**BIODIVERSITAS**
Volume 25, Number 3, March 2024
Pages: 1135-1143

ISSN: 1412-033X
E-ISSN: 2085-4722
DOI: 10.13057/biodiv/d250328

# Predicting the current and future distributions of *Pinus merkusii* in Southeast Asia under climate change

**MUHAMMAD NUR SULTON[1], DEVI MAYANG AURINA[1], FARHAN MUHAMMAD[1], FARIZ PRADHANA ADIL FADZILAH[1], ZAHRA HANUN[1], MUHAMMAD INDRAWAN[1], SUGENG BUDIHARTA[2], JATNA SUPRIATNA[3], ILYAS NURSAMSI[4], AHMAD DWI SETYAWAN[1,5,♥]**

[1]Department of Environmental Science, Faculty of Mathematics and Natural Sciences, Universitas Sebelas Maret. Jl. Ir. Sutami 36A Surakarta 57126, Central Java, Indonesia. Tel./fax.: +62-271-663375, ♥email: volatileoils@gmail.com

[2]Purwodadi Botanic Gardens, Research Centre for Plant Conservation, Botanical Gardens and Forestry, National Research and Innovation Agency. Jl. Raya Surabaya-Malang Km. 65, Purwodadi, Pasuruan 67163, East Java, Indonesia

[3]Department of Biology, Faculty of Mathematics and Natural Sciences, Universitas Indonesia. Jl. Prof. Dr. Sudjono D. Pusponegoro, Kampus UI, Depok 16424, West Java, Indonesia

[4]School of Earth and Environmental Science, Faculty of Science, The University of Queensland. St Lucia 4072, Brisbane, Queensland, Australia

[5]Biodiversity Research Group, Universitas Sebelas Maret. Jl. Ir. Sutami 36A, Surakarta 57126, Central Java, Indonesia

Manuscript received: 9 July 2023. Revision accepted: 24 March 2024.

**Abstract.** *Sulton MN, Aurina DM, Muhammad F, Fadzilah FPA, Hanun Z, Indrawan M, Budiharta S, Supriatna J, Nursamsi I, Setyawan AD. 2024. Predicting the current and future distributions of* Pinus merkusii *in Southeast Asia under climate change. Biodiversitas 25: 1135-1143. Pinus merkusii* Jungh. Et de Vriese is a native pine species of Southeast Asia with primary distribution in Indonesia, especially in the mountainous areas of northern Sumatra. The *P. merkusii* has an important role in the forest ecosystem including maintaining ecosystem stability, reducing soil erosion, and providing habitat for various types of flora and fauna. Climate change is expected to affect the growth, development and distribution of plants, so this study aims to predicting the current dan future distribution of *P. merkusii* in Southeast Asia under climate change. We used Maxent and Geographic Information System (GIS), which incorporated bioclimatic, edaphic, and UVB radiation variables, to predict the suitable areas of *P. merkusii* under current and future climate scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) and three time periods (2030, 2050, and 2080). Our findings indicate that compared to current, there will be an increase of suitable areas for *P. merkusii* in 2030 across all climate scenarios with RCPs 2.6, 4.5, 6.0, and 8.5 represent 9.53%, 9.66%, 9.73%, and 9.91% of Southeast Asia terrestrial area, respectively. In 2050, such increase will continue under all climate scenarios with RCP 4.5 has the largest proportion of suitable area (10.39%). However, in 2080, the suitable areas are likely to reduce compared with 2050 with RCPs 2.6, 4.5, 6.0, and 8.5 have a percentage of 9.21%, 9.69%, 10.29%, and 9.81%, respectively. Our predictions showed that there will be a geographical shift of suitable area of *P. merkusii* into higher elevation and low latitude, migrating southeastward. Our findings about the potential future distribution of *P. merkusii* might be used as a reference for cultivation according to predicted suitable areas in the future.

**Keywords:** Climate change, elevation, Maxent, *Pinus merkusii*

## INTRODUCTION

*Pinus*, which belongs to the Pinaceae family, has a wide distribution ranging from the northern to southern hemispheres and consists of nearly 100 species. Of the various species, tropical pine (*P. merkusii* Jungh. Et de Vriese) or also known as *tusam*, is the only species of pine that has a distribution in most parts of Southeast Asia, such as Thailand, Vietnam, Malaysia, and Indonesia (Melinda et al. 2022). It is characterized by its tall and sturdy form, with long needle-shaped leaves and distinctive seed cones (Ramadhani et al. 2021). The *P. merkusii* has an important role in forest ecosystem including maintaining ecosystem stability, reducing soil erosion, and providing habitat for various types of flora and fauna (Ng'awe et al. 2021; Sulton et al. 2023). The *P. merkusii* has Vulnerable (VU) status based on the IUCN Red List (Heyne 1987; IUCN 2006).

Sadili (2015) stated that *P. merkusii*, a pine species native to Southeast Asia, is widely found in Indonesia, especially in the mountainous areas of northern Sumatra. The *P. merkusii* is among the most important forestry species in Indonesia with a broad range of products including its resin used in gumrosin industries and its wood used as raw material for building construction, furniture, pulp and paper (Wijayanto et al. 2015). The *P. merkusii* generally grows at an altitude of 400-1,500 msl, but has also been reported to grow in lowlands (± 90 m asl) and mountains (± 2,000 m asl). The *P. merkusii* is fast-growing species and does not require special growing sites (Siregar and Diputra 2013) and can even grow on poor soils. Nonetheless, temperature and rainfall play an important role in influencing the growth and distribution of *P. merkusii* in Southeast Asia. Latest study shows that the optimal temperature for *P. merkusii* growth is in the range of 18-25°C (Sandri et al. 2016). The *P. merkusii* grows well in areas with high annual rainfall between 1,000-2,000 mm (Masendra et al. 2021), making this species suitable to grow in Southeast Asia which generally has high rainfall.

In general, Southeast Asia has two seasons, i.e. a wet season and a dry season, that generally occur with variations across the region. The wet season usually occurs between November-April, when the western monsoon brings water vapor from the Indian Ocean and causes heavy rainfall (Numata et al. 2022). Rainfall in Southeast Asia is generally abundant throughout the year, with the wet season dominating the dry season (Zhang et al. 2023a). Meanwhile, the dry season in Southeast Asia occurs between May-October. During this period, the Timor monsoon carries dry air masses from the Pacific Ocean (Zhang et al. 2023b). This causes rainfall to decrease dramatically, the weather to become drier and hotter.

Rising temperatures, extreme weather, and changing seasonal patterns are some of the impacts of climate change, which are primarily driven by an increase in greenhouse gases in the atmosphere caused by anthropogenic activities (Gray and Brady 2016). Climate change impacts pose a major challenge to plant development and growth, phenology (Parmesan and Hanley 2015), and changes in the geographic distribution of species (Zhang et al. 2018). The shifts in species distributions that occur in response to climate change pose major challenges for conservation planning, prioritization and land protection decisions, making predicting these shifts in distribution patterns a major focus in climate change ecology (McLaughlin et al. 2017). Modeling that predicts the potential distribution of a species plays an important role in many biological conservation applications (Khanum et al. 2013; Yang et al. 2013). Species Distribution Models (SDMs) are a key tool in predicting the spatial response of species to environmental change (Kaky et al. 2020), such as the likely impacts of climate change on natural and artificial ecosystems (Woodin et al. 2013). Various species distribution models have been widely applied to determine or evaluate ecological suitability, ecological response, and species distribution areas, one of which is Maximum Entropy (Maxent) (Zhang et al. 2018). Maxent is a model that is often used in predicting species distribution (Wang et al. 2014). In predicting species distribution, Maxent only uses species presence data to predict based on maximum entropy theory (Khanum et al. 2013) and environmental information (Yang et al. 2013).

Considering the sensitivity of *P. merkusii* to climate variables, climate changes might have potential impact on the distribution of this species. An increase in temperature above its suitable climatic ranges (i.e. 25°C) is likely to shift its geographic occurrence in Southeast Asia to higher latitude and altitude, yet this hypothesis needs to be tested. Therefore, the aim of this study was to predict the current and future distribution of *P. merkusii* in Southeast Asia under climate change using species distribution model of Maxent. We hope that the findings of this study can be utilized by stakeholders, both government and non-governmental organizations, in managing this species.

## MATERIALS AND METHODS

### Study area

This study examines the projected impacts of climate change on the distribution of *P. merkusii* in Southeast Asia. *Pinus* species has distribution in most of Southeast Asia (Sitompul 2019). Southeast Asia consists of 11 countries: Indonesia, Malaysia, Singapore, Thailand, Philippines, Brunei, Vietnam, Laos, Myanmar, Cambodia, and East Timor (Figure 1). Geographically, Southeast Asia countries are located at 28°N-11°S, most of these countries have a tropical climate.

### Procedures

*Data collection*

There were 96 presence data of *P. merkusii* Southeast Asia collected from primary and secondary data. Primary data were obtained from the presence of *P. merkusii* around Mt. Lawu and Yogyakarta, Indonesia with 8 coordinate points and secondary data were obtained from Global Biodiversity Information Facility (GBIF) (http://www.gbif.org/) with 88 coordinate points. The obtained data was further converted into CSV format for further analysis. Correction of sampling bias is necessary to minimize biases that can affect the results and interpretation of the model. We use ArcMap 10.5 and SDM Toolbox v2.5 to select sampling points and sampling uses MCP buffers (Maxent Tools) to reduce the buffer distance bias of 10 km. The use of MCP buffer samples to achieve file bias is due to species distribution which makes species locations unsuitable.

*Current environmental and bioclimatic variables*

Bioclimatic and environmental variables were used to model species distribution. We selected a subset of variables that may affect the occurrence of *P. merkusii* in Southeast Asian countries. We applied 19 bioclimatic variables, 2 edaphic variables, and 5 environmental variables assumed to have a significant effect on plant growth (Table 1). We collected bioclimatic datasets from the Worldclim website (https://www.worldclim.org/) (Fick and Hijmans 2017). We retrieved historical climate data with a spatial resolution of 2.5 minutes (about 20.25 $km^2$). We obtained the global dataset of UVB radiation layers (UVB1, UVB2, UVB3, UVB4) from the glUV dataset (https://www.ufz.de/gluv/) (Beckmann et al. 2014). GlUV is a supporting dataset to the bioclimate dataset that contains information on the distribution of UVB radiation. Soil data consists of soil organic carbon and soil pH. We obtained the soil dataset from ISRIC (https://data.isric.org/geonetwork/) (Hengl et al. 2017). After obtaining the dataset, we delineated it according to the study area, resampled, and converted it into (.asc) format using ArcMap 10.5. We realized that each bioclimatic variable in Maxent is highly correlated, so it needs to be reduced to improve the quality of species distribution estimation. We used the SDM toolbox v2.5 In ArcMap 10.5 (Brown 2014; Brown et al. 2017). We used the Principal Component Analysis tool to reduce the number of bioclimatic variables used for prediction since some variables might have strong correlation. Eventually, we used only six bioclimatic variables (bio4, bio5, bio8, bio9, bio10, bio11) plus two soil variables (soc, pH) and five environmental variables (elevation, UVB1-4) (Yoon and Lee 2021).

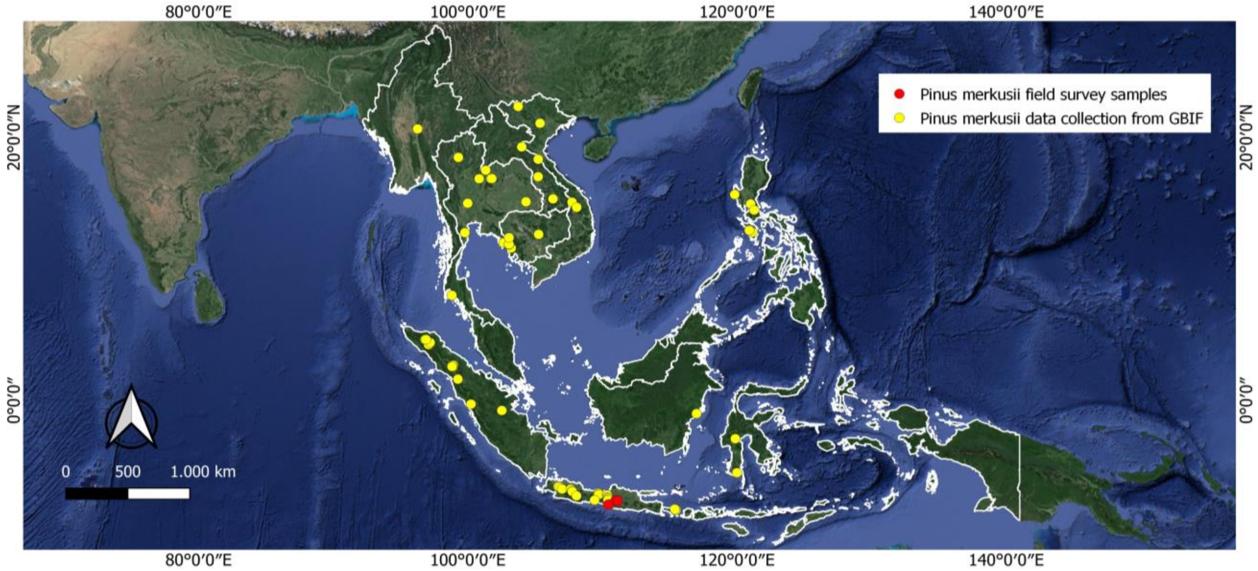


**Figure 1.** Study area and presence data of *Pinus merkusii* in Southeast Asia

**Table 1.** Bioclimatic variables used to model species distribution

| Variable | Description |
|---|---|
| elev | Altitude |
| wc2.1_2.5m_bio_4 | Temperature seasonality (standard deviation x 100) |
| wc2.1_2.5m_bio_5 | Max temperature of warmest month |
| wc2.1_2.5m_bio_8 | Mean temperature of wettest quarter |
| wc2.1_2.5m_bio_9 | Mean temperature of driest quarter |
| wc2.1_2.5m_bio_10 | Mean temperature of warmest quarter |
| wc2.1_2.5m_bio_11 | Mean temperature of coldest quarter |
| soc | Soil organic carbon |
| ph | Soil pH |
| uvb1 | Annual mean UVB |
| uvb2 | UVB seasonality |
| uvb4 | Mean UVB of lowest month |
| uvb3 | Mean UVB of lightest month |

*Future climate scenarios*

We created future climate scenarios by simulating species distributions using representative concentration pathways (RCPs). We obtained future climate data from the International Center for Tropical Agriculture (CIAT) and the Climate Change, Agriculture and Food Security (CCAFS) Program (https://www.ccafs-climate.org/data_spatial_downscaling/). We used the mohc_hadgem2_es model (Hadley Center Global Environment Model 2 Earth System). The model selection was based on the availability of the desired scenarios of RCP 2.6, 4.5, 6.0 and 8.5 from CMIP5 (Coupled Model Intercomparison Project Phase 5) (Mohan and Bhaskaran 2019). We used three time periods (2030, 2050, 2080) to compare the impact of climate change on *P. merkusii* distribution in Southeast Asia countries. We assumed that the other seven variables (altitude, soil organic carbon, soil pH, UVB1-4) would not change significantly due to increasing greenhouse gases. Global Climate Models (GCMs) are important information for understanding the impacts and effects of climate change at local and global scales. However, climate change prediction models cannot be used as the main reference because differences in spatial resolution and numerical schemes in data processing can cause bias (error).

*Model development*

In this study, we used Maxent to predict the current distribution of *P. merkusii* and its redistribution under the influence of future climate change scenarios. We used Maxent version 3.4.4 (https://biodiversityinformatics.amnh.org/open_source/maxent/). Maxent can predict species distribution from Presence-Only (PO) data. Maxent provides setting options to simplify the analysis and customize the results according to our needs. The maximum number of iterations for the model is the parameter value to be changed, and is set to 5,000 per run to allow sufficient time for convergence. We used a convergence threshold of $1x10^{-6}$. To "cross-validate" the model, the data should be partitioned ten times, with 10% of each partition used to train the model ten times on 90% of the data, and alternately test the model on 10% of the partitions.

*Core distribution change*

By calculating and differentiating the centroids of current and future projected areas, we sought to further investigate trends in the size of projected areas (Brown 2014; Brown et al. 2017; Duan et al. 2022). The main distribution changes in the range of suitable habitats for *P. merkusii* were summarized. Between the two binary models (i.e. current and future SDM), we used SDM Toolbox, a Python-based GIS toolbox. By averaging the latitude and longitude of the binary input pixels, the tool creates a center of mass, which is then used to represent the center of the species range and indicate the magnitude and direction of change (He et al. 2023). Furthermore, we exclusively used projections of future climate conditions up to 2080 to reflect the largest changes at the center of the geometric distribution. We concentrate on distribution shifts of species on Sumatra Island. Sumatra was chosen since it is the origin of *P. merkusii* (Sadili 2015).

**Data analysis**

Maxent was used to obtain a prediction map that displays the distribution of potential ecological niches for species in the study area. Based on Phillips and Dudik (2008), the degree of potential suitability displayed is on a linear scale between 0 (lowest) to 1 (highest) probability. In addition, Maxent will make calculations regarding the contribution of each variable to the entire model and the amount of influence on the predictions made. Furthermore, to obtain alternative values regarding the importance of variables, the jackknife test is performed, which will display variables that have the most information and are not owned by other variables (Phillips et al. 2006). By applying binary computation and categorizing values into suitable and unsuitable habitats using selected threshold criteria, the geographic distribution of habitats can be compared and quantified as expected. One of the many sources of bias that Maxent users should strive to reduce is the selection of threshold rules (Phillips and Dudik 2008). According to Phillips and Dudik (2008), in selecting threshold criteria, it is best to avoid randomness and consider the relative relevance of commission error and omission error. To reduce commission error, we chose the threshold criterion of "maximum training sensitivity plus specificity". As in the research of Padalia et al. (2014), Maxent will determine the Area Under Curve (AUC) to assess model performance. The AUC value ranges from 0 (lowest) to 1 (highest), with a value of 0 to 0.5 meaning the model is no better than random prediction, between 0.5 to 0.7 means low discrimination, between 0.7 to 0.9 means good discrimination, and a value between 0.9 to 1 means the model is better than random prediction (Setyawan et al. 2018; Setyawan et al. 2021).

## RESULTS AND DISCUSSION

**Contribution of the variables and model evaluation**

Based on the presence data of *P. merkusii*, we created a habitat suitability map of *P. merkusii* using climatic, topographic, edaphic, and UVB radiation variables (Table 2). The model shows the variables with high contribution to explain suitable geographical areas as habitats for *P. merkusii* in Southeast Asia with AUC value of 0.875 (Figure 3.A). Elevation (elev) had the highest relative contribution to the model with 25.1% while the combined variables of wettest quarter mean temperature (wc2.1_2.5m_bio_8), soil pH, and seasonal temperature (wc2.1_2.5m_bio_4) explained a total of 50.3% and the remaining variables each contributed less than 10% to the model (Table 2). In addition, we also obtained alternative estimates for important variables through the use of the jackknife test (Figure 3.B). The results showed that the environmental factor with the highest contribution when used in isolation was the mean temperature of the wettest quarter (wc2.1_2.5m_bio_8) which therefore had the most information (Figure 3). The jackknife test results showed different findings regarding which factor would reduce the contribution the most when it was removed. The wettest quarter average temperature (wc2.1_2.5m_bio_8), warmest quarter average temperature (wc2.1_2.5m_bio_10), hottest month maximum temperature (wc2.1_2.5m_bio_5), driest quarter average temperature (wc2.1_2.5m_bio_9), and coldest quarter average temperature (wc2.1_2.5m_bio_11) appeared to have the most information that is not present in other variables, so not using these variables would reduce the accuracy of the *P. merkusii* model indicating that these five variables have the most useful information that is not present in other variables (Figure 3).

**Current predicted suitable habitat of *P. merkusii* in Southeast Asia**

Based on the distribution mapping of *P. merkusii* species modeled with Maxent, it is estimated that about 7.6% (316,770.75 km$^2$) of Southeast Asia's land area is suitable for *P. merkusii* (Figure 2). The predicted suitable habitats spread across Indonesia, Thailand, Philippines, Cambodia, Vietnam, Laos, Malaysia, and Myanmar with the largest distribution in Indonesia. In contrast, three countries in the Southeast Asian region, namely Brunei Darussalam, Singapore, and East Timor, no suitable areas for *P. merkusii* species were predicted. The distribution of *P. merkusii* in Indonesia is widely spread in three islands, namely Sumatra, Java, and Sulawesi.

Naturally, the distribution of *P. merkusii* is widespread in Southeast Asia, especially in Indonesia, Thailand, the Philippines, Laos, Cambodia, Vietnam (Imanuddin et al. 2020) and Myanmar (Grote and Srisuk 2021). The distribution of *P. merkusii* in Indonesia is found mainly in the mountainous areas of Sumatra (Alhamd and Rahajoe 2013). Distribution on the island of Sumatra is spread in Aceh, Kerinci, and Tapanuli which grow under different altitude conditions (Imanuddin et al. 2020). In addition, based on the results of the study it is also known that its distribution is also found on the islands of Java and Sulawesi. Meanwhile, the distribution of *P. merkusii* in the Philippines is found on Luzon and Mindoro Islands and in the lowlands at an altitude of 100 m asl. (Mustaqim 2021).

**Future predicted suitable habitat of *P. merkusii* in Southeast Asia**

Figure 4 and Table 3 present the future distribution of suitable habitats of *P. merkusii* under several climate change scenarios. While it is predicted that there are some areas become suitable habitats in the future, the current suitable areas are expected to decrease significantly under all RCP scenarios over three different time periods.

Under the RCP 2.6 climate scenario (lowest GHG emissions), the suitable terrestrial habitat area for *P. merkusii* in 2030 represents $3.96 \times 10^5$ km$^2$ or an increase of 9.53% from the current distribution. Then in 2050, almost all countries in Southeast Asia experience an increase in the distribution area of *P. merkusii* species with the most significant increase occurring in Myanmar, the Philippines, Thailand and Sumatra Island in Indonesia. The suitable habitat area for *P. merkusii* increases by an estimated 9.15%. Maxent projects that in 2050 the terrestrial distribution of *P. merkusii* in Southeast Asia will be 3.8 × $10^5$ $km^2$. In 2080, there is a slight increase of suitable habitat to 1.78% which mainly occurs in Brunei Darussalam, the Philippines and the island of Java in Indonesia, but a significant decrease occur in the countries of Myanmar, Thailand and the island of Papua in Indonesia.

Under the RCP 4.5 climate scenario, the suitable terrestrial habitat area of *P. merkusii* in 2030 is estimated at 4.02 × $10^5$ $km^2$. In the following 20 years, a significant increase in suitable area is predicted in 2050 in almost all Southeast Asia countries with a total percentage increase of 10.39%. However, a decrease in the distribution area of *P. merkusii* species is expected by 2080. Maxent projects an estimated loss of 2.08% in that year. The decline is expected to occur in several Southeast Asia countries including Myanmar, Cambodia, the Philippines, Singapore and the Indonesian island of Papua. Whereas the predicted increase occurred in Brunei Darussalam and Malaysia, which is expected to decline in the previous period (2050).

Under the RCP 6.0 climate scenario, there will be a significant increase (9.73%) of suitable area for *P. merkusii* in 2030 compared to the current habitat. In 2050, suitable habitat is predicted to increase significantly, and is expected to further affect the sustainability of suitable habitat for *P. merkusii*. In addition, approximately 10.36% of the suitable habitat area will be lost by the end of 2050. By the end of 2080, approximately 2.86% of the suitable habitat for *P. merkusii* under the influence of this future climate trajectory. During the aforementioned time period, there are indeed also areas that are predicted to be suitable habitats for *P. merkusii*.

Under the RCP 8.5 climate scenario, by 2030, the suitable area for *P. merkusii* will be significantly increased by about 9.91% compared to the present. Suitable habitat is projected to increase significantly in 2050. About 10.32% of the suitable habitat area will remain by the end of 2050. However, this loss can be made up for by the increase in the species' distribution area, which is much higher than in 2030, especially in Thailand, the Philippines, and the Moluccas Islands and Papua in Indonesia and is expected to further affect the sustainability of suitable habitat for *P. merkusii*. By the end of 2080, approximately 2.38% of suitable habitat for *P. merkusii* will be affected by this future climate trajectory. Areas predicted to be suitable for *P. merkusii* do exist during the above time period.

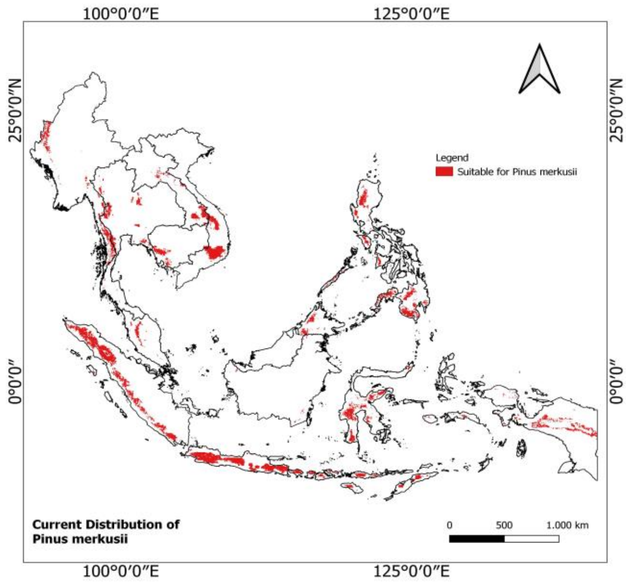


**Figure 2.** Current distribution of suitable habitat of *Pinus merkusii* in Southeast Asia predicted using Maxent

**Table 2.** Percentage of variable contribution to the final model

| Variable | Description | Contr. (%) |
|---|---|---|
| elev | Altitude | 25.1 |
| wc2.1_2.5m_bio_8 | Mean temperature of wettest quarter | 21.9 |
| wc2.1_2.5m_bio_4 | Temperature seasonality (standard deviation x 100) | 17.1 |
| ph | Soil pH | 11.3 |
| uvb4 | Mean UVB of lowest month | 9.7 |
| uvb1 | Annual Mean UVB | 6.2 |
| wc2.1_2.5m_bio_9 | Mean temperature of driest quarter | 4.8 |
| soc | Soil organic carbon | 2.9 |
| uvb2 | UVB Seasonality | 0.4 |
| uvb3 | Mean UVB of lightest month | 0.2 |
| wc2.1_2.5m_bio_11 | Mean temperature of coldest quarter | 0.2 |
| wc2.1_2.5m_bio_5 | Max temperature of warmest month | 0.2 |
| wc2.1_2.5m_bio_10 | Mean temperature of warmest quarter | 0.1 |

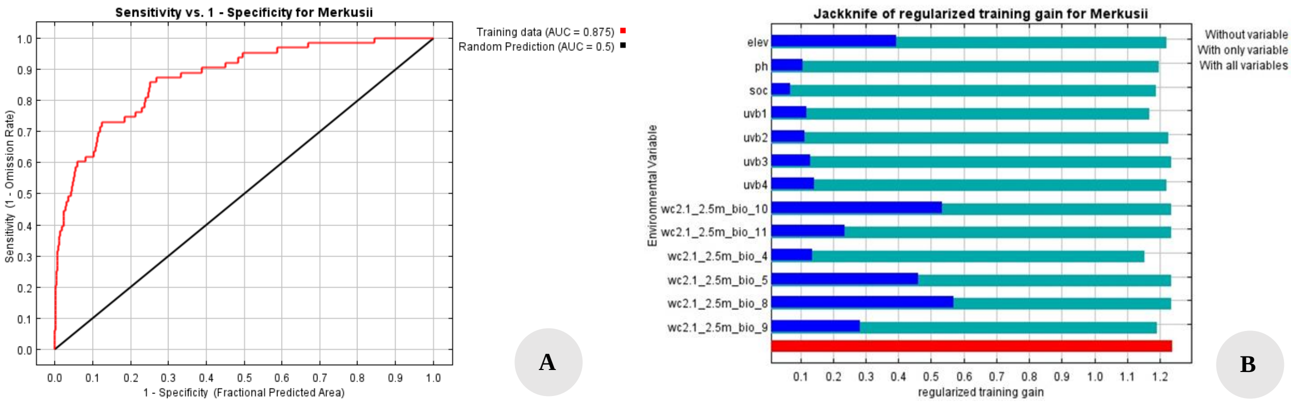


**Figure 3.** A. AUC graph of *Pinus merkusii*, B. Result of jackknife test of relative importance of predictor variables for *P. merkusii*

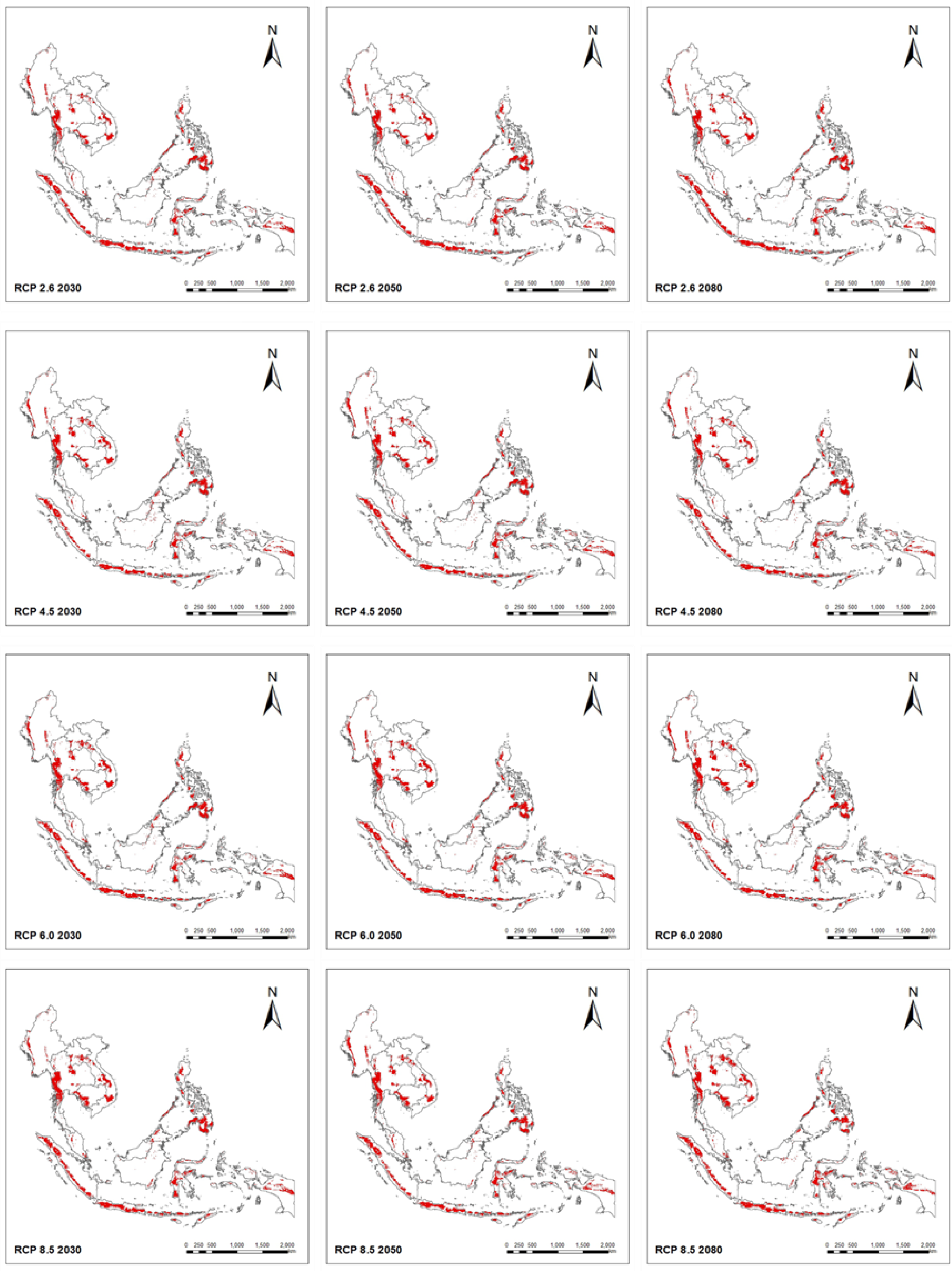


**Figure 4.** Spatial distribution of suitable habitat of *Pinus merkusii* in Southeast Asia under future climate projections

**Table 3.** Changes in suitable habitat area for *Pinus merkusii* under four future climate scenarios within three different periods of time

| Year | RCP Projection | *P. merkusii* (Area × $10^5$ $km^2$) | | | |
|---|---|---|---|---|---|
| | | Gain | Loss | Total | Future |
| 2030 | RCP 2.6 | 0.87 (2.10%) | -0.79 (-1.92%) | 1.67 | 3.96 (9.53%) |
| | RCP 4.5 | 0.92 (2.23%) | -0.85 (-2.05%) | 1.78 | 4.02 (9.66%) |
| | RCP 6.0 | 0.95 (2.30%) | -0.88 (-2.12%) | 1.84 | 4.04 (9.73%) |
| | RCP 8.5 | 1.03 (2.48%) | -0.95 (-2.30%) | 1.99 | 4.12 (9.91%) |
| 2050 | RCP 2.6 | 0.71 (1.72%) | -0.63 (-1.54%) | 1.35 | 3.80 (9.15%) |
| | RCP 4.5 | 1.23 (2.96%) | -1.15 (-2.78%) | 2.39 | 4.32 (10.39%) |
| | RCP 6.0 | 1.21 (2.92%) | -1.14 (-2.75%) | 2.36 | 4.31 (10.36%) |
| | RCP 8.5 | 1.20 (2.88%) | -1.12 (-2.71%) | 2.33 | 4.29 (10.32%) |
| 2080 | RCP 2.6 | 0.73 (1.78%) | -0.66 (-1.60%) | 1.40 | 3.83 (9.21%) |
| | RCP 4.5 | 0.94 (2.26%) | -0.86 (-2.08%) | 1.81 | 4.03 (9.69%) |
| | RCP 6.0 | 1.18 (2.86%) | -1.11 (-2.68%) | 2.31 | 4.28 (10.29%) |
| | RCP 8.5 | 0.98 (2.38%) | -0.91 (-2.20%) | 1.90 | 4.08 (9.81%) |

Note: - = Negative mark indicates suitable habitat area contractions

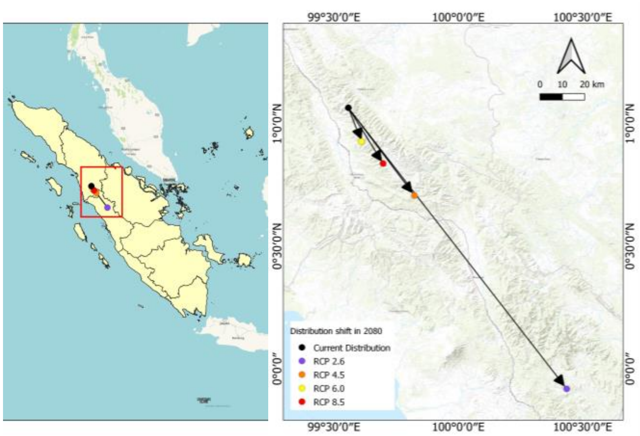


**Figure 5.** Distribution shift of *Pinus merkusii* in Sumatra Island, Indonesia

## Geographical shifts

Under current climatic conditions, it is estimated that about 7.6% (316,770.75 $km^2$) of the terrestrial area is suitable habitat for *P. merkusii* in Southeast Asia. Our findings are expected to expand gradually as future climate change will alter the ability of the habitat to support *P. merkusii* survival. By 2080, under all GHG emission trajectories, the current area of suitable habitat for *P. merkusii* will increase by 21% to 36% because *P. merkusii* is likely suited to future climate projections. In addition, the distribution of suitable habitat predicted for *P. merkusii* under future climate conditions will also change its geographical distribution. The suitable area on Sumatra Island, in the future based on all RCPs is expected to shift towards the southeast. The centroid shifts in RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 are 160.13 km, 49.4 km, 16.24 km, and 29.54 km, respectively (Figure 5).

## Discussion

Research on the ecology and cultivation of *P. merkusii* has been widely conducted, but research on the prediction of the current and future distribution of *P. merkusii* is still lacking, especially in Southeast Asia. The *P. merkusii* is native to Southeast Asia (especially norhern Sumatra Island), with the main distribution in Southeast Asia, a small part of Papua New Guinea, China, and India (GBIF 2023). GBIF data shows that 88 points of *P. merkusii* were reported. The results showed that the largest distribution of *P. merkusii* in Southeast Asia is in Indonesia with the initial distribution found on the island of Sumatra (Hartiningtias et al. 2020). The existence of *P. merkusii* is essential for the people in Southeast Asia because it is used for wood products such as furniture and pulp (Imanuddin et al. 2020), and non-timber forest products (NTFPs) such as gumrosin (Adalina et al. 2014; Dalya et al. 2021). The *P. merkusii* is also used as an agroforestry fence plant in Indonesia (Rahmawaty et al. 2019), and Vietnam (Hara et al. 2021).

Our study has shown that elevation, the mean temperature of the wettest quarter, temperature seasonality, and soil pH have the most impact on the distribution of *P. merkusii* in Southeast Asia (Table 2). We found that elevation makes the most contribution (25.1%) to the suitable habitat of the species. Elevation is one of the variables driving plant development (Negari et al. 2023). The *P. merkusii* may survive in both warm and cold climates within elevation range between 200 and 2000 m asl (Siregar and Diputra 2013). In Southeast Asia, *P. merkusii*'s growth and distribution are also influenced by temperature. Ritung et al. (2011) stated that 19-21°C is the ideal temperature for *P. merkusii* to grow and develop. Furthermore, we examined edaphic variables to ascertain their impact on *P. merkusii*. Our findings are that soil pH contributes to the distribution of *P. merkusii*. The nutrients in the soil are directly correlated with the pH of the soil (Penn and Camberato 2019; Mukrimin et al. 2021). Agroforestry systems have a positive impact on the distribution of *P. merkusii*. In addition to increasing soil fertility, agroforestry systems improve soil macrofauna (Prayogo et al. 2019). Sunlight radiation also contributes to the distribution of *P. merkusii*. Sallata's (2013) research revealed that *P. merkusii* requires full sunlight throughout the year for photosynthesis.

Future climate change is likely to affect the area suitable for *P. merkusii*. Our findings indicate that by 2030, there will be increase in suitable areas for the species across all climate scenarios with RCP 2.6, 4.5, 6.0, and 8.5

representing 9.53%, 9.66%, 9.73%, and 9.91% of Southeast Asia terrestrial area, respectively. Under all climate scenarios, the suitable area of *P. merkusii* will continue to increase by 2050 with RCP 4.5 scenario representing the most significant percentage (10.39%). However, in 2080 the predicted suitable area is lower than in 2050 in which under RCPs 2.6, 4.5, 6.0, and 8.5, the percentages are 9.21%, 9.69%, 10.29%, and 9.81%, respectively. Based on our investigations, the suitable habitat of *P. merkusii* shifts into low latitudes and high altitudes are migrating southeastward to West Sumatra (Figure 5). Changes in low latitudes and high altitudes are in line with previous studies that showed similar results (Hama and Khwarahm 2023; Khairunnisa et al. 2023; Wang et al. 2024).

Climate change affects forest ecosystems, so mitigation and adaptation efforts are needed (Pecchi et al. 2020). One species that needs to be managed is *P. merkusii*. The model we presented here is a habitat suitability model based on the environmental variables. We are aware of other possibilities that can affect species distribution such as anthropogenic activities that greatly affect species distribution (Antúnez et al. 2018; Bouderbala et al. 2023) considering that *P. merkusii* is one of the commodities that is used economically (Lukmandaru et al. 2020). So, it is necessary to make conservation efforts in the face of climate change. Despite the increase in the predicted suitable habitat, there needs to be monitoring and management by the community. Our findings about the potential future distribution of *P. merkusii* can also be used as a reference for planting according to suitable areas.

It can be concluded that under four climate change scenarios, namely RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 in 2030, 2050, and 2080, climate change will likely not reduce the suitable area of *P. merkusii* and even it is likely to increase. The largest increase in area will occur in the RCP 4.5 scenario in 2050 with an increase of $1.23 \times 10^5$ $km^2$ as well as having the largest area, namely $4.32 \times 10^5$ $km^2$. Meanwhile, the smallest total area occurred in the RCP 2.6 scenario in the same year with an additional area of $0.71 \times 10^5$ $km^2$, resulting in an estimated distribution area of $3.80 \times 10^5$ $km^2$. The results of our study can be used as a reference to increase the distribution of *P. merkusii* in Southeast Asia.

## REFERENCES


Adalina Y, Nurrochmat DR, Darusman D, Sundawati L. 2014. Harvesting of non-timber forest products by the local communities in Mount Halimun-Salak National Park, West Java, Indonesia. Jurnal Manajemen Hutan Tropika 20 (2): 103-111. DOI: 10.7226/jtfm.20.2.103.

Alhamd L, Rahajoe JS. 2013. Species composition and above ground biomass of a pine forest at Bodogol, Gunung Gede Pangrango National Park, West Java. J Trop Biol Conserv 10: 43-49. DOI: 10.51200/jtbc.v10i0.253.

Antúnez P, Suárez-Mota ME, Valenzuela-Encinas C, Ruiz-Aquino F. 2018. The potential distribution of tree species in three periods of time under a climate change scenario. Forests 9 (10): 628. DOI: 10.3390/f9100628.

Beckmann M, Václavík T, Manceur AM, Šprtová L, von Wehrden H, Welk E, Cord AF. 2014. glUV: A global UV-B radiation dataset for macroecological studies, Methods Ecol Evol 5: 372-383. DOI: 10.1111/2041-210X.12168.

Bouderbala I, Labadie G, Be´land J-M, Tremblay JA, Boulanger Y, He´bert C, Desrosiers P, Allard A, Fortin D. 2023. Long-term effect of forest harvesting on boreal species assemblages under climate change. PLOS Clim 2 (3): e0000179. DOI: 10.1371/ journal.pclm.0000179.

Brown JL. 2014. SDMtoolbox: A python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. Methods Ecol Evol 5 (7): 694-700. DOI: 10.1111/2041-210X.12200.

Brown, JL, Bennett, JR, Prancis, CM. 2017. SDMtoolbox 2.0: The next generation Python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. PeerJ. 5: 4095. DOI: 10.7717/peerj.4095.

Dalya N, Yuniar F, Muin AVF. 2021. Analysis of the farmers' income for pine tappers (*Pinus merkusii*) koakan method at KPH Mamasa Tengah. IOP Conf Ser: Earth Environ Sci 870 (1): 012035. DOI: 10.1088/1755-1315/870/1/012035.

Duan X, Li J, Wu S. 2022. MaxEnt modeling to estimate the impact of climate factors on distribution of *Pinus densiflora*. Forests 13: 402. DOI: 10.3390/f13030402.

Fick SE, Hijmans RJ. 2017. WorldClim 2: New 1km spatial resolution climate surfaces for global land areas. Intl J Climatol 37 (12): 4302-4315. DOI: 10.1002/joc.5086.

Global Biodiversity Information Facility (GBIF). 2023. GBIF Occurrence of *Pinus merkusii*. DOI: 10.15468/dl.pfyfmc

Gray SB, Brady SM. 2016. Plant developmental responses to climate change. Dev Biol 419: 64-77. DOI: 10.1016/j.ydbio.2016.07.023.

Grote PJ, Srisuk P. 2021. Fossil *Pinus* from the cenozoic of Thailand. Rev Palaeobot Palynol 295: 1-12. DOI: 10.1016/j.revpalbo.2021.104501.

Hama AA, Khwarahm NR. 2023. Predictive mapping of two endemic oak tree species under climate change scenarios in a semiarid region: range overlap and implications for conservation. Ecol Inf 73: 101930. DOI: 10.1016/j.ecoinf.2022.101930.

Hara M, Hoàng TT, Tiến TV, Ohsawa M. 2021. Composition and structure of mountain forests containing two tropical pines, *Pinus krempfii* and *Pinus dalatensis*, on the Da Lat Plateau, southern Vietnam. J Trop Ecol 37 (2): 51-63. DOI: 10.1017/S0266467421000092.

Hartiningtias D, Fule PZ, Gunawan AA. 2020. Wildfire effects on forest structure of *Pinus merkusii* in Sumatra, Indonesia. For Ecol Manag 457: 117660. DOI: 10.1016/j.foreco.2019.117660.

He XH, Si JH, Zhu L, Zhou DM, Zhao CY, Jia B, Wang CL, Qin J, Zhu XL. 2023. Modeling habitat suitability of *Hippophae rhamnoides* L. using MaxEnt under climate change in China: A case study of *H. r. sinensis* and *H. r. turkestanica*. Front For Glob Change 5: 1095784. DOI: 10.3389/ffgc.2022.1095784.

Hengl T, Mendes de Jesus J, Heuvelink GBM, Ruiperez Gonzalez M, Kilibarda M, Blagotić A et al. 2017. SoilGrids250m: Global gridded soil information based on machine learning. PLoS ONE 12(2): e0169748DOI: 10.1371/journal.pone.0169748.

Heyne K. 1987. Tumbuhan Berguna Indonesia. Terjemahan: Badan Litbang Kehutanan Jakarta. Jilid II dan III. Cetakan kesatu. Yayasan Sarana Wana Jaya, Jakarta. [Indonesian]

Imanuddin R, Hidayat A, Rachmat HH, Turjaman M, Pratiwi, Nurfatriani F, Indrajaya Y, Susilowati A. 2020. Reforestation and sustainable management of *Pinus merkusii* forest plantation in Indonesia: A review. Forests 11: 121235. DOI: 10.3390/f11121235.

IUCN (International Union for Conservation of Nature and Natural Resources). 2006. The IUCN Red List of Threatened Species. http://www.iucnredlist.org.

Kaky E, Nolana V, Alatawia A, Gilbert F. 2020. A comparison between Ensemble and MaxEnt species distribution modelling approaches for conservation: A case study with Egyptian medicinal plants. Ecol Inform 60: 101150. DOI: 10.1016/j.ecoinf.2020.101150.

Khairunnisa H, Dewi MAK, Faqiih MAH, Putrayuda MR, Nugroho GD, Indrawan M, Sutarno, Sugiyarto, Sunarto, Supriatna J, Nursamsi I, Gunawan, Pradhan P, Setyawan AD.2023. Prediction of potential climate change impacts on the geographic distribution shift of *Casuarina junghuhniana* and *C. equisetifolia* in Southeast Asia. Biodiversitas 24: 6360-6371. DOI: 10.13057/biodiv/d241161.

Khanum R, Mumtaz AS, Kumar S. 2013. Predicting impacts of climate change on medicinal asclepiads of Pakistan using Maxent modeling. Acta Oecologica 49: 23-31. DOI: 10.1016/j.actao.2013.02.007.

Lukmandaru G, Amri S, Sunarta S, Listyanto T, Pujiarti R, Widyorini R. 2020. Oleoresin yield of *Pinus merkusii* trees from East Banyumas. IOP Conf Ser: Earth Environ Sci 449 (1): 012024. DOI: 10.1088/1755-1315/449/1/012024.

Masendra, Purba BAV, Lukmandaru G. 2021. An evaluation of the antifungal and antioxidant activity of *Pinus merkusii* bark ethyl acetate extract. Jurnal Ilmu Kehutanan 15 (1): 102-110. DOI: 10.22146/jik.v15i1.149.

McLaughlin BC, Ackerly DD, Klos PZ, Natali J, Dawson TE, Thompsom SE. 2017. Hydrologic refugia, plants, and climate change. Glob Change Biol 23 (8): 1-21. DOI: 10.1111/gcb.13629.

Melinda V, Andini R, Yanti LA. 2022. Analisis morfologi *Pinus* (*Pinus merkusii* Jungh. Et De Vriese) studi kasus: Laut Tawar dan Linge, Aceh Tengah. Jurnal Ilmiah Mahasiswa Pertanian 7 (2): 766-804. DOI: 10.17969/jimfp.v7i2.20427. [Indonesian]

Mohan S, Bhaskaran PK. 2019. Evaluation of CMIP5 climate model projections for surface wind speed over the Indian Ocean region. Clim Dyn 53: 5415-5435. DOI: 10.1007/s00382-019-04874-2.

Mukrimin M, Ghiffary MI, Anshari MF, Gusmiaty G, Restu M. 2021. Dynamic of soil properties under an exotic pine (*Pinus* sp.) species growing in Bantaeng Regency. IOP Conf Ser: Earth Environ Sci 807 (2): 022043. DOI: 10.1088/1755-1315/807/2/022043.

Mustaqim WA. 2021. *Pinus merkusii* Jungh. & de Vriese Pinaceae. In: Franco FM (eds). Ethnobotany of the Mountain Regions of Southeast Asia. Ethnobotany of Mountain Regions. Springer, Cham. DOI: 10.1007/978-3-030-38389-3_177.

Negari SIT, Ningtyas SRA, Hanun Z, Sulton MN, Kusumaningrum L, Indrawan M, Sugiyarto, Sutomo, Setyawan AD. 2023. Agroforestry suitability evaluation using remote sensing in Jatiyoso Sub-district, Karanganyar District, Central Java, Indonesia. Biodiversitas 24: 6761-6769. DOI: 10.13057/biodiv/d241239.

Ng'awe P, Chungu D, Tailoka F. 2021. Data for modeling the height and diameter of *Pinus merkusii* and *Pinus michoacana* in Zambia. Data Brief 38: 107444. DOI: 10.1016/j.dib.2021.107444.

Numata S, Yamaguchi K, Shimizu M, Sakurai G, Morimoto A, Alias N, Azman NZN, Hosaka T, Satake A. 2022. Impacts of climate change on reproductive phenology in tropical rainforests of Southeast Asia. Comm Biol 5: 311. DOI: 10.1038/s42003-022-03245-8.

Parmesan C, Hanley ME. 2015. Plants and climate change: Complexities and surprises. Ann Bot 116: 849-864. DOI: 10.1093/aob/mcv169.

Pecchi M, Marchi M, Moriondo M, Forzieri G, Ammoniaci M, Bernetti I, Bindi M, Chirici G. 2020. Potential impact of climate change on the forest coverage and the spatial distribution of 19 key forest tree species in Italy under RCP4.5 IPCC trajectory for 2050s. Forests 11 (9): 934. DOI: 10.3390/f11090934.

Penn CJ, Camberato JJ. 2019. A critical review on soil chemical processes that control how soil pH affects phosphorus availability to plants. Agriculture 9 (6): 120. DOI: 10.3390/agriculture9060120.

Phillips SJ, Anderson RP, Schapire RE. 2006. Maximum entropy modeling of species geographic distributions. Ecol Model 190: 231-259. DOI: 10.1016/j.ecolmodel.2005.03.026.

Phillips SJ, Dudik M. 2008. Modeling of species distributions with Maxent: New extensions and a comprehensive evaluation. Ecography 31: 161-175. DOI: 10.1111/j.0906-7590.2008.5203.x.

Prayogo C, Sholehuddin N, Putra EZHS, Rachmawati R. 2019. Soil macrofauna diversity and structure under different management of pine-coffee agroforestry system. J Degrad Min Lands Manag 6 (3): 1727-1736. DOI: 10.15243/jdmlm.2019.063.1727.

Rahmawaty, Frastika S, Rauf A. 2019. Spatial analysis for *Pinus merkusii* land suitability at agroforestry land in Telagah Village Sumatera Utara Indonesia. IOP Conf Ser: Mater Sci Eng 593 (1): 012017. DOI: 10.1088/1757-899X/593/1/012017.

Ramadhani F, Girsang E, Florenly. 2021. The bioactive of *Pinus merkusii* needle and bark extract as antioxidant and antiaging. Jurnal Kimia dan Pendidikan Kimia 6 (1): 78-88. DOI: 10.20961/jkpk.v6i1.45371.

Ritung S, Nugroho K, Mulyani A, Suryani E. 2011. Petunjuk Teknis Evaluasi Lahan untuk Komoditas Pertanian. Edisi Revisi 2011. Balai Besar Penelitian dan Pengembangan Sumberdaya Lahan Pertanian, Bogor. [Indonesian]

Sadili A. 2015. Autekologi pertumbuhan *Pinus* (*Pinus merkusii* Jungh. Et De Vriese) paska erupsi di Gunung Galunggung, Kabupaten Tasikmalaya-Jawa Barat. Jurnal Ilmu-Ilmu Hayati 14 (3): 241-248. [Indonesian]

Sallata MK. 2013. *Pinus* (*Pinus merkusii* Jungh et de Vriese) dan keberadaannya di Kabupaten Tana Toraja, Sulawesi Selatan. Info Teknis EBONI 10 (2): 85-98. [Indonesian]

Sandri Y, Maideliza T, Masyurdin, Febriamansyah R. 2016. Kajian anatomi kayu pada tiga ekotipe *Pinus merkusii* Sumatera dan potensinya sebagai indikator perubahan iklim. Jurnal Metamorfosa 3 (2): 103-111. [Indonesian]

Setyawan AD, Supriatna J, Nisyawati, Nursamsi I, Sutarno, Sugiyarto, Sunarto, Pradan P, Budiharta S, Pitoyo A, Suhardono S, Setyono P, Indrawan M. 2021. Projecting expansion range of *Selaginella zollingeriana* in the Indonesian archipelago under future climate conditions. Biodiversitas 22: 2088-2103. DOI: 0.13057/biodiv/d220458.

Setyawan AD, Supriatna J, Nisyawati, Sutarno, Sugiyarto, Nursamsi I. 2018. Predicting impacts of future climate change on the distribution of the widespread selaginellas (*Selaginella ciliaris* and *S. plana*) in Southeast Asia. Biodiversitas 19: 1960-1977. DOI: 10.13057/biodiv/d190548.

Siregar UJ, Diputra IMMM. 2013. Keragaman genetik *Pinus merkusii* Jungh. et de Vriese strain Tapanuli berdasarkan penanda mikrosatelit. Jurnal Silvikultur Tropika 4 (2): 88-99. [Indonesian]

Sitompul H. 2019. Analisis vegetasi tumbuhan bawah pada tegakan alam *Pinus merkusii* Jungh et de Vriese strain Tapanuli di Kabupaten Tapanuli Utara, Provinsi Sumatera Utara. Departemen Konservasi Sumberdaya Hutan Fakultas Kehutanan Universitas Sumatera Utara, Medan. [Indonesian]

Sulton MN, Putri NRA, Nugraheni RS, Afifah RN, Fadilah RN, Indrawan M, Kusumaningrum L, Sutarno, Sunarto, Sugiyarto, Pradhan P, Setyawan AD. 2023. Estimating carbon storage using remote sensing in the Selo Resort forest area of Mount Merbabu National Park, Central Java, Indonesia. Biodiversitas 24: 6264-6270. DOI: 10.13057/biodiv/d241149.

Wang F, Yuan X, Sun Y, Liu Y. 2024. Species distribution modeling based on MaxEnt to inform biodiversity conservation in the Central Urban Area of Chongqing Municipality. Ecol Indic 158: 111491. DOI: 10.1016/j.ecolind.2023.111491.

Wang W, Tang X, Zhu Q, Pan K, Hu Q, He M, Li J. 2014. Predicting the impacts of climate change on the potential distribution of major native non-food bioenergy plants in China. PLoS ONE 9 (11): e111587. DOI: 10.1371/journal.pone.0111587.

Wijayanto A, Dumarcay S, Charbonnier CG, Sari RK, Syafii W, Gerardin P. 2015. Phenolic and lipohilic extractive in *Pinus merkusii* Jungh. Et de Vries knots and stemowood. Ind Crops Prod 69: 466-471. DOI: 10.1016/j.indcrop.2015.02.061.

Woodin SA, Hilbish TJ, Helmuth B, Jones SJ, Wethey DS. 2013. Climate change, species distribution models, and physiological performance metrics: predicting when biogeographic models are likely to fail. Ecol Evol 3 (10): 3334-3346. DOI: 10.1002/ece3.680.

Yang XQ, Kushwaha SPS, Saran S, Xuc J, Roy PS. 2013. Maxent modeling for predicting the potential distribution of medicinal plant, *Justicia adhatoda* L. in Lesser Himalayan foothills. Ecol Eng 51: 83-87. DOI: 10.1016/j.ecoleng.2012.12.004.

Yoon S, Lee WH. 2021. Methodological analysis of bioclimatic variable selection in species distribution modeling with application to agricultural pests (*Metcalfa pruinosa* and *Spodoptera litura*). Comput Electron Agric 190: 106430. DOI: 10.1016/j.compag.2021.106430.

Zhang J, Hu Y, Zhu C, Flogel S, Fang X, Sun J. 2023a. Modeling The effects of global cooling and the Tethyan Seaway closure on North African and South Asian climates during the middle miocene climate transition. Palaeogeogr Palaeoclimatol Palaeoecol 619: 111541. DOI: 10.1016/j.palaeo.2023.111541.

Zhang K, Yao L, Meng J, Tao J. 2018. Maxent modeling for predicting the potential geographical distribution of two peony species under climate change. Sci Total Environ 634: 1326-1334. DOI: 10.1016/j.scitotenv.2018.04.112.

Zhang Q, Shen Z, Pokhrel Y, Farinotti D, Singh VP, Xu CY, Wu W, Wang G. 2023b. Oceanic climate changes threaten the sustainability of Asia's water tower. Nature 615: 87-93. DOI: 10.1038/s41586-022-05643-8.