Future Spatial Prediction of Invasive Plant *Merremia peltata* in Indonesia

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**Abstract.** *Merremia peltata* is a woody vine that considered as invasive plant. It causes serious threats to the regeneration of native plant. Many strategies to control its invasiveness have been continuously implemented, but climate change causes complicated problems. This study aimed to understand the impact of climate change to its current and future distribution. Ensemble model by combining Random Forest and Support Vector Machine was used to predict its distribution. There were 33 occurrence records derived from Global Biodiversity Information Facility and reliable scientific journals. The 19 climatic variables were tested using a multicollinearity test. AUC and TSS were used to evaluate the model. Multicollinearity test using 0.7 threshold produces 7 selected climatic variables. AUC and TSS have the value >0.80 indicating the model has good performance. The predictive future distribution map shows that its distribution shifts to other regions in 2070 compared to the predictive current distribution. The predictive current distribution covers 30.4 % of the total land areas of Indonesia, while the predictive future distribution (RCP 4.5) covers 28.12 % and RCP 8.5 covers 23.59 %. It indicates that the suitable geographic distribution areas of *M. peltata* reduces around 3-7 % of the total areas of Indonesia in 2070.

1. **Introduction**

*Merremia peltata* is a woody climbing vine that has a large underground tuber [1]. It has a long stem which is able to climb and smother a tall tree up to 20 m [2]. It is considered as a fast-growing species that occupying the edges of primary and secondary lowland rainforest [3], forest clearing areas and plantation areas [2]. It can be able to grow by emerging the roots from its nodes, the broken stem fragments are able to resprouting and rooting [4]. It also spreads by seeds and unintentionally transporting by human activities or movement of soils [5].

Climate change causes the distribution shift of invasive plant species in global and regional scale [6,7,8]. It creates a suitable habitat for invasive species and increases the risk of invasion process in the new invaded areas [9,10]. The invasive species tend to more adaptable and tolerant to the new climate condition [11]. The management control of invasive plant species by considering the impact of climate change is expected to minimize the invasion risk of this species in the future [12]. In addition, identifying the potential distribution is required to understand the further spread of this species [13]. Bioclimatic
modelling by using several climatic variables as predictors, is one of approaches to know the effect of climate change to the distribution of species [14]. Species Distribution Modelling incorporates presence records and several climate variables to predict the distribution of invasive plant species [15,10]. It is widely used to predict the potential suitable condition for invasive species [8,16,17]. Ensemble model is one of algorithms of machine learning that has been implemented to predict the species distribution [18,19] It produces more accurate prediction than single model [20,21]. This study aimed to identify the geographic distribution that have similar environmental factors where this species found. It is not possible to survey all locations to collect occurrence records due to financial limitation and time restriction. The modelling approach is expected to provide plausible predictive distribution map across the island of Sumatra.

2. Methods

2.1. Occurrence records
There are 33 occurrence points that recorded throughout regions of Indonesia. Those occurrence records are recorded in Sumatra, Kalimantan, Java, Sulawesi, North Moluccas, Moluccas, and West Papua (figure 1).

![Figure 1. The occurrence records that were extracted from Global Biodiversity Information Facility (GBIF).](image)

2.2. Species Distribution Modelling (SDM)
A total of 33 Occurrence records were derived from Global Biodiversity Information Facility [22]. The current climate data was extracted from the WorldClim 1.4 database [23,24]. The 19 climatic variables were used as predictors of the model. The future climate data were extracted from climate projection from Global Climate Models (GCM) that were downscaled and calibrated using WorldClim 1.4 as baseline climate. Two greenhouse gas scenarios (RCP 4.5 and RCP 8.5) in time period 2070 (average for 2061-2080) were used to predict the future distribution of the species. Spatial data was prepared using Quantum GIS Version 2.18.24 [25]. Multicollinearity test was used to eliminate strong variables among each other. Multicollinearity test was run using the R package “usdm” [26]. The R “dismo” and R “sdm” package were used to produce the predictive current and future geographic distribution model [27]. The modelling process requires several steps to produce the spatial prediction of invasive plant species M. peltata (figure 2).
Figure 2. The modelling process by involving bioclimatic variables as predictors of the model.

3. Results and discussion

The multicollinearity test eliminates strong collinearity among variables. There are 7 climatic variables are selected as the inputs of model, these are Mean diurnal range, mean temperature of wettest quarter, precipitation of coldest quarter, precipitation of warmest quarter, precipitation of wettest month, precipitation seasonality, and temperature seasonality (figure 3). Collinearity creates a serious problem because it leads the wrong identification of important predictors on statistical analysis [28]. Therefore, removing some strong correlated variables are necessarily required.

According to the observed occurrence records, Merremia pelatata is evenly distributed in entire regions of Indonesia. Most of the occurrence records are found in Kalimatan, followed by Sumatra and Java. This species is commonly found in dry lowland areas from above sea level up to 700 m [29, 3]. It often occupies the edge of primary forest, secondary forest, forest plantation and other commercial plantations [3, 30, 31]. The areas that have been opened and cleared to plantation and agriculture uses are prone to be invaded by this species. Predictive current distribution maps demonstrates that several regions that considered as the suitable geographic distribution of M. pelatata, these areas are small islands that located in Western Coast of Sumatra, small parts of Western side of Sumatra along Bukit Barisan Mountains range, small parts of Aceh, North Sumatra, Riau, most areas of Jambi, South Sumatra, Lampung, Banten, West Java, Central Java, small parts of East Java, most regions of West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, small part of North Kalimantan, most regions of West Sulawesi, some regions of Central Sulawesi, South Sulawesi, North Maluku and West Papua (figure 4).
Figure 3. Selected climatic variables using multicollinearity test.

Figure 4. Predictive current geographic distribution.

Future distribution in 2070 (RCP 4.5) shows that almost all regions in Western side of Sumatra along Bukit Barisan Mountains range, most regions of Banten, West Sumatra and small parts of Central Java, Bangka Belitong, small parts of Central Kalimantan, small parts of South Kalimantan, some regions of East Kalimantan, most regions of North Sulawesi, Gorontalo, South Sulawesi, some regions of West Sulawesi, Central Sulawesi, some regions of North Maluku, small parts of West Papua and some regions of Papua (figure 5). Future distribution in 2070 (RCP 8.5) prediction shows that some regions of Aceh, Jambi, South Sumatra, Lampung, some regions of Banten, West Java, East Java, and East Java, most regions of Central Kalimantan, East Kalimantan, South Kalimantan, most regions of West Sulawesi, some regions of South Sulawesi, some regions of Southeast Sulawesi, some regions of Central Sulawesi, most regions of North Moluccas, Moluccas and some regions of West Papua (figure 6).
Figure 5. Predictive future geographic distribution (RCP 4.5).

Figure 6. Predictive future geographic distribution (RCP 8.5).

*M. peltata* has the suitable geographic distributions around 30.4% of total terrestrial areas of Indonesia based on predictive current distribution map (figure 7). It is aligned to the observed occurrence records in which this species is evenly spread in almost entire regions in Indonesia. The predictive future distribution in RCP 4.5 scenario shows that the suitable geographic distribution tends to decrease compared to predictive current distribution. Its predictive future distribution in year 2070 covers the areas around 28.12% of total areas of Indonesia (figure 8). The predictive future distribution using RCP 8.5 tends to decrease with the covering areas around 23.15% of total areas (figure 9). The suitable geographic areas of invasive species *M. peltata* tends to reduce in 2070 for both RCP 4.5 and 8.5 scenarios. It is presumably that the change of temperature and precipitation in the future climate projection may create unsuitable habitat for this invasive plant species. The land and ocean temperature has increased at an average rate of 0.08 degree Celsius per decade since 1880 [32]. Furthermore, the global surface temperature tends to be warmer around 0.5 degree Celsius compared to 1986-2005 average [33].
Figure 7. The suitable geographic distribution in predictive current distribution.

Figure 8. The suitable geographic distribution in predictive future distribution (RCP 4.5_2070).
**Figure 9.** The suitable geographic distribution in predictive future distribution (RCP 8.5_2070).

**Figure 10.** Species response curve to the climate variables.

Species response curve refers to the distribution of species along environmental gradients [34]. The response curve shows that precipitation of the warmest quarter is the most important factor that affecting the distribution of an invasive species *M. peltata*, followed by precipitation of the wettest month (figure 10). The temperature in tropics is not significantly different compared to the temperate regions, but the precipitation is very varied in every season. The climate change is not limited to rising temperature, but it also changes the precipitation rate. The higher temperature causes the greater evapotranspiration rate.
It leads the surface areas become drying and causes long period of drought [35]. However, the precipitation rate increases in some areas during the global warming periods. According to the CIMP 5 model prediction between 1981-2000 and 2081-2100, global warming causes the dry areas becoming drier and wet areas becoming wetter, especially in the mid and high latitude areas. Another finding showed that the areas near equator tend to largely increase in precipitation [35].

4. Conclusion

The predictive future distribution of *Merremia peltata* tends to shift in another region as the impact of global climate change. The invaded areas in the future prediction will decrease compared to the predictive current distribution.

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