MODELING SPECIES DISTRIBUTION OF *Shorea guiso* (Blanco) Blume AND *Parashorea malaanonan* (Blanco) Merr IN MOUNT MAKILING FOREST RESERVE USING MAXENT

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ABSTRACT:

Climate change is regarded as one of the most significant drivers of biodiversity loss and altered forest ecosystems. This study aimed to model the current species distribution of two dipterocarp species in Mount Makiling Forest Reserve as well as the future distribution under different climate emission scenarios and global climate models. A machine-learning algorithm based on the principle of maximum entropy (Maxent) was used to generate the potential distributions of two dipterocarp species – *Shorea guiso* and *Parashorea malaanonan*. The species occurrence records of these species and sets of bioclimatic and physical variables were used in Maxent to predict the current and future distribution of these dipterocarp species. The variables were initially reduced and selected using Principal Component Analysis (PCA). Moreover, two global climate models (GCMs) and climate emission scenarios (RCP4.5 and RCP8.5) projected to 2050 and 2070 were utilized in the study. The Maxent models predict that suitable areas for *P. malaanonan* will decline by 2050 and 2070 under RCP4.5 and RCP 8.5. On the other hand, *S. guiso* was found to benefit from future climate with increasing suitable areas. The findings of this study will provide initial understanding on how climate change affects the distribution of threatened species such as dipterocarps. It can also be used to aid decision-making process to better conserve the potential habitat of these species in current and future climate scenarios.

1. INTRODUCTION

Globally, it is estimated that 20-30% of plant and animal species will be at higher risk of extinction due to global warming; a significant portion of endemic species may become extinct by the year 2050 or 2100 consequently as global mean temperatures exceed 2-3 °C above pre-industrial levels (Garcia et al., 2013). Over the last three decades, the global climate change has produced numerous shifts in species distribution and in the near future, it is likely to act as a major cause of species extinction—either directly or collegially with other drivers of extinction (Deb et al., 2017). Hence, intensifying endangerment and extinction of species that are already vulnerable, particularly those with strict habitat requirements and dispersal capabilities (Banag et al., 2015; Garcia et al., 2013).

The Dipterocarpaceae family includes around 45 species in 6 genera of which about 46% has been recorded as endemic to the country (Fernando, 2009). Dipterocarps play a significant role in the global timber market industry of South and Southeast Asian countries (Appanah & Turnbull, 1998). The dipterocarps grow in evergreen, semi-evergreen, and deciduous forests. This characteristic of dipterocarps, when it comes to geographical range, flowering phenology, fruiting phenology, and ecological characteristic, makes them highly variable (Deb et al., 2017). Guijo (*Shorea guiso*) and Bagtikan (*Parashorea malaanonan*) are part of the dominant dipterocarp trees in (MMFR) and are classified as Critically Endangered and Vulnerable in the International Union for Conservation of Nature (IUCN) Red List (2017), respectively.

In the recent years, various modeling methods of species distribution have been developed for assessing the potential impacts of climate change, even for areas that undergo incomplete and biased samplings, or for areas where no collections have been made (Garcia et al., 2013). Species distribution models (SDMs) are based on the assumption that the relationship between a given pattern of interest (e.g. species abundance or presence/absence)—a set of factors assumed to control it—can be quantified (Trisurat et al., 2011). Maxent is one of the popular SDMs that is based on presence-only modeling method, which involves maximum entropy modeling (Philips et al., 2006, Philips & Dudik, 2008, Royle et al., 2012). Maxent has been used successfully to predict the distributions of different floral and faunal species (Garcia et al., 2013, Elith et al., 2006). Likewise, Maxent, and SDM in general, is mostly used in conservation-oriented studies (Elith & Leathwick, 2006, Elith et al., 2006,).

In the Philippines, there is currently a little emphasis on the conservation of individual species. This situation is a manifestation of the lack of information about the distribution and conservation status of the species. Given that inadequacy in information, the number of threatened species in the country is just incessantly increasing and various anthropogenic habitat alterations, including climate change, intensify it. The SDMs may be used to derive spatially explicit predictions of environmental suitability for species. According to several studies, SDMs potentially have the capability to play crucial supportive roles in the decision making that concerns spatial conservation (Margules & Pressey, 2000; Addison et al., 2013). With the use of SDMs as a guide in management decisions, it can be utilized in managing biological invasions, identifying and protecting critical habitats, reserve selections, and translocating threatened or captive-bred populations in the country.

The general objective of the study is to model the species distribution of Guijo and Bagtikan in Mt. Makiling Forest Reserve using Maxent. Specifically, this study aims to identify the different variables affecting the habitat distribution of Guijo and Bagtikan; generate the potential habitat distributions of Guijo and Bagtikan in MMFR using Maxent; model future distribution of the species under different climate emission scenarios and global climate models; and recommend potential conservation strategy for the dipterocarp species.

2. METHODOLOGY

2.1 Study Area

Mount Makiling is located at 121°11’ East longitude and 14°08’ North latitude in which it reaches the sky at 1, 090 meters above sea level. It covers a total 4, 244.37 hectares straddling the provinces of Laguna and Batangas in Luzon, Philippines. The Mount Makiling Forest Reserve (MMFR) is an ASEAN Heritage Park which lies within 65 km of Metro Manila. With jurisdiction under the University of the Philippines Los Baños (UPLB), the forest reserve is managed by the Makiling Center for Mountain Ecosystems (MCME) under the College of Forestry and Natural Resources. The mountain has a fair to rough topography culminating at the top with three separate peaks. Several kinds of plants and animals were found abode at the Mt. Makiling Forest Reserve. It houses numerous species of flora with 940 genera, 2, 038 species, 19 sub-species, 167 varieties, and several forms, and cultivars representing 225 families of flowering plants and ferns (Lapitan et al., 2013). The forest reserve has four sub-watersheds namely Molawin-Dampalit, Cambantoc, Greater Sipit, and Tigbi. The four sub-watersheds serve as the basic units for the management of the mountain. In which, the species occurrences of *Shorea guiso* (Guijo) and *Parashorea malaanonan* (Bagtikan) will be taken in the forest reserve.

2.2 Collection and Selection of Species Occurrence Data

The occurrence data of *P. malaanonan* and *S. guiso* used for this study came from a variety of sources including field survey, georeferenced database developed by Ramos et al. (2012) containing 2, 067 records of 47 threatened forest tree species of the Philippines, and literature records.

The Dipterocarpaceae were largely reduced due to massive deforestation in the country during the mid-1900s. However, some of these species were left and are currently dominating the MMFR. The preservation of the species is the aftermath of handiwork efforts of MCME under UPLB. These species were selected for species distribution modeling since they are ecologically, economically, and socio-culturally significant, requiring urgent science-based adaptation strategies to protect them. Only 56 and 34 occurrences of Bagtikan and Guijo, respectively, have been collected, which are still within the minimum requirement to predict occurrence of species for SDM is (van Proosdij et al., 2016).

2.3 Environmental Variables

Twenty-six (26) environmental variables were used in the study. These included seven biophysical variables and 19 bioclimatic variables. All 26 environmental variables in 5m x 5m resolution were used as potential predictors of species distribution. All data were processed using the same extent, cell size, and projection system (WGS84 Longitude-Latitude Projection) in ArcGIS 10.5 and converted to Environmental Systems Research Institute (ESRI), American Standard Code II (ASCII), grid format (.asc). The variables were then classified into climatic, topographic, vegetation-related, edaphic, and anthropogenic groups.

2.4 Climate Models and Scenarios

Global Circulation Models (GCMs) are regarded as the most advanced tools nowadays when the aim is to create a simulation of the global climate system’s response to greenhouse gas concentrations that are continuously increasing (Intergovernmental Panel on Climate Change, 2013). To model the future distribution of the species under different climate emission scenarios and global climate models, bioclimatic variables with a spatial resolution of 30 seconds in the period of the year 2041-2060 (2050s) and 2061-2080 (2070s) were collected. These were based on the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC) from http://www.worldclim.com. Two GCMs were selected to be used in this study: Hadley Centre Global Environmental Model, version 2, Earth System (HadGEM2-ES) and Model for Interdisciplinary Research on Climate, Earth System Model (MIROC-ESM). Hereafter, referred to as GCM 1 and GCM 2. These two GCMs were based on the global climate models used by Department of Science and Technology-Philippine Atmospheric, Geophysical and Astronomical Services Administration (DOST-PAGASA) in PAGASA Coupled Model Intercomparison Project Phase 5 (CMIP5) climate change projections in the Philippines (Basconsillo, 2014). For each GCM, two IPCC Representative Concentration Pathways (RCP) scenarios were used, which represented the future greenhouse trajectories: RCP 4.5 and RCP 8.5 for two different time periods (2050 and 2070).

2.5 Species Distribution Modeling

The primary and secondary data collected were processed through editing for checking of some errors and tabulation of the coordinates gathered as an input to the Maxent software and ArcGIS (Figure 1). For the modeling changes in species distribution, Maximum Entropy Species Distribution Modeling (version 3.4.1) software was used in this study (Phillips et al., 2006). Maxent, based on georeferenced occurrence records and environmental, derives the probability of species. It has advantages over other SDMs as it requires species presence-only data, both continuous and categorical variables can be used in Maxent (Deb et al., 2017). During modeling, 75% of the species occurrence data were used as training data to generate species distribution models, and the remaining 25% were kept as testing data to test the accuracy of each model (Deb et al., 2017; Garcia et al., 2013). Initial records of species occurrence were filtered to avoid the bias of clustered points on a cell, ensuring that there was only one record per 5m x 5m pixel (De Alban et al., 2015). The maximum number of background points for sampling was kept at 10,000. The species distribution modeling was executed with the five-cross validated sample model for each run to measure the amount of variability in the model and averaged the results. A maximum number of iterations was set to 1,000 to allow the model to have adequate time for convergence, with 1 x 10^{-5} set as the convergence threshold (Deb et al., 2017). The default auto features were used. These include all features (i.e. linear, quadratic, product, threshold, and hinge features; Merow et al., 2013).

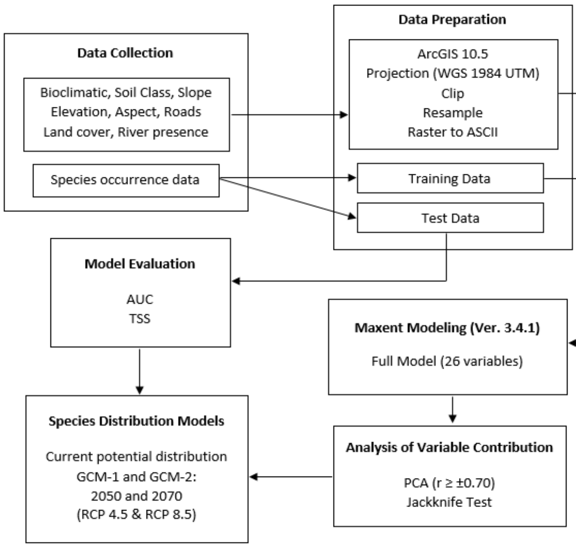

Figure 1. The research flow diagram.

A series of variable reduction and selection stages were done prior to the final modeling. Similar to the procedure of Torres et al. (2016), a series of 'pre-final modeling stages' was done.

Pre-Final Modeling I. The relative variable contribution from the two species probability models were averaged and ranked through the measurement of the jackknife test.

Pre-Final Modeling II. Multi-collinearity test was applied for all 26 variables that were used in the two models to avoid model overfitting. The test was done using the Principal Component Analysis (PCA) tool in ArcGIS 10.5, as demonstrated by Garcia et al. (2013). Through PCA, the variables that were highly correlated ($r \geq \pm 0.70$) were grouped, and only one was retained within each group while the others were removed (Garcia et al., 2013; Torres et al., 2016). The remaining variables were selected based on the ranking of the percentage contribution from the initial Maxent modeling runs.

Final Modeling. All variables remained from 'pre-final modeling' stages were used as inputs for the Final Model.

3. RESULTS AND DISCUSSION

3.1 Determining Variables for Pre-Final and Final Modeling

Only 14 environmental variables out of the 26 original variables were used in the Final Modeling. Table 1 shows the variables used in the Final Model with categorized seven bioclimatic and seven biophysical variables.

3.2 Multi-collinearity Test

All 26 variables were subjected to multi-collinearity by examining the cross-relations between variables (Pearson correlation coefficient, r). Principal Component Analysis (PCA) in ArcGIS 10.5 was used in reducing and selecting the variables as demonstrated by Garcia et al. (2013) and Torres et al. (2016).

Variable Groups	Variables
Bioclimatic Variables	Bio2 Bio3 Bio4 Bio12 Bio15 Bio16 Bio19
Biophysical Variables	Soil type Land Cover Elevation Slope Aspect Distance to Rivers Distance to Roads

Table 1. Variables used in the Final Model.

This was done to avoid harmful collinearity of the variables, as a careful analysis is required in the selection of the most appropriate for each group of highly correlated variables. Based on the result of pre-model runs, only one variable from a set of highly correlated variables was included in the Final Model. The results of the collinearity test showed that 18 variables were highly correlated with other variables.

Of the 18 variables, two variables (Bio 11 and Bio 12) had the highest counts (18) of highly correlated variables, followed by elevation (17), which was correlated with other 8 variables. Elevation had seven climatic variables, which had positive linear correlations, and ten climatic variables, which had negative linear correlations. One topographic variable (slope), one temperature variable and five precipitation variables had positive linear correlations ($r = 0.7659$ to 0.9489) with elevation. This datum suggests that in higher elevations, there is a higher chance of rainfall (Torres et al., 2016). On the other hand, ten climatic variables had negative linear correlations with elevation, suggesting that the temperature is higher in lower elevations (Torres et al., 2016). The other five environmental variables that had no correlation with other variables were used in final modeling.

3.3 Analysis of Variable Significance

Only 14 environmental variables (seven biophysical and seven bioclimatic variables) were used in the Final Modeling. Based on the results, the distributions of the dipterocarp species are largely determined by biophysical variables (89%) more than bioclimatic variables (11%). However, this does not suggest that biophysical variables are more important than bioclimatic variables as they are inherently, spatially, and temporally auto-correlated (Schrag et al., 2007). This only suggests that groups of biophysical variables are acting together to influence the occurrence of each species. As such, it is difficult to separately interpret the importance of each variable from the models based on their percent contribution alone.

Moreover, it also suggests that there might be some bioclimatic variables that could have provided further explanation for the occurrence of threatened forest tree species that were not included in the final modeling process. Therefore, it is suggested that the quantity and types of variables must be considered in the modeling stage. Likewise, limiting the number and selecting only the most appropriate ones for a species is crucial to maximize the performance of SDMs and the accuracy of the predictions (Araújo & Guisan, 2006; Barbet-Massin & Jetz, 2014; Braunisch et al., 2013). Consequently, having inaccurately predicted distribution could impede the success of conservation management efforts and decision- making. As such, expert opinion and knowledge of the ecological niche of the species should be taken into account as much as possible during the identification and selection of environmental variables. This also suggests that in future studies, knowledge of the edaphic requirements of the species should be considered as these may have an influence on the dipterocarp community composition at the local scale (Sukri et al., 2012). This can be explained by identifying the soil classification using soil taxonomy of the forest soils, which would integrate climate factors such as rainfall and temperature at the soil sub-family level. Moreover, the phenological patterns of the two dipterocarp species are also important to be considered. Additionally, their relationship with climatic seasonality as a change in plant phenology will be one of the earliest responses to rapid global climate change and could have potentially serious consequences for plants that depend on periodically available plant resources (Corlett & Lafrankie, 1998).

Among the bioclimatic variables, Bio 16 (precipitation of wettest quarter) has the highest percent contribution (4.3%) for *S. guiso*, while Bio 19 (precipitation of coldest quarter) has the highest percent contribution (5%) for *P. malaanonan*. This means that the occurrence of Guijo and Bagtikan are mainly influenced by these two bioclimatic variables: Bio 16 and Bio 19, respectively (Figure 2). Precipitation of wettest quarter (Bio 16) is a quarterly index, approximating the total precipitation that prevails during the wettest quarter, while the precipitation of coldest quarter (Bio 19) is a quarterly index, approximating the total precipitation that prevails during the coldest quarter (O'Donnell & Ignizio, 2012). This suggests that the two dipterocarp species favor habitat with abundant rainfall all year-round. However, significant seasonal variation in temperature and rainfall may also restrict the growth of these two dipterocarp species. In Southeast Asia, the distributions of dipterocarps are being controlled by climatic conditions at different elevation gradient (Appanah et al., 1998 as cited by Torres et al., 2016). Moreover, its distribution was obstructed by the conjunction of altitude and other natural barriers, and occupancy of several phytogeographical regions, which mainly conform to climatic and ecological factors.

Dipterocarps are usually confined mainly in areas with a mean annual rainfall exceeding 1,000 mm and/or dry season of only short duration, with the majority of the species occurring in areas with 2,000 mm mean annual rainfall (Ashton, 1982). Forests in which the dominant trees are species of Dipterocarpaceae, the species usually reside on deep clay loam soil. However, dipterocarp trees may also occur over different substrates with different degrees of water stress and they may not often be the dominant species in the area. On the other hand, Bio 2 (Annual mean diurnal range) and Bio 4 (temperature seasonality) have the least percent contribution (0.1%) to the Maxent models of Bagtikan. Bio 3 (Isothermality) and Bio 4 have no percent contribution for Guijo.

For biophysical variables, land cover (60.3%) has the highest percentage contribution, followed by roads (15.2%), and slope (5.9%) for *P. malaanonan*. For *S. guiso*, slope (35.5%) has the highest percentage contribution, followed by soil classification (28.2%) and land cover (16.9%). Hence, land cover and slope have more impact on predicting the occurrence of Bagtikan and Guijo, respectively (Figure 3). On the other hand, elevation has the least impact for both dipterocarp species with 0.6% and 0%, respectively. Dipterocarp forests usually occur in the lowlands ranging from 0 to 1,200 meters in elevation and they occupy the emergent stratum, although they are also found in the understory (Ashton, 1988). Dipterocarp trees can occupy mature stages of primary forest and they can also colonize secondary forests (Appanah & Turnbull, 1998).

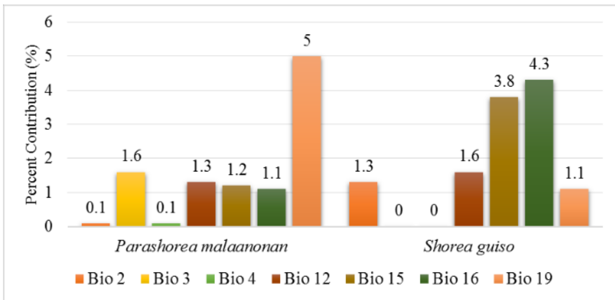

Figure 2. Percent contribution of bioclimatic variables derived from Maxent models and its influence on the geographic distribution of *P. malaanonan* and *S. guiso*.

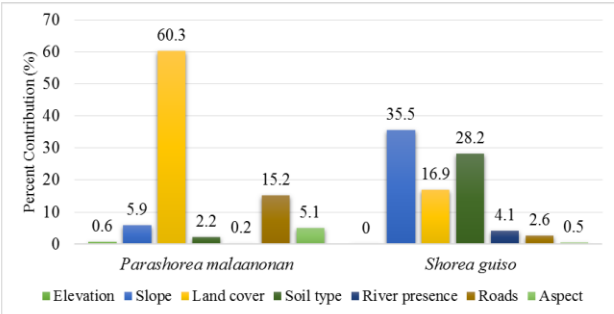

Figure 3. Percent contribution of biophysical variables derived from Maxent models and its influence on the geographic distribution of *P. malaanonan* and *S. guiso*.

Based on the study of Torres et al. (2016), land cover (6.72%) significantly contributed to four threatened dipterocarp species in Northern Sierra Madre Natural Park (NSMNP). The study also found out that distance to roads (27.14%) also significantly contributed to the prediction of the distribution of four dipterocarp species in NSMNP. In relation to this, the impacts of land use change. An example of which is the planned main road construction crossing the NSMNP; it will be a major influence on species distributions, especially in the creation of access points for logging and land transition. Relating to the study, the construction and improvement of access roads in MMFR may also affect the prediction of the distribution of *P. malaanonan* (15.2%). This suggests that the distribution of *P. malaanonan* may be determined by anthropogenic factors (human activity) and not only by topographic and climatic factors.

Among the four topographic variables, slope was the highest contributor for both dipterocarp species. Distance to rivers contributed with values of 0.2% and 4.1% for Bagtikan and Guijo, respectively. Moreover, aspect and elevation contributed 5.1% and 0.6% for Bagtikan. As for Guijo, aspect contributed 0.5% while elevation has no contribution in predicting the occurrence of Guijo. In the study conducted by Sukri et al., 2012, it was shown that environmental variables, particularly topography, are associated with dipterocarp community compositions at a local scale. Similar results about the significant associations of dipterocarps with topography were also reported

(Bunyavechewin et al., 2003; Gunatilleke et al., 2006; Suzuki et al., 2009). However, topographic factors may also vary from one species to another (Torres et al., 2016) since it will affect the distribution of soil nutrients in a particular area (John et al., 2007). In MMFR, Macolod (Lithic Eutrudalfs) and Lipa (Typic Eutrudalfs) soil classification dominate the mountain ranging from 200 – 800 meters (Khan, 1969). These soil types may have different characteristics related to the underlying parent material which may contributed greatly to the growth and survival of dipterocarps.

3.5 Jackknife Test of Variable Importance

Maxent provides an analysis of the importance and relative contributions of the variables to the model using jackknife. This test can help the modelers to decide on which variables are relevant. According to Phillips et al. (2004), the jackknife is designed to predict areas which fulfill the requirements for species' ecological niche where conditions are suitable for the survival of species. For *P. malaanonan*, results of the test showed that land cover had the highest gain of 2.2606 when used in isolation, which appears to have the most useful information. Then, annual precipitation (Bio 12) had the next highest gain with 1.7760, followed by slope with 1.7061. The environmental variable with the most decrease in gain when it is omitted was roads—appearing to have the most information that was absent in other variables. The Jackknife test also revealed that distance to rivers and distance to roads had the lowest gain of 0.0667 and 0.1644 when used in isolation, respectively. For *S. guiso*, the Jackknife test results showed that the variable with the highest gain, when used in isolation, was slope (2.0157). Slope appears to have the most useful information by itself. Then, it was followed by soil classification with a gain of 1.7528 and annual precipitation (Bio 12) with a gain of 1.5364. On the other hand, the environmental variable that decreases the gain the most was land cover when it is omitted. It appears to have the most information that is absent from other variables. The jackknife test also revealed that distance to roads and annual mean diurnal range (Bio 2) had the lowest gain of 0.1120 and 0.1488 when used in isolation, respectively. This study was able to determine the environmental factors that influence and limit the distribution of *P. malaanonan* and *S. guiso* using Jackknife test in Maxent. All of the biophysical (land cover, soil classification, and slope) and bioclimatic (Bio 12 and Bio 19) variables played significant roles in influencing the presence and distribution of species.

3.6 Shift in geographic distribution of suitable and unsuitable areas of dipterocarp species between potential current and future distribution

Based on the results of the Maxent modeling, the predicted current and future habitat ranges of *P. malaanonan* and *S. guiso* were likely to be affected positively and negatively by future climate. *S. guiso* was found to benefit from future climate while *P. malaanonan* will experience a decline in its suitable habitat. As shown in Figure 4, about 193.40 hectares of land is suitable for *P. malaanonan*. However, the suitable areas will be decreased by 7.21% and 3.13% under RCP 4.5 and RCP 8.5 in the year 2050; and decreased by 10.11% and 16.44% under RCP 4.5 and RCP 8.5 in the year 2070, respectively. This suggests that the predicted distribution of suitable habitat for *P. malaanonan* will be disturbed by future climate condition. Dipterocarp trees are confined to wet climates, with a dry season of four months and more abundant in a seasonal than seasonal climates (Ashton, 1988). Significant climatic anomalies such as increasing temperature seasonality and drought conditions may affect the growth of these dipterocarp trees (Deb et al., 2017).

However, *S. guiso* will benefit from future climate since the prediction showed an increase in suitable areas from 86.55 ha to 105.97 ha, and 140.05 ha under RCP 4.5 and RCP 8.5 in the year 2050; to 102.56 ha and 101.49 ha under RCP 4.5 and RCP 8.5 in the year 2070 (Figure 7). This suggest that different climate scenarios could have positive effects on predicting suitable areas of *Shorea guiso*.

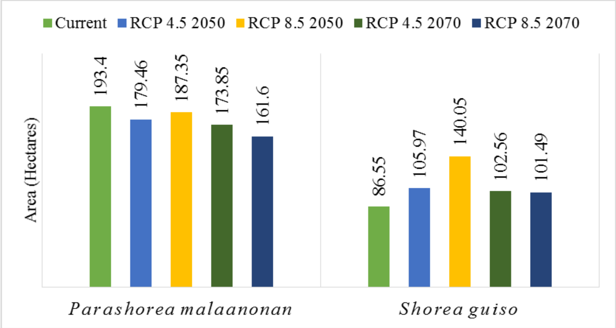

Figure 4. Current and future suitable areas of *P. malaanonan* and *S. guiso* under different climate scenarios.

The current distributions of *P. malaanonan* and *S. guiso* in Mt. Makiling are shown in Figures 5. Moreover, the projected distribution of the dipterocarp species is shown in Figures 6 to 9 for *P. malaanonan* and *S. guiso*.

4. CONCLUSIONS AND RECOMMENDATIONS

Besides deforestation, climate change is becoming another serious threat to the world's biodiversity nowadays because it causes drastic impacts on the distribution of species and the composition of habitats. In this study, the effect of climate change on the geographical distribution of *P. malaanonan* and *S. guiso* were assessed in Mt. Makiling Forest Reserve. The study incorporated the use of global climate models, MIROC-ESM and HadGEM2-ES in RCP 4.5 and RCP 8.5 for years 2050 and 2070, for the modeling of future distributions of the dipterocarp species. The environmental variables with the highest contribution were also identified. These are the environmental variables which may affect the habitat distribution of *P. malaanonan* and *S. guiso*. Following this, a machine-learning algorithm based on the principle of maximum entropy (Maxent) was used to generate the potential distributions of the dipterocarp species.

The study revealed that biophysical variables (89%) more than bioclimatic variables (11%) largely determined the distributions of *P. malaanonan* and *S. guiso*. For *P. malaanonan*, land cover (60.3%) had the highest percentage contribution followed by roads (15.2%), and slope (5.9%). As for *S. guiso*, slope (35.5%) had the highest percentage contribution, followed by soil classification (28.2%), and then land cover (16.9%). Among the bioclimatic variables, Bio 16 (precipitation of wettest quarter) had the highest percent contribution (4.3%) for *S. guiso* while Bio 19 (precipitation of coldest quarter) had the highest percent contribution (5%) for *P. malaanonan*. However, these do not necessarily imply that bioclimatic variables are less important than biophysical variables as they are spatially and temporally correlated (Garcia et al., 2013). It could have resulted from the

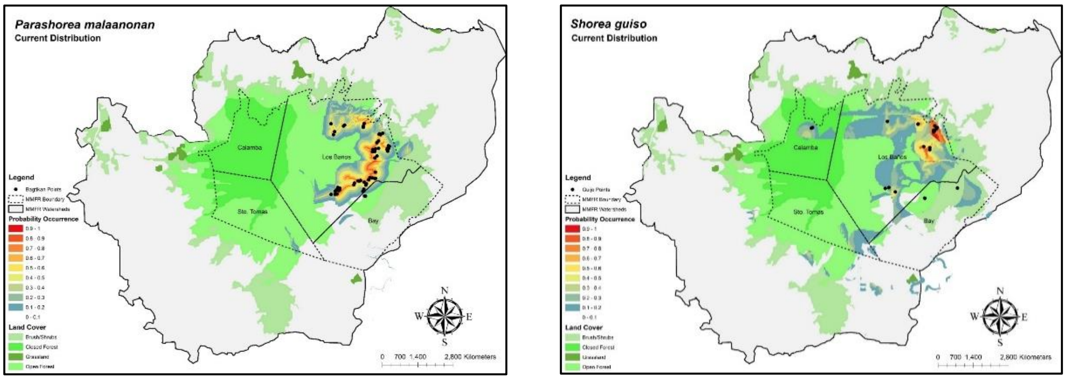

Figure 5. Current distribution of *Parashorea malaanonan* (L) and *Shorea guiso* (R) in MMFR.

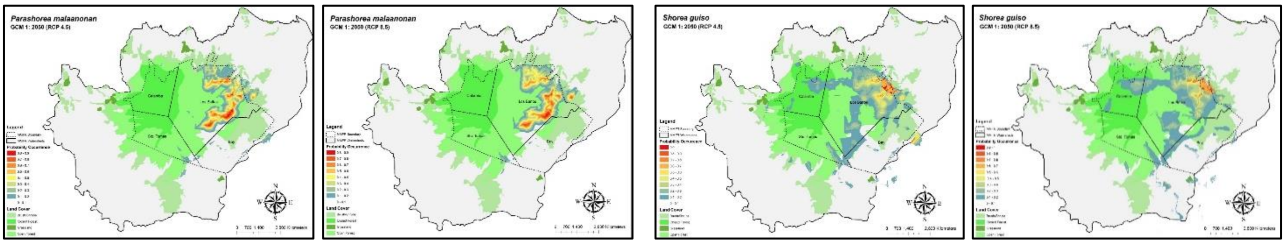

Figure 6. Predicted distribution of *Parashorea malaanonan* (L) and *Shorea guiso* (R) for GCM-1 by year 2050 under RCP 4.5 and RCP 8.5.

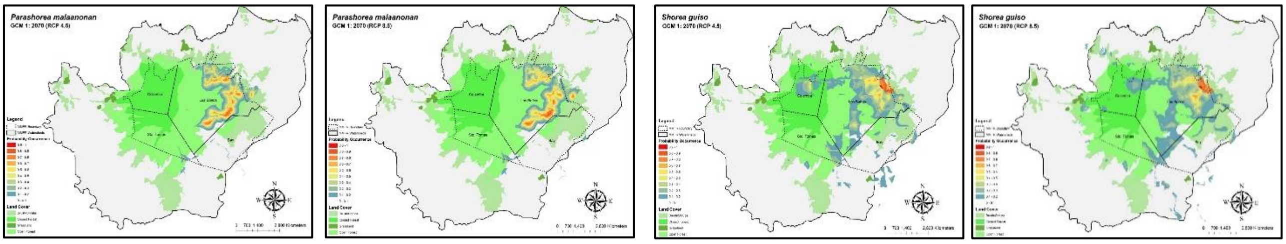

Figure 7. Predicted distribution of *Parashorea malaanonan* (L) and *Shorea guiso* (R) for GCM-1 by year 2070 under RCP 4.5 and RCP 8.5.

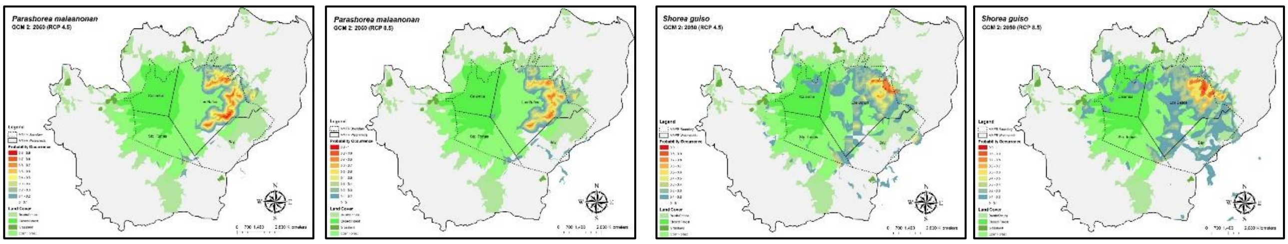

Figure 8. Predicted distribution of *Parashorea malaanonan* (L) and *Shorea guiso* (R) for GCM-2 by year 2050 under RCP 4.5 and RCP 8.5.

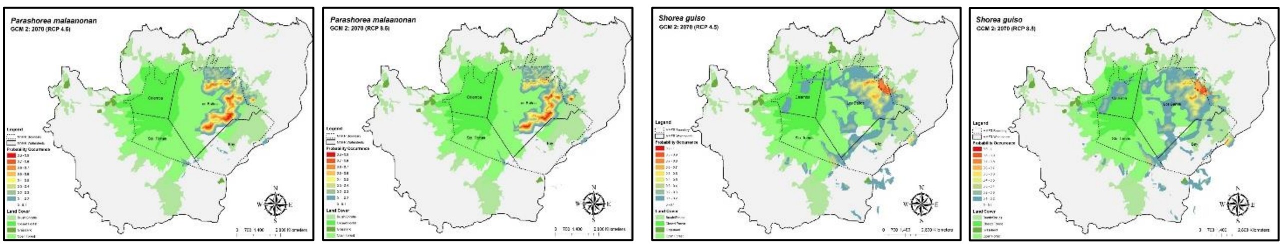

Figure 9. Predicted distribution of *Parashorea malaanonan* (L) and *Shorea guiso* (R) for GCM-2 by year 2070 under RCP 4.5 and RCP 8.5.

reduction of spatially and auto-correlated variables, in which there might be some bioclimatic variables that could have further explained the occurrence of dipterocarp species. Hence, careful consideration is recommended for the quantity and types of variables to be included in the modeling especially on the selection of climate variables, which should be based on sound ecological causality and strict physiological tolerance thresholds to climatic conditions (Braunisch et al., 2013). Aside from the future effects of climate change, land cover/land use changes should also take into account in the modeling, since it is considered as one of the main drivers in predicting species' potential distribution (Sirami et al., 2016). The high correlation of land cover and habitat distribution of *P. malaanonan* and *S. guiso* suggest that the protection of the forest cover of MMFR should be maintained in order to conserve these dipterocarp species.

Results also showed that the potential distributions of *P. malaanonan* will likely experience a decline in its suitable habitats while *S. guiso* will benefit under projected climate scenarios. However, the study only assessed how *P. malaanonan* and *S. guiso* responded geographically to climate change using Maxent modeling, which is a correlative model that only required readily available species occurrence data and environmental information. Hence, it is recommended to apply other than SDM such as alternative ecological niche modeling (ENM), mechanistic model, which determined the fundamental niche of species by its physiology. It could build a causal relationship between species distribution and environmental variables. Incorporating both correlative and mechanistic models in future studies could provide a more accurate prediction of species' responses to climate change.

The findings of this study can be tailored to suit conservation guidelines for *Parashorea malaanonan* and *Shorea guiso*. It will also provide initial knowledge and literature on how climate change affects the distribution of threatened species of dipterocarps. Moreover, it can be used as a guide in decision-making to better conserve the potential habitat of the species in current and future climate scenarios as well as basis in developing appropriate science-based conservation strategies, policies, and initial measures that could enhance the resilience of these particular dipterocarp species.

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