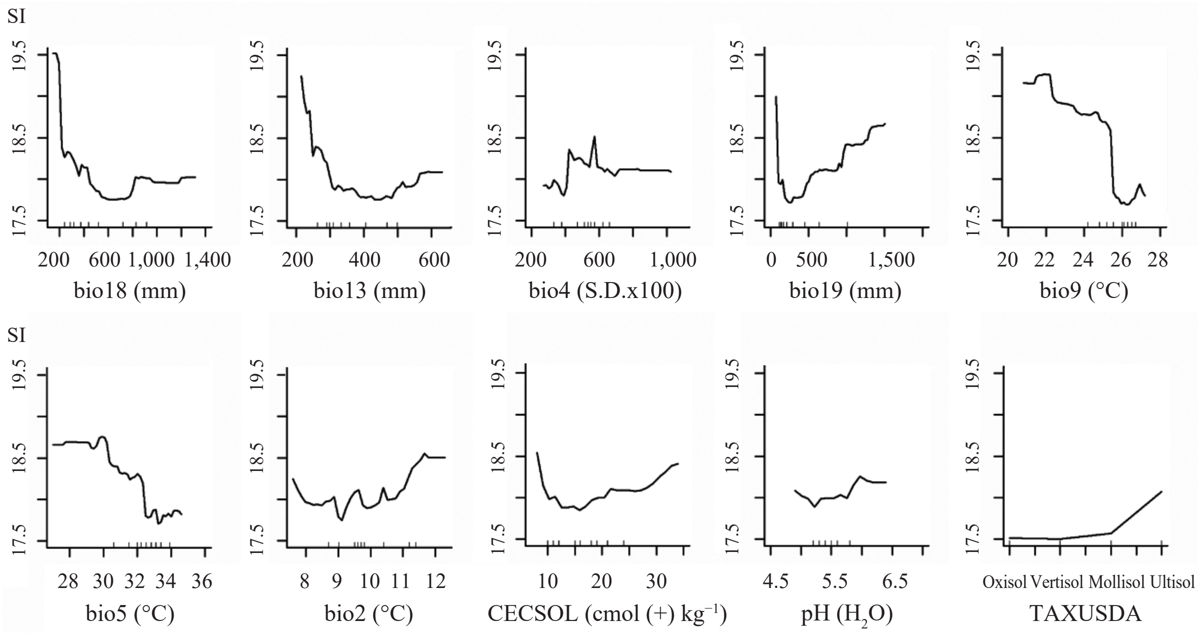


Fig. 5. Response curve of each variable in the random forest

3. Current and future SI maps

The SI values were categorized into four classes (see Fig. 6): very low (SI < 16.5), low (SI = 16.5-19), high (SI = 19-21.5), and very high (SI > 21). The SI map for current climatic data showed very high SI areas in a small region of northeast East Java Province. The high SI for *T. grandis* growth was patchy across Java, although *T. grandis* has a wide range of climatic and edaphic habitat variability. By contrast, the northwest of Central Java showed particularly low SI values (Fig. 6a).

The RF model predicted that between 48.9% and 56.0% of Java would experience an increase in SI values in the 2050s and 2070s under the HadGEM2-ES climate change scenario (Table 4). This trend is obvious on future maps: areas with high and very high SI values appeared northwest of East Java provinces under the HadGEM2-ES scenario (Fig. 6b-e). These locations show potential for the development of *T. grandis* plantations in the future. A similar trend of increasing SI values was also observed under the CCSM4 scenario (Fig. 6f-i). Furthermore, CCSM4 showed other increasing SI values in northern West Java Province.

All prediction maps of future SI values were subsequently overlaid to categorize the future changes (Fig. 7a-d). Approximately 12.6% of the area was predicted to experience an increase in SI values under all future climatic scenarios (Table 4, Fig. 7e). Overall, the four locations were expected to become more suitable for future *T. grandis* plantations, i.e., northeast of Banten Province, northeast and northwest of Central

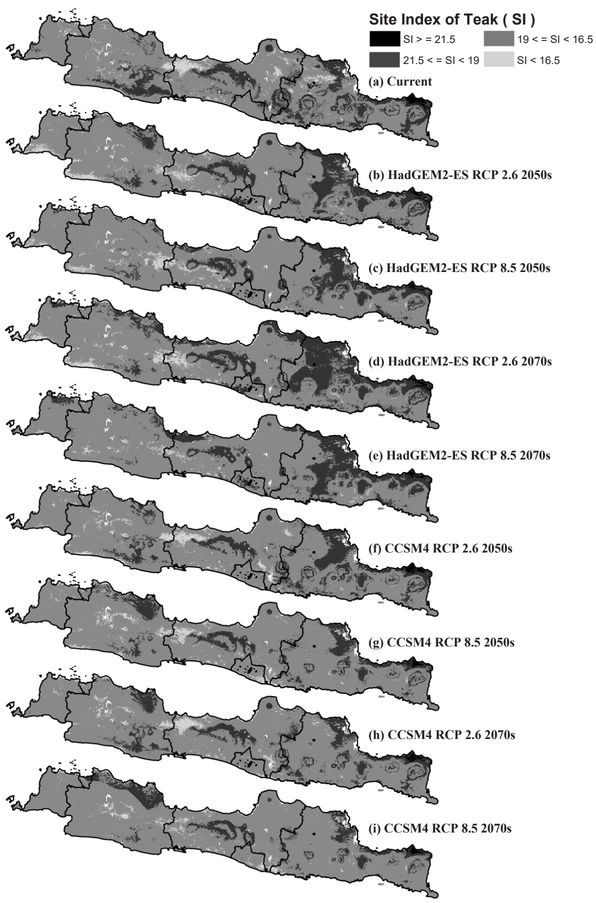


Fig. 6. Predicted site index (SI) distributions of *T. grandis* on Java under current conditions (averaged for 1950-2000; a) and under the HadGEM2-ES and CCSM4 scenarios, with two RCPs (2.6 and 8.5) and two time periods (the 2050s and 2070s; b-i)

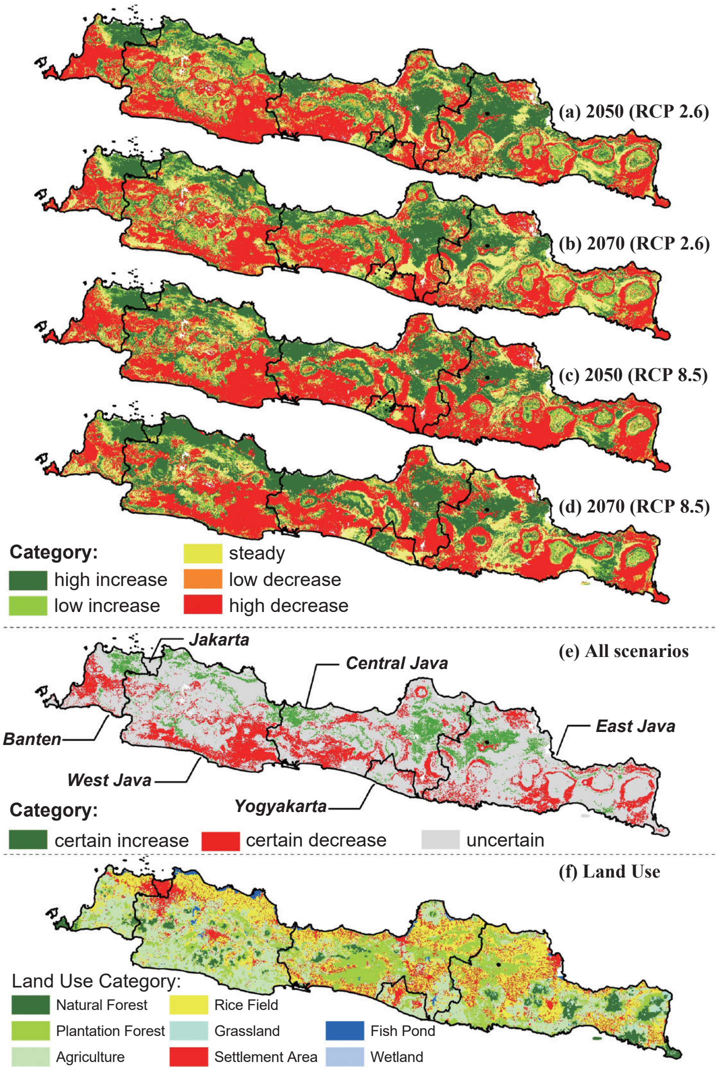


Fig. 7. Integrated evaluation of site index (SI) distributions under the two projected time periods (the 2050s and 2070s) and two RCP (2.6 and 8.5) scenarios (a-d), and under all scenarios (e) and land use on Java (f)

Table 4. Percentage of grid cells showing an increase in SI under each climate change scenario

GCM [a]	RCP [b]	Time period	Sample sites (%)	Java Island (%)
HadGEM2-ES	2.6	2050s	51.4	42.1
HadGEM2-ES	2.6	2070s	56.0	45.2
HadGEM2-ES	8.5	2050s	48.9	38.3
HadGEM2-ES	8.5	2070s	52.1	44.8
CCSM4	2.6	2050s	47.5	35.4
CCSM4	2.6	2070s	46.1	32.7
CCSM4	8.5	2050s	46.5	32.8
CCSM4	8.5	2070s	42.9	36.5
Both (HadGEM2-ES & CCSM4)	Both (2.6 & 8.5)	Both (2050s & 2070s)	32.3	12.6

[a] GCM: global climate model

[b] RCP: representative concentration pathway

Java Province, and northwest of East Java Province. Conversely, approximately 22.9% of the Java was projected to undergo a decrease in SI value in the southern region of the island.

4. Suitable climatic conditions for *T. grandis* plantations on Java

Figure 8 shows the climatic conditions resulting in increased SI values under current and future climate change (HadGEM2-ES RCP 8.5 in the 2050s). Compared with current conditions (Fig. 8a), the characteristics of future climate change are decreased precipitation in the warmest quarter (bio18) and increased mean temperature in the driest quarter (bio9; Fig. 8b). The climatic conditions of the increased SI values under both future climatic conditions represent a wide range of precipitation in the warmest quarter (bio18, approximately 250 mm-1,100 mm, Fig. 8c).

Discussion

1. Climatic conditions and the ecology of *T. grandis*

Precipitation in the warmest quarter (bio18), precipitation in the wettest month (bio13), temperature seasonality (bio4), and precipitation in the coldest quarter (bio19) have an important impact on overall growth (Table 3). Overall, the precipitation seasonality is a better predictor than temperature for *T. grandis* growth. Thus, the first hypothesis is clearly accepted in this study. This finding supports a previous study that growth rest in the dry season is directly linked to the annual growth of *T. grandis* (Tondjo et al. 2018). For optimum growth, *T. grandis* should be between 1,200 and 2,500 mm annual rainfall and a dry season of 3-5 months (Kaosa-Ard 1998). This study supports our result that SI of *T. grandis* increases when bio18 and bio19 are < 200 mm in 3 months. This species prefers the contrast in rainfall between the dry and wet seasons (Palanisamy et al. 2009). In the present study, precipitation in the warmest quarter (bio18) was the best predictor of SI, with values ranging from 250 to 1,250 mm, likely representing the distinct differences between the dry and wet seasons. The physiological and genetic responses to the dry season were explained by Galeano et al. (2019), i.e., reduction in stomatal conduction and reduction in photosynthesis.

Java is a well-known region for *T. grandis* plantations in Indonesia because of its climatic and edaphic suitability (Tanaka et al. 1998). This study showed that areas with temperature seasonality (bio4) higher than 400, or standard deviation 4°C of 12 monthly temperature values, will experience a consistent increase in the SI of *T. grandis* (Fig. 5). Likewise, the seasonal and extreme temperature is the significant predictor for the *T. grandis* plantation in Bangladesh (Deb et al. 2017). This result might be correlated with the wide range of temperature from 11 to 43°C (Pandey & Brown 2000). This finding is in line with Deb et al. (2017), who showed that climate seasonality is more critical than annual climate.

Soil type was the least important predictor for *T. grandis* in our model (Table 3). By contrast, soil type was a stable soil property that was not strongly affected by climate change (Bonfante et al. 2019). Although the *T. grandis* plantation in this study was dominated by ultisol, vertisol, oxisol, and mollisol, the soil was suitable for *T. grandis* because of the adequate drainage and water retention (Tanaka et al. 1998). Other factors supporting the optimum growth of *T. grandis* include deep subsoil, slightly acidic or alkaline soil pH, and an abundance of exchangeable bases, especially calcium (Tanaka et al. 1998, Kaosa-ard 1989). This suggests that

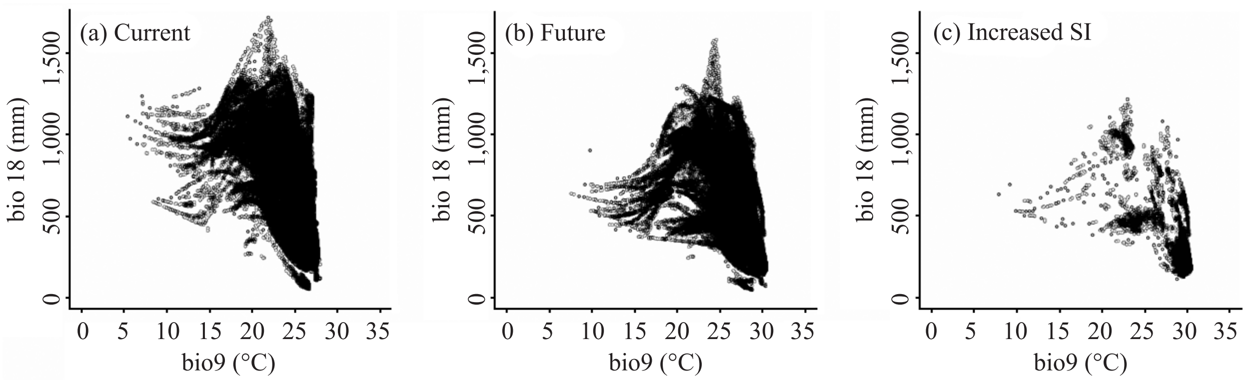


Fig. 8. Distribution of precipitation in the warmest quarter (bio18) and mean temperature of the driest quarter (bio9) under current conditions (averaged for 1950-2000; (a) and future climatic conditions (HadGEM2-ES RCP 8.5 during the period 2041-2060; (b) and increased SI (c))

the soil type at the study site was relatively unimportant for predicting *T. grandis* growth on Java.

2. Future potential SI areas

The SI values of *T. grandis* changed under future climate conditions. Precipitation gives more contribution to increases in SI compared with the temperature in this study (Table 4). Another study (Shah et al. 2007) provides the same result regarding tree-ring growth in India. In particular, increased SI mostly distributed in the area under 1,000 mm precipitation in the warmest quarter (bio18, Fig. 8c). So, increased SI is likely to be located in the area with lower precipitation. Hence, the second hypothesis is rejected in the present study. Furthermore, some values of precipitations do not presently exist on Java (Fig. 8). For instance, values of bio18 > 1.600 mm do not exist under future climate conditions (Fig. 8b) but do exist under the current climate conditions (Fig. 8a). Likewise, values of bio9 between 29°C and 30°C do exist under future climate conditions (Fig. 8b). This finding is consistent with previous research on *T. grandis*, which predicted that habitats that are currently suitable for this species would no longer be suitable under future climate conditions (Gopalakrishnan et al. 2011, Deb et al. 2017). This phenomenon occurs in its native habitats or nonnative plantation areas (Deb et al. 2017). Although the predicted result has uncertainty due to statistical calculation, subsequent plantation programs after harvest should consider future growth that reflects increased SI areas (Fig. 7e).

In the present study, future potential areas with a high increase in SI were identified in the northeast of Banten Province, northeast and northwest of Central Java Province, and northwest of East Java Province (Fig. 7a-e). These findings indicate that these areas should be prioritized for future *T. grandis* plantation programs because their climate, particularly precipitation, will be favorable in the future (Table 3). Although the aforementioned areas were found to be climatically suitable, the soil's physical and chemical characteristics should be managed to realize optimal growth (Fernandez-Moya et al. 2014).

3. Forest management of *T. grandis* in the future

The model predictions obtained here suggest that the best location for long-term *T. grandis* plantations is in the northeast of Banten Province, northeast and northwest of Central Java Province, and northwest of East Java Province. According to land use maps, that location is already used for plantation forests as well as rice field areas (Fig. 7f). Based on this map, we should carefully consider maintaining the natural forest. These findings suggest that model predictions can be used for future planning, thus encouraging consideration of site selection for the next future commercial plantation. For example, the "certain decrease" area should be avoided for the planting program to mitigate climate change. Therefore, the modeling results will provide a basis for more sustainable future plantation development. Furthermore, clones of *T. grandis* that have adapted to climate change should be collected as soon as possible so that *T. grandis* plantations can be adapted to climate change and remain productive.

The results of this study can also be applied to community forest areas. Under both future climate change scenarios, high SI values were predicted in northern West Java and Banten Province, indicating their suitability for smallholder *T. grandis* plantations. Similar findings were also highlighted by Imaya et al. (2020) in Lao People's Democratic Republic, who recommended that cultivators of *T. grandis* should carefully select appropriate sites, even within small areas.

Conclusions

Using SDM analysis, this study revealed that precipitation in the warmest quarter is the best predictor of *T. grandis* growth on Java. By contrast, all three soil characteristics examined were unimportant in the model. Further, this study identified potentially sustainable plantation areas suitable for *T. grandis* growth, not only under present climatic conditions but also in the future. These areas were located northeast of Banten Province, northeast and northwest of Central Java Province, and northwest of East Java Province should be the target of future *T. grandis* plantation and management.

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