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Modeling Future Spatial Distribution of *Shorea palosapis* (Blanco) Merr and *Shorea polysperma* (Blanco) Merr in Northern Sierra Madre Natural Park Using Maxent

ABSTRACT

This study determined the potential effects of present and future climates on the geographical distribution of Shorea palosapis (Blanco) Merr. and Shorea polysperma (Blanco) Merr in Northern Sierra Madre Natural Park (NSMNP) using Maximum Entropy model. A total of seven models were generated for each species: one Climatic-Only model, four Partial models (combination of four variable groups with climatic variables), one Full model (used 30 original variables), and one Final model (used 18 uncorrelated variables after a series of variable reduction methods). The models' relative predictive performance was evaluated using Area Under Curve (AUC) and True Skill Statistics (TSS). The Final model performed best both for S. palosapis (AUC = 0.8763; TSS = 0.8176) and S. polysperma (AUC = 0.8626; TSS = 0.8332). Analysis of variable importance revealed that species distributions were largely determined by climatic variables (34.35%) followed by anthropogenic variables (27.25%) and topographic variables (24.15%), while vegetation-related (7.58%) and edaphic variables (6.67%) had relatively lesser contribution. The probabilities of occurrence of the species changed and were found to benefit from future climate with increasing suitable habitat range. This study will provide practitioners with early warning estimates of how climate change may affect the distribution of endangered species. Furthermore, this will also assist decision-makers especially in mainstreaming climate change in the NSMNP management plan to better conserve potential suitable habitats of priority species.

Key words: *Maximum Entropy, forest trees, climate change, species distribution, protected area*

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INTRODUCTION

The Northern Sierra Madre Natural Park (NSMNP) is one of the largest and most diverse protected areas (PAs) in the Philippines. It covers a total of 359,486 ha of terrestrial and coastal areas in the province of Isabela in northeast Luzon. It houses numerous species of flora, of which many are rare and endemic but threatened due to habitat alteration. Due to its inherent high conservation value, it was selected to be one of the ten priority sites of the National Integrated Protected Area System (NIPAS). Through the years, NSMNP has experienced massive exploitation that led to the decline of its forest resources and biodiversity (*DENR 1997; Nordic Agency for Development and Ecology; DENR 2001*). It is believed that climate change will exacerbate current conditions of the forests and their biodiversity.

Currently, there is very little knowledge on how future climates can affect the potential distribution of forest tree species in the Philippines. Prediction of potential suitable habitat of these species is critical for conservation and monitoring, and is also vital information in the restoration efforts of the country. Nowadays, species distribution models (SDMs) are increasingly proposed to support conservation decision-making. However, evidence of SDMs supporting solutions for on-ground conservation problems is still scarce in the scientific literature (*Guisan et al. 2013*). To effectively guide conservation actions, modelers need to better understand the decision process, and decision makers need to provide feedback to modelers regarding the actual use of SDM to support conservation decisions (*Guisan et al. 2013*). This could be facilitated by individuals or institutions playing the role of 'translators' between modelers and decision makers.

In the face of ongoing and future changes in climate, species must adapt or shift their geographical distributions in order to avoid habitat loss and eventual extinction. Species will shift their geographic distribution to remain at equilibrium with climate. However, tropical forest tree species may not be able to adapt to changing climate due to rapid and sustained changes in climate (*Feeley et al. 2012*). This study aimed to assess the consequences of climate change on the geographical distributions of *S. palosapis* and *S. polysperma* in the NSMNP using Maximum Entropy (Maxent) Model. Specifically, the study evaluated and compared the relative predictive performance of different Maxent species distribution models; identified the variables that affect the geographical distribution of dipterocarp species; and determined the potential suitable habitats of dipterocarp species.

Threatened, indigenous and endemic forest tree species in NSMNP were the priority for species distribution modeling since their ecological, economical and socio-cultural values require urgent science-based adaptation strategies be developed to protect them. On the other hand, environmental variables were chosen based on their biological relevance to plant species distribution and citation frequency in other habitat modeling studies (e.g. *Kumar et al. 2006*; *Guisan et al. 2007a*; *Pearson et al. 2007*; *Muriene et al. 2009*). To save a threatened species is a critical problem in conservation biology because one needs to know first where the species prefers to live and what its requirements are for survival (i.e. ecological niche) (*Hutchinson 1957*). There are various SDM methods available to predict the distribution of a species (*Guisan and Zimmermann 2000*; *Guisan and Thullier 2005*; *Elith et al. 2006*; *Guisan et al. 2007a, b*; *Wisz et al. 2008*). However, comparatively few predictive models have been used for threatened plant species (*Engler et al. 2004*). The species distribution modeling particularly on trees has opened a new perspective in the field of conservation biology. Species distribution data is most of the time not available and collecting such data is costly and labor intensive. Hence, SDMs could be a reliable alternative of conservationist since they have in many cases rely on predictive models for estimating patterns of species distribution and for making conservation strategies. Moreover, SDMs provide one of the best ways to overcome sparseness typical of distributional data, by relating them to a set of geographic or environmental predictors.

A number of recent studies have proven that Maxent performs well in predicting species distribution of floral and faunal species (*Baldwin 2009*; *Kumar and Stohlgren 2009*; *Trisurat et al. 2009 and 2011*; *Weber 2011*; *Garcia et al. 2013*; *Singh 2013*). *Kumar and Stohlgren* (*2009*) used Maxent to predict potential habitats of *Canacomyrica monticola*, a threatened tree species in New Caledonia, using few occurrence records. Results of *Singh* (*2013*) predicted suitable habitats for two critically-endangered dipterocarp tree species, *Shorea johorensis* and *Shorea inappendiculata*, in Borneo. Results showed bioclimatic variables had insignificant effects, given the study was conducted in a relatively small area. However, factors such as land-use and tree cover play a prominent role in determining the distribution of the two species. In Thailand, *Trisurat et al.* (*2009) and Trisurat et al. (2011*) studied the effects of climate change on the distributions of both evergreen and deciduous tree species in peninsular and northern Thailand. In the Philippines, *Garcia et al.* (*2013*) were the first to use Maxent in predicting geographic distributions and habitat suitability based on changes in climate for 14 threatened forest tree species in the Philippines. Of the 14 species, seven forest tree species were found to likely benefit from future climate with potential increases in suitable habitat areas, while the other half will likely experience declines.

This study can provide initial understanding on how changes in the regional climate will affect the distribution of *S. palosapis* and *S. polysperma* in the NSMNP. It may further improve understanding of species-habitat relationships in space and time. The species distribution models and habitat suitability maps generated may also be used as basis in the formulation of appropriate science-based adaptation policies, strategies and measures that can enhance the resilience of those selected forest tree species and their natural ecosystem to current and future climate.

MATERIALS AND METHODS

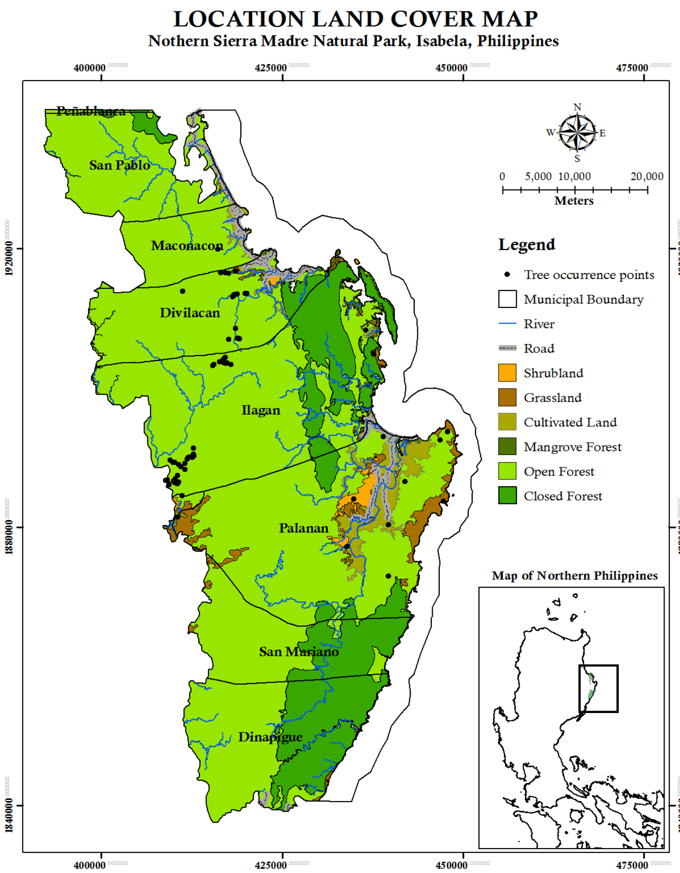
Study Area

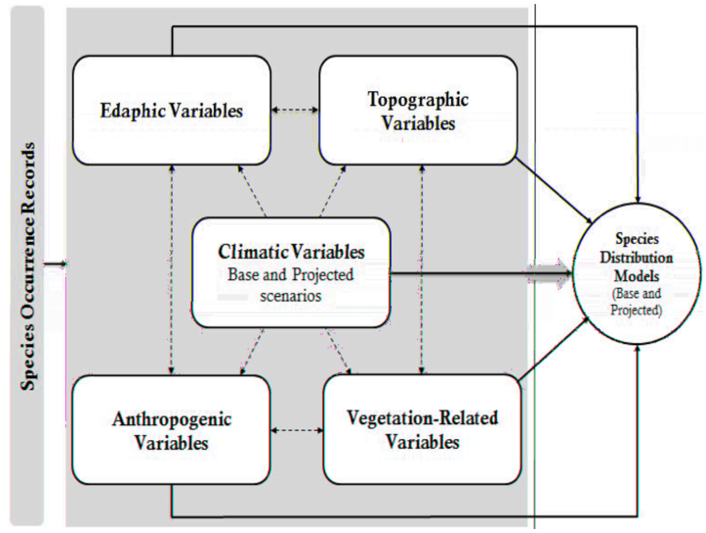
The NSMNP lies on the eastern part of Isabela province covering the municipalities of Maconacon, Divilacan, Dinapigue and Palanan along the eastern seaboard and San Pablo, Cabagan, Tumauini, Ilagan and San Mariano on the western side, as bordered by the Cagayan Valley (**Figure 1**). It includes the mid-section, which stretches from Aurora to Cagayan, of the Sierra Madre Mountain Range. It is bounded by the Dikatayan River to the north, Disabuyan River to the south, Cagayan Valley to the west and the Philippine Sea to the east (*Van der Ploeg et al. 2011*).

The NSMNP is home to a large number of commercially important but severely threatened tree species of the dipterocarp family such as *Shorea* spp. and *Hopea* spp. It also provides habitats to 240 bird species, 78 of which are endemic. Two of the birds found in the park are the Philippine Eagle (*Pithecophaga jefferyi*) and the endemic Isabela Oriole (*Oriolus isabellae*), which is one of the rarest birds in the world (*CI 2011*). The park is also home to two groups of indigenous people, the Agta and the Kalinga, who are highly dependent on its natural resources for their livelihoods. About 25,000 migrant farmers and fishermen live within the multiple-use zone of the park and two million people living in Cagayan Valley depend on the ecosystem services provided by the park.

Study Framework

The prediction and mapping of potential suitable





habitats for threatened and indigenous species is critical in the monitoring and restoration of the declining native populations. However, a challenge to habitat modeling approaches is that the distribution data of these species are often sparse and clustered (*Ferrier et al. 2002; Engler et al. 2004*). Nowadays, species distribution modeling tools are becoming increasingly popular, and are widely used in ecology (*Elith et al. 2006; Peterson 2006*). These models help establish the underlying relationships between the occurrence of species in a particular area and its environment.

Forest trees species distribution, or species habitat requirement is defined by certain environmental variables, and the optimal combination of these factors allows a particular species to thrive in certain areas. This set of environmental variables for plants may directly or indirectly affect its patterns of abundance and distribution in NSMNP. The variables are: topographic factors, climatic factors, anthropogenic factors or threats to species loss, edaphic factors and vegetation-related factors (**Figure 2**). Thus, the study emphasizes the interplay of forces between environmental variables that affect the overall suitability of a given species in a particular region. The Maxent modeling technique then recognizes the relationship between the known range of the species and environmental factors, and uses this relationship to identify species distribution.

Collection and Selection of Species Occurrence Records

The occurrence records of the forest tree species used for this research come from two sources: biodiversity assessments conducted in NSMNP under the B+WISER program; and georeferenced database developed by *Ramos et al.* (*2012*) which contains 2,067 records of 47 threatened forest tree species of the Philippines. These species are often rare and have limited occurrences, posing challenges for creating accurate species distribution models. As such, *S. palosapis* (Blanco) Merr and *S. polysperma* (Blanco) Merr with 24 and 27 occurrences, respectively, were selected for the species distribution modeling.

Environmental Variables

Thirty environmental variables in 1km x 1km resolution were used as potential predictors of species distribution. All data were projected and masked to the NSMNP boundary and converted to 1 km Environmental Systems Research Institute (ESRI) American Standard Code II (ASCII) grid format (.asc). The variables were then classified into five groups: 1) climatic, 2) topographic, 3) edaphic, 4) vegetation and, 5) anthropogenic. In addition, it is assumed that environmental variables were stable, except climatic variables (**Table 1**).

Species Distribution Modeling

Maxent modeling software v3.3 was used for this study. Pre-selected independent variables based on previous studies served as predictors while the occurrence records of selected dipterocarp species were the dependent variable for the study. The data were then entered into the

Variable	Variable (Unit)	Description/Source
Climatic Factors		
Bio 1	Annual mean temperature (°C)	The mean of all the monthly mean temperatures. Each monthly mean temperature is the mean of the monthly maximum and minimum temperatures over the whole year
Bio 2	Mean diurnal temperature range (mean(period max-min) (°C)	The mean over the whole year of the monthly diurnal temperature ranges. Each monthly diurnal range is the difference between that month's maximum and minimum temperature.
Bio 3	Isothermality (Bio 2 ÷ Bio 7)	The mean diurnal range (parameter 2) divided by the annual temperature range (parameter 7).
Bio 4	Temperature seasonality (C of V)	The temperature Coefficient of Variation (C of V) is the standard deviation of the monthly mean temperatures expressed as a percentage of the mean of those temperatures. For this calculation, the mean in degrees Kelvin is used. This avoids the possibility of having to divide by zero, but it does mean that the values are usually quite small.
Bio 5	Max temperature of warmest month (°C)	The highest maximum temperature in all months of the year.
Bio 6	Min temperature of coldest month (°C)	The lowest minimum temperature in all months of the year.
Bio 7	Temperature annual range (Bio 5-Bio 6) (°C)	The difference between the max temperature of warmest period and the min temperature of coldest period.
Bio 8	Mean temperature of wettest quarter (°C)	The wettest quarter of the year is determined (to the nearest week), and the mean temperature of this period is calculated.
Bio 9	Mean temperature of driest quarter (°C)	The driest quarter of the year is determined (to the nearest week), and the mean temperature of this period is calculated.
Bio 10	Mean temperature of warmest quarter (°C)	The warmest quarter of the year is determined (to the nearest week), and the mean temperature of this period is calculated.
Bio 11	Mean temperature of coldest quarter (°C)	The coldest quarter of the year is determined (to the nearest week), and the mean temperature of this period is calculated.
Bio 12	Annual precipitation (mm)	The sum of all 12 monthly precipitation estimates.
Bio 13	Precipitation of wettest month (mm)	The precipitation of the wettest month
Bio 14	Precipitation of driest month (mm)	The precipitation of the driest month
Bio 15	Precipitation seasonality (C of V)	The Coefficient of Variation (C of V) is the standard deviation of the weekly precipitation estimates expressed as a percentage of the mean of those estimates.
Bio 16	Precipitation of month (mm)	The wettest quarter of the year is determined (to the nearest week), and the total precipitation over this period is calculated.
Bio 17	Precipitation of driest quarter (mm)	The driest quarter of the year is determined (to the nearest week), and the total precipitation over this period is calculated.
Bio 18	Precipitation of warmest quarter (mm)	The warmest quarter of the year is determined (to the nearest week), and the total precipitation over this period is calculated.
Bio 19	Precipitation of coldest quarter (mm)	The coldest quarter of the year is determined (to the nearest week), and the total precipitation over this period is calculated.
Edaphic Factors		
Geology	Geology	Bureau of Agricultural Research/Bureau of Soils and Water Management-Department of Agriculture
soil class	Soil type classification	Bureau of Soils and Water Management-Department of Agriculture
Vegetation-Related Factors		
land cover	Philippine land cover classification (2010)	National Mapping Resources Information Authority/Forest Management Bureau
NDVI	Normalized Difference Vegetation Index (-1 to 1)	Processed Landsat 5 image using ERDAS 9.2
Topographic Factors		
aster_elev	Elevation (m)	Derived from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) 30m of NASA

Variable	Variable (Unit)	Description/Source
Topographic Factors		
aster_slope	Slope (%)	Derived from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) 30m of NASA
aster_aspect	Aspect	Derived from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) 30m of NASA
dist_rivers	Euclidean distance (distance in meters)	www.geofabrik.de
Anthropogenic Factors		
Population	Global Population Distribution Database	LandScan Global Population Database
dist_roads	Euclidean distance (distance in meters)	www.geofabrik.de
dist_settlements	Euclidean distance (distance in meters)	www.geofabrik.de

software. During modeling,occurrence records were further subdivided into two parts: 75% were used to generate species distribution models while the remaining 25% were kept as independent data to test the accuracy of each model (*Huberty 1994; Franklin 2009; Gracia et al. 2013*). The software had an upper limit of 1000 for each run. Different sets of testing and training samples were randomly selected for each iteration. Maxent utilized background points in place of absence data. Samples were randomly selected from a set of 10,000 background points to represent pseudo-absence points (*Phillips et al. 2006; Barbet-Massin et al. 2012*).

A total of seven models for each dipterocarp species were created in this study: 'Climatic-Only Model', Climatic-Topographic Model', 'Climatic-Edaphic Model', 'Climatic-Anthropogenic Model', 'Climatic-Vegetation Model', 'Full Model' and 'Final Model'. The 'Climatic-Only Model' considered only the climatic factors as variables while the 'Full Model' took into account all 30 environmental variables. The 'Final Model' is the result from a series of variable reduction and selection stages, a methodology adopted from *Garcia et al.* (*2013*) and *Kendal et al.* (*2013*). Each model was replicated five times using the five synthetic climate scenarios developed by IRI (Base1-5 and Projected1-5).

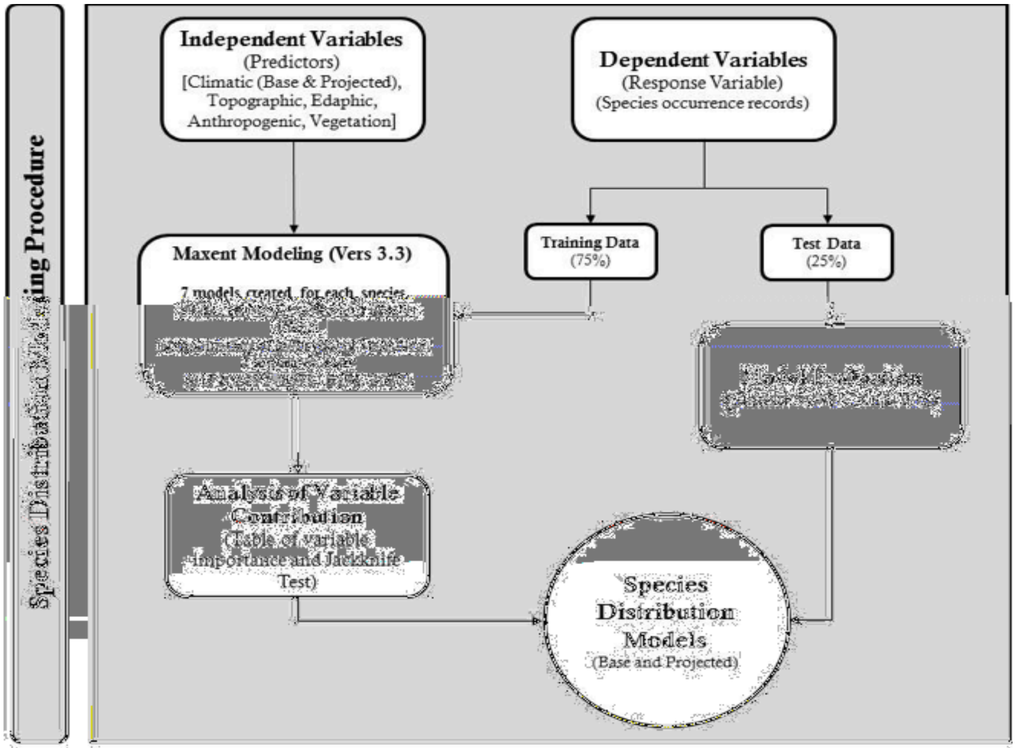
Reduction and selection of variables were done through pairwise correlation values to eliminate redundancy with the independent variables (*Rinnhofer et al. 2012*). This was done using Principal Component Analysis tool in ArcGIS as demonstrated by *Garcia et al.* (*2013*). After this test, the variables were trimmed down to just 18 (**Figure 3**).

Maxent provides table of analysis of variable contributions that summarizes the percent predictive contribution of each environmental variable during model building. Analysis of variable relative contribution is one natural application of SDM. Using this analysis, variables that matter most in SDM were determined. As the percent contribution increases, the influence of a particular variable also increases. Alternatively, Maxent used jackknife test as a measure of the relative importance of each variable within the model. This test calculated the model gain for each variable when used in isolation and the average gain for the remaining variables when a particular variable is omitted from the model to determine which variable are the most important individually to the Maxent models of the species (*Phillips et al. 2006*).

This study used logistic format of probability distribution where each pixel has a probability value ranging from 0 to 1 (*Phillips et al. 2006*). Pixels with high probability value are areas with better predicted conditions (*Trisurat et al. 2011*). Hence, as the value departs from 0 to 1, it indicates an increasing level of suitability. The default probability of occurrence was classified into 10 classes of equal interval. Thus, value from 0 to 0.5 indicated unsuitable habitats where species will unlikely be found, while 0.5 to 1.0 represented suitable habitats where species will likely be present.

Evaluation and Assessment of Model Performance

The Area under the Receiver Operating Characteristics (ROC) curve was used to evaluate model performance as introduced by *Swets* (*1988*). The AUC is a threshold independent measure of a model's ability to discriminate presence from absence (or background points). The AUC values vary from 0.5 to 1 where AUC value of 0.5 shows that model prediction were not better than random. The AUC values departing from 0 to 1 means increasing model accuracy. The average AUC of all 7 models were compared and ranked. The proposed classification of



AUC by *Swets* (*1988*) was used to interpret the AUC (**Table 2**). Among the traditional approaches of SDM, Maxent calculates AUC values differently because it defines specificity using the predicted area and not true commission (*Phillips et al. 2006*).

Another evaluation method employed in this study is the True Skill Statistics (TSS). It is also known as Hanssen-Kuipers Discriminant that compares the number of correct forecasts, minus those forecasts, minus those attributable to random guessing to that of a hypothetical set of perfect forecast (*Allouche et al. 2006*). TSS is a binomial test that is threshold dependent (*Herkt 2007*) and can be used to compare prediction performance independent of both validation dataset size and prevalence (*Allouche et al. 2006*). The scale on how TSS statistics can be interpreted is shown in **Table 3** (*as cited by Garcia et al. 2013 from Monserud and Leemans 1992*).

Species Distribution Change

Parmesan (*2006*) reported that species can shift their distributions, or migrate, to remain at equilibrium with climate. The Maxent outputs were continuous probability of occurrence (0.0 – 1.0) where higher probability values mean better suitability and lower values mean poorer suitability. Predicted probability values were transformed to binary prediction. The predicted values equal to or greater than 0.5 was assigned as ‘present’. On the other hand, values less than 0.5 was for ‘absent’. The percentage change between the area of suitable and unsuitable habitats was also determined.

RESULTS AND DISCUSSION

Model Evaluation Using AUC values

All AUC values were greater than 0.5. Based on the AUC classification by *Swets* (*1988*), it could be concluded

AUC Value	Description
0.90 – 1.0	Excellent
0.80 – 0.90	Good
0.70 – 0.80	Fair
0.60 – 0.70	Poor
< 0.60	Fail

TSS Value	Degree of Agreement
0.00 – 0.05	None
0.05 – 0.19	Very Poor
0.20 – 0.39	Poor
0.40 – 0.54	Fair
0.55 – 0.69	Good
0.70 – 0.84	Very Good
0.85 – 0.99	Excellent
1.00	Perfect

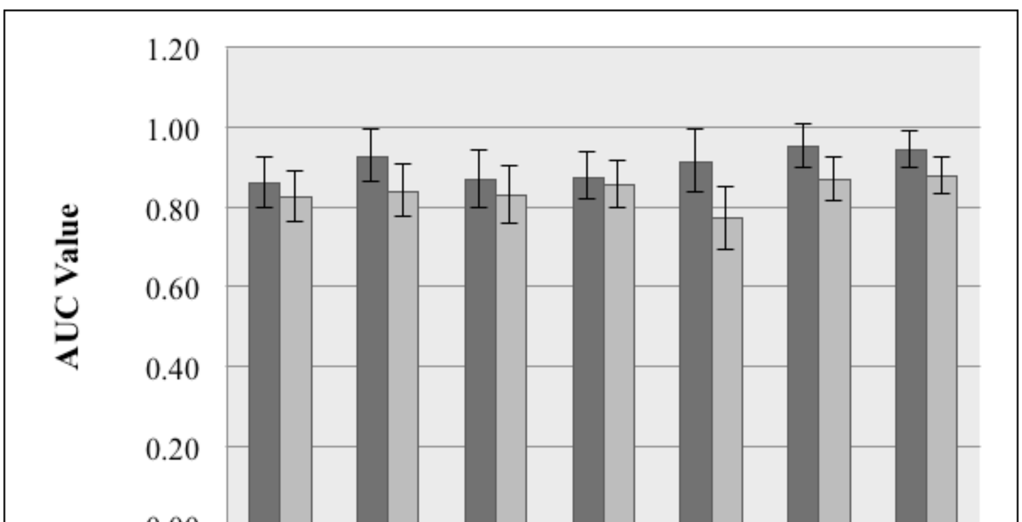
that all seven probability models for *S. palosapis* and *S. polysperma* species showed better performance than a null model. As seen in **Figures 4** and **5**, the models' level of accuracy derived from test points (light bars) are relatively lower compared to the training points (dark bars). This difference may have occurred because of fewer test points and their random distribution. However, AUC of test points was used in the analysis (*Trisurat et al. 2009; Trisurat et al. 2011; Garcia et al. 2013*).

For *S. palosapis*, the Final Model had the best performance with an AUC value of 0.8763, while the Full Model ranked second with an AUC value of 0.8706. The Climatic-Only model performed quite well (AUC=0.8262). Among the Partial Models, the Climatic-Vegetation worked best (AUC=0.8542) while Climatic-Anthropogenic (AUC=0.7708) was the least performing one. Climatic-Topographic and Climatic-Edaphic had AUC values of 0.8381 and 0.8304, respectively. It should be noted however that the models had fair to good predictive performance, with AUC values ranging from 0.7708 to 0.8763 (**Figure 4**). Similar to *S. palosapis*, the Final Model showed the best performance (AUC=0.8626) for *S. polysperma*. The Climatic-Only model performed fairly (AUC=0.7080) while the Partial Models are in the following order based on decreasing AUC values: Climatic-Vegetation>Climatic-Edaphic>Climatic-Topographic>Climatic-Anthropogenic. The Climatic-Anthropogenic model showed poor performance with AUC equivalent to 0.6741 but it is still better than a null model. The Full Model had AUC of 0.8273 which ranked third overall. Among the seven models, one model had poor performance, three had fair performances and the remaining three had good performances (**Figure 5**).

In general, the Final Models consistently outperformed all other models for both *S. palosapis* and *S. polysperma* species. This suggests that a model with a diversified set of variables is more desirable than the more complicated ones (*Nicopior 2014*). However, differences in the AUC values were also observed as performances varied from fair to good (*S. palosapis*) and poor to fair to good (*S. polysperma*). These differences might be attributed to the generalization of variables for both dipterocarp species. It should be noted that not all forest tree species of the same family or even of the same genus live in the same environmental conditions. *Fernando* (*2009*) found out that dipterocarps could be found in at least four different forest formations, including tropical lowland evergreen rainforest, tropical lower montane rainforest, tropical semi-evergreen rainforest and forest over limestone. Other forest habitats such as the freshwater, peat swamp forest and forests over ultramafic rocks in the country may likely contain dipterocarp species if extensive surveys could be conducted. Thus, each species may have different sets of environmental requirements restricting their occurrence and distribution (*Garcia et al. 2013*).

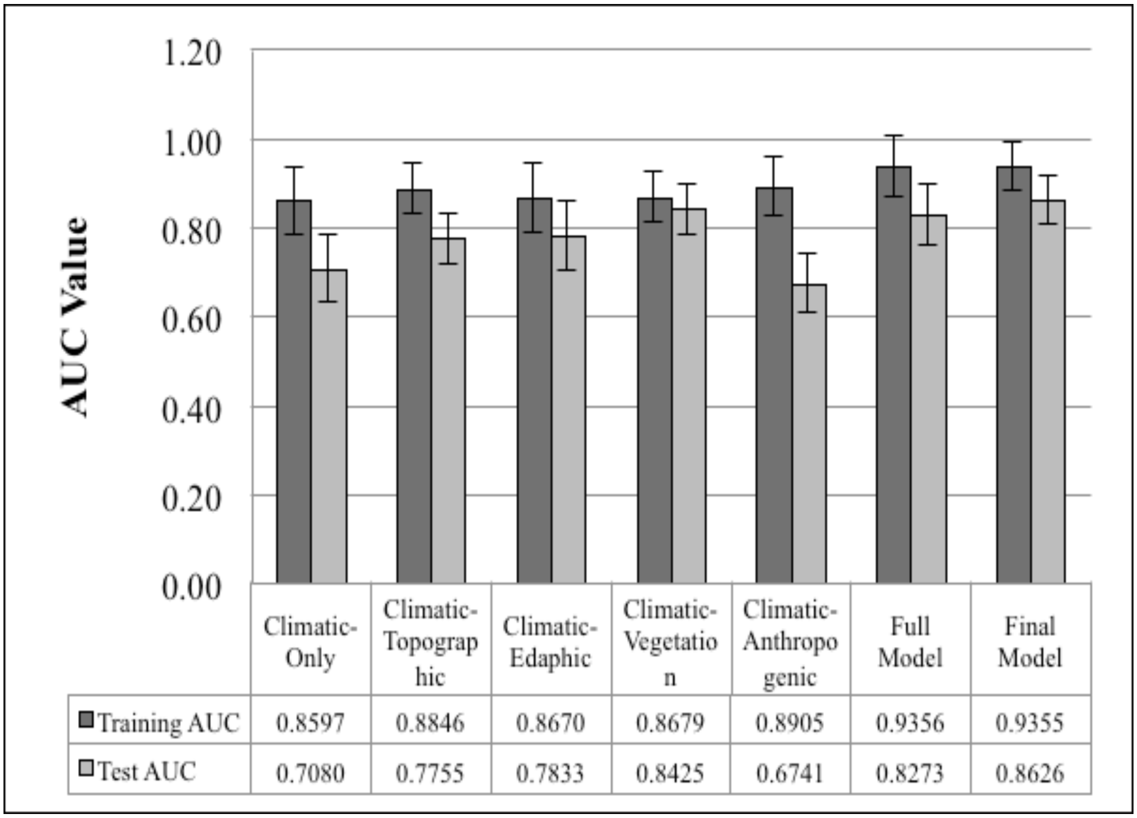
Model Evaluation Using TSS values

The True Skill Statistics (TSS) method (*Allouche et al. 2006*) is also called Hanssen-Kuipers Discriminant, it is a threshold dependent measure used for assessing model



	Climatic-Only	Climatic-Topographic	Climatic-Edaphic	Climatic-Vegetation	Climatic-Anthropogenic	Full Model	Final Model
Training AUC	0.8605	0.9267	0.8681	0.8757	0.9150	0.9510	0.9451
Test AUC	0.8262	0.8381	0.8304	0.8542	0.7708	0.8706	0.8763

Shorea palosapis



Shorea polysperma

performance. Average TSS values were computed with fve replicates for the seven probability models and were then ranked (**Table 4**). Based on the TSS values, the Final Model for *S. polysperma* (TSS=0.8332) performed very well. The*S. palosapis* Final Model was found to perform as well as the Climatic-Anthropogenic model for the same species (TSS=0.8176). However, the Climatic-Anthropogenic model for *S. polysperma* showed poor performance (TSS=0.2977). The Climatic-Only model was second least performing but its performances are still considered fair for *S. polysperma* (TSS=0.4718) and good for *S. palosapis* (TSS=0.5460). The predictive performances of the models improved when the climatic variables were combined with other environmental variable groups, except in the Climatic-Edaphic model of *S. palosapis* (TSS=0.4310) and Climatic-Anthropogenic model of *S. polysperma* (TSS=0.2977). This difference suggests that a model with a diversifed set of variables as shown by the Final model is more desirable than the more complicated ones (*Nicopior 2014*).

To compare the results of the two evaluation methods, the AUC and TSS values of all models for both species are presented in **Table 5**. The rankings of all seven models based on TSS values were not the same as with the AUC-based index. However, the values for the Final Models always ranked on top for both species. This suggests that the relative predictive performance of a model improves as the number of variables increase, but only up to a certain extent. For instance, the Final Model with only 18 variables performed better than the Full Model with all 30 original variables. Again, this suggests that a model with a diversifed set of variables is more desirable than the more complicated ones (*Nicopior 2014*). *Homer and Lemeshow* (*2000*) suggested that patterns or relationships between variables may be more stable when fewer variables are involved, thus it is easier to make generalizations.

Determinant Variables in the Pre-Final Modeling

The Final model was used in determining the variables' importance since it showed the best performance among the seven probability models. Out of the 30 original variables, only 18 environmental variables were used in the Final Modeling and these are: climatic (Bio2, Bio3, Bio4, Bio6, Bio7, Bio14, Bio17); edaphic (geology,

S. palosapis

S. polysperma

Models	*S. palosapis* (Rank)	*S. polysperma* (Rank)
Climatic-Only	0.5460 (5)	0.4718 (6)
Climatic-Topographic	0.5944 (3)	0.7099 (2)
Climatic-Edaphic	0.4310 (6)	0.6522 (4)
Climatic-Vegetation	0.5877 (4)	0.6819 (3)
Climatic-Anthropogenic	0.8176 (1)	0.2977 (7)
Full Model	0.6751 (2)	0.5058 (5)
Final Model	0.8176 (1)	0.8332 (1)

S. palosapis S. polysperma

Models	*S. palosapis*		*S. polysperma*	
	AUC (Rank)	**TSS (Rank)**	**AUC (Rank)**	**TSS (Rank)**
Climatic-Only	0.832 (6)	0.546 (5)	0.7080 (6)	0.4718 (6)
Climatic-Topographic	0.8381 (4)	0.5944 (3)	0.7755 (5)	0.7099 (2)
Climatic-Edaphic	0.830 (5)	0.4310 (6)	0.7833 (4)	0.6522 (4)
Climatic-Vegetation	0.854 (3)	0.5877 (4)	0.8425 (2)	0.6819 (3)
Climatic-Anthropogenic	0.771 (7)	0.8176 (1)	0.6741 (7)	0.2977 (7)
Full Model	0.871 (2)	0.6751 (2)	0.8273 (3)	0.5058 (5)
Final Model	0.876 (1)	0.8176 (1)	0.8626 (1)	0.8332 (1)

soil type); vegetation-related (Land cover, NDVI; topographic (ASTER_Elevation, ASTER_Slope, ASTER_Aspect, distance to rivers); and anthropogenic (human population, distance to roads, distance to settlements).

Multi-collinearity Test. All the variables were tested for multi-collinearity by examining the cross-correlations (Pearson correlation coeffcient, r) among the variables. This was done to avoid misinterpretations of model's results arising from either positive or negative collinearity and to facilitate interpretation. Only one variable (r > 0.70) from a set of highly cross-correlated variables was included in the Final Model. Seventeen climatic variables were highly correlated to at least two variables. Of the 17 variables, 12 variables had the highest counts of highly correlated variables (Counts = 16). The minimum temperature of coldest month (Bio6) was correlated to 15 other variables while four other variables, annual temperature range (Bio7), precipitation of driest quarter (Bio17), precipitation of coldest quarter (Bio19) and elevation, were correlated with 13 other variables. Of the 13 correlated variables, elevation had negative linear correlations with eight climatic variables and positive linear correlations with fve climatic variables. Seven temperature variables (r value ranges from -0.8420 to -0.8476) and one precipitation variable, precipitation seasonality (Bio15) (r = -0.7748) had negative linear correlations with elevation, which affrmed the fact that temperatures are higher in lower elevations (*Shepson 2003*). In contrast, elevation had positive linear correlations with fve other precipitation variables (r value ranges from 0.7501 to 0.8256). Thus this again affrmed the fact that the chance of rainfall is higher in higher elevations. According to PAGASA, the amount of rainfall that we can experience depends on the geographical location. In the Philippines, the east coast can see over 5,000 mm especially in the mountainous region like the NSMNP. The remaining 13 environmental variables that had no correlation with the other variables were used in the Final Model.

Variable Reduction and Selection. The highly correlated variables were classifed into eighteen groups. Only one variable from each set of highly correlated variables (r > 0.70) was retained and included in the Final Model. Each set of highly correlated variables were further analyzed, and from each set, one variable set was selected to be included in the Final Model. The selections were based on the average relative importance of the variable in predicting species probability of occurrence using the Climatic-Only, Partial and Full Models. For instance, in Group II, which includes the precipitation of driest quarter (Bio17) and precipitation of coldest quarter (Bio19), the precipitation of driest quarter (Bio17) was retained because it ranked second overall (with an average contribution of 16.5871%) while the precipitation of coldest quarter (Bio19) ranked only eighteenth (1.6842%). In Group VII, 12 climatic variables (six variables each under temperature and precipitation) were clustered together. Among the 12 climatic variables, the precipitation of driest month (Bio14) was retained because it ranked fourteenth overall (8.1222%). The precipitation of driest month (Bio14) is followed by the precipitation of wettest month (Bio13) (1.8269%) and maximum temperature of warmest month (Bio5) (1.2051%), while the other nine climatic variables showed very little contribution to the models (average contribution ranges from 0.0350% to 0.8651%).

After the selection, the number of environmental variables went down from 30 to 18. Nevertheless, all fve variable groups were still represented. All variables from four of the fve classifcations were retained, except for climatic variables which were reduced from 19 to seven. This explains that species probability of occurrence cannot be explained by one variable group alone but the interplay of forces of all variable groups. It is also worthy to note to carry out a series of variable reduction and selection methods prior to species distribution modeling primarily to reduce errors in the model especially those caused by spatial autocorrelation of the presence data or the multi-collinearity of environmental variables used.

Determinant Variables in the Final Modeling

In order to meet the third objective, Final Modeling was implemented using only the variables that passed the

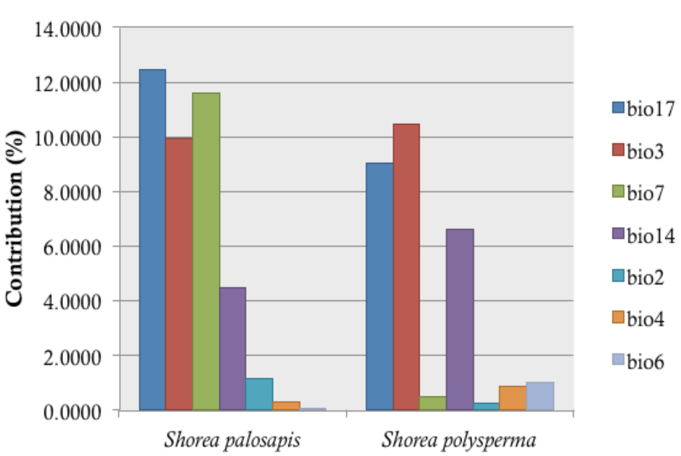
Pre-Final modeling stages. The Final Model was fitted using 18 environmental variables. It was run with five replicates (representing the five synthetic climate scenarios) and was then averaged. Each model replicate was set for 1,000 iterations to allow enough time for the model to converge, though the number of iterations was not usually maximized because iterations automatically stop when the convergence threshold has already been satisfied. In the Final Modeling, replicates had iterations ranging from 440 to 700 for *S. palosapis*, and 500 to 840 for *S. polysperma*.

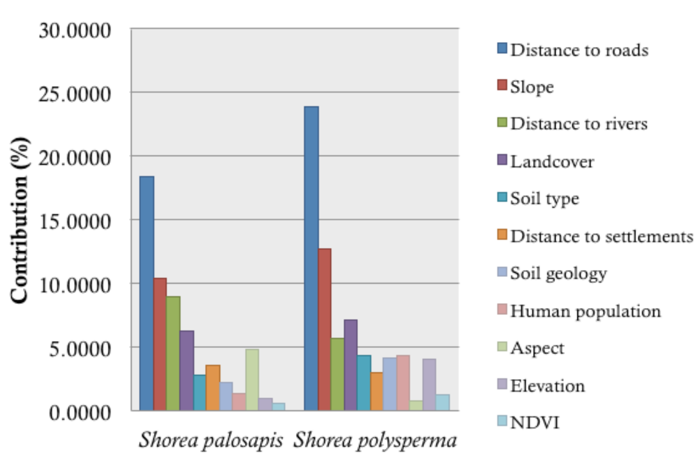
Analysis of Variable Importance

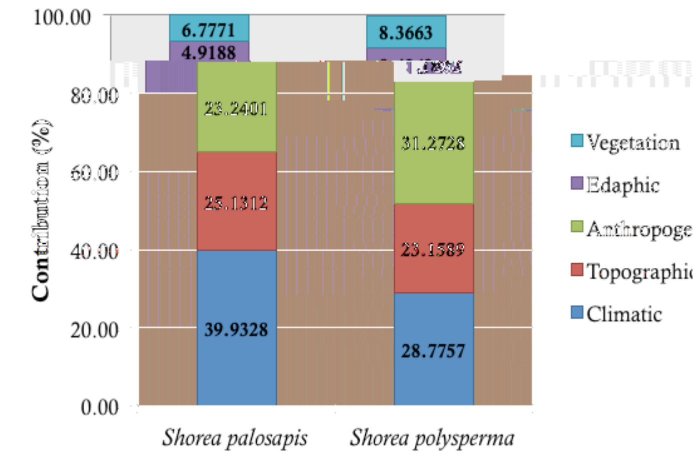
Among the seven climatic variables used in predicting the species distribution, precipitation of driest quarter (Bio17) had the highest contribution (10.76%), followed by isothermality (Bio3) with 10.19% (**Figure 6**). This means that these two climatic variables explained the occurrence of the two dipterocarp tree species. However, the sole occurrence of *S. palosapis* is determined by the annual temperature range (Bio17) with an average percent contribution of 11.62%. Temperature seasonality (Bio4) had the least average percent contribution to the Maxent models of the two dipterocarp tree species with only 0.60%. According to *Symington* (*1943*) and *Wyatt-Smith* (*1963*) *as cited by Appanah et al. 1998*, the distributions of dipterocarps in Asia particularly in the southeast asia are being controlled by climatic conditions at different elevation gradient. Furthermore, the conjunction of altitude and other natural barriers obstructed its distribution. The dipterocarps occupy several phytogeographical regions that mainly conform to climatic and ecological factors.

As to the topographic variables used in predicting distributions of *S. palosapis* and *S. polysperma*, slope had the highest contribution (11.58%) followed by distance to rivers with an average contribution of 7.28%. Elevation had the least average contribution (2.52%) to the Maxent models of *S. palosapis* species while for *S. polysperma*, aspect (0.74%) had the least influence. As to the anthropogenic variables used in predicting distribution of the two species, distance to roads had the highest contribution (27.15%). Distance to settlement and human population had lesser average percent contribution to the Maxent models of the dipterocarp tree species with 3.27% and 2.83%, respectively (**Figure 7**). *Trisurat et al.* (*2009*) also found that anthropogenic factors such as distance to road and village are also important and negatively correlated to the distribution of tree species in Northern Thailand. In his study, importance of distance to road and village reached up to 21.6% and 17.1%, respectively. Another study conducted by *Snelder et al.* (*2013*) projected the impacts of land use change, including the planned construction of a main road crossing the NSMNP, on forest bird distribution. The researchers found that land use change, especially the creation of access points for logging and land transitions, will be a major influence on species distributions. Population also showed low contribution with 5.10%, on the average. For edaphic variables, geology (4.02%) had greater impact than soil type (2.59%) on predicting the occurrence of two dipterocarp tree species. For the vegetation-related variables, land cover (6.7217%) had a greater impact than NDVI (1.4082%) on predicting the occurrence of two dipterocarp tree species.

Overall, predicting the occurrence of the two tree species was largely determined by climatic variables (34.35%) followed by anthropogenic variables (27.25%) and topographic variables (24.15%). Vegetation-related and edaphic variables had relatively lesser contribution with 7.58% and 6.67%, respectively (**Figure 8**). Similar trend was observed by *Garcia et al* (*2013*) wherein climatic variables contributed less than the biophysical variables (e.g topographic, edaphic, anthropogenic, vegetation). However, it does not necessarily mean that biophysical variables are more important than climatic variables as the biophysical and bioclimatic variables are inherently spatially







and temporally autocorrelated (*Schrag et al. 2007*). It is instead more likely that groups of biophysical variables are acting together to influence the occurrence of the species.

Jackknife Test of Variable Importance

The Jackknife test calculates the “model gain” when one variable is used in isolation and the “average gain” for the model which used all variables except one (*Garcia et al. 2013; Phillips et al. 2006*). Variable with highest gain when used in isolation is precipitation of driest quarter (Bio17). Regularized training gain for this variable is 0.5683, which therefore appears to have the most useful information by itself. It is then followed by annual temperature range (Bio7) with training gain of 0.5519. The variable that decreases the gain the most when it is omitted is distance to rivers with a regularized training gain equal to 1.3266, which therefore appears to have the most information that is not present in the other variables. On the other hand, for *S. polysperma*, results of the jackknife test showed that precipitation of driest quarter (Bio17) is the most important variable since it gives the highest gain (0.4391) when used singly. This implies that precipitation of driest quarter (Bio17) has the most the most useful information by itself, followed by annual temperature annual (Bio7) with 0.4192. The variable that decreases the gain the most when it is omitted is distance to roads with a regularized training gain equal to 1.1590, which means that it has the most information not present in the other variables.

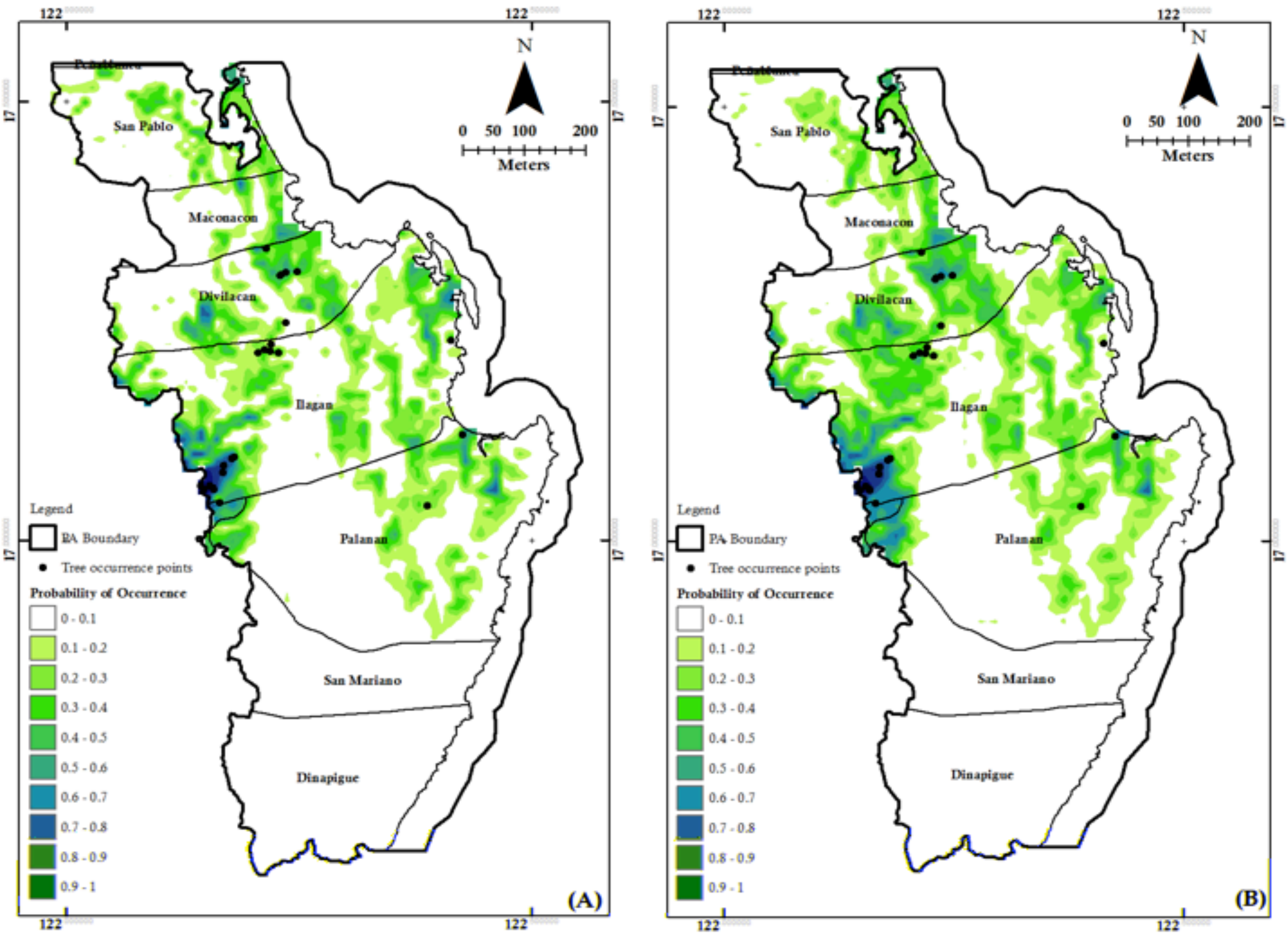
Potential Species Distributions

Maxent outputs in logistic format of species probability distribution were generated in this study wherein each pixel has a probability value ranging from 0 to 1 (*Phillips et al. 2006*). This is useful for displaying information whether the species is either suitable or unsuitable in a particular area. Pixels with high probability value are areas with better predicted conditions (*Trisurat et al. 2011*). Hence, as the value departs from 0 to 1 indicates increasing level of suitability. The default probability of occurrence was classified into 10 classes of equal interval. Thus, value from0 to 0.5 indicated unsuitable habitats where species will likely not to be found, while 0.5 to 1.0 represented suitable habitats where species will likely to be present.

Areas which have darker blue color indicate the high probability of occurrence of *S. palosapis* (**Figure 9**). As the color fades probability of occurrence decreases. About 11,543.21 ha are suitable to *S. palosapis*. It is worthy to note however that the whole 11,543.21 ha has varying degree of suitability to *S. palosapis*. Distribution of the area based on suitability is as follows: fairly suitable (5,689.15 ha), moderately suitable (2,720.90 ha), suitable (1,813.93 ha), very suitable (906.97 ha) and extremely suitable (412.26 ha). Under future climate, *S. palosapis* will gain more suitable ecological niche. Suitable areas will increase from 11,543.21 ha under baseline climate scenario to 14,264.11 ha under future climate scenario representing about 24% increase.

The map using baseline climate scenario (A) predicted high probability of occurrence in western and eastern sections of Ilagan, northeastern part of Palanan close to the eastern seaboard and some part in Divilacan (**Figure 10**). Total suitable area under baseline climate scenario for *S. polysperma* is around 13,522.04 ha. Under future climate, the extent of unsuitable habitat areas decreased by 5.14% while the extent of suitable habitat areas increased by 100%. This suggests that *S. polysperma* will benefit from future climate since the prediction revealed an increase in suitable area from 13,522.04 ha to 27,044.09 ha. The map using baseline climate scenario (A) shows a high probability of occurrence in the western and eastern sections of Ilagan, northeastern part of Palanan close to the eastern seaboard and in some parts of Divilacan.

In the study of *Trisurat et al.* (*2009*), the total extent of occurrences under current conditions and under predicted climate condition in 2050 are not substantially different from most plant species. An increase in total suitable areas was observed for the twelve plant species. For instance, forecasted climate leads to an increase from 19% to 29% in the suitable location of *Hopea odorata* in 2050. Other plant species that gained at least 10% in suitable areas are: *Dalbergia conchinchinnensis*, *Pinus kesiya*, *Pinus merkusii*, *Wrightia tomentosa*, *Dipterocarpus alatus and Mangifera* spp. Another study of *Trisurat et al.* (*2011*) found out that 35 out of 66 tree species will gain more niches under the predicted climate conditions. *Garcia et al.* (*2013*) also found that seven species: *Afzelia rhomboidea*,

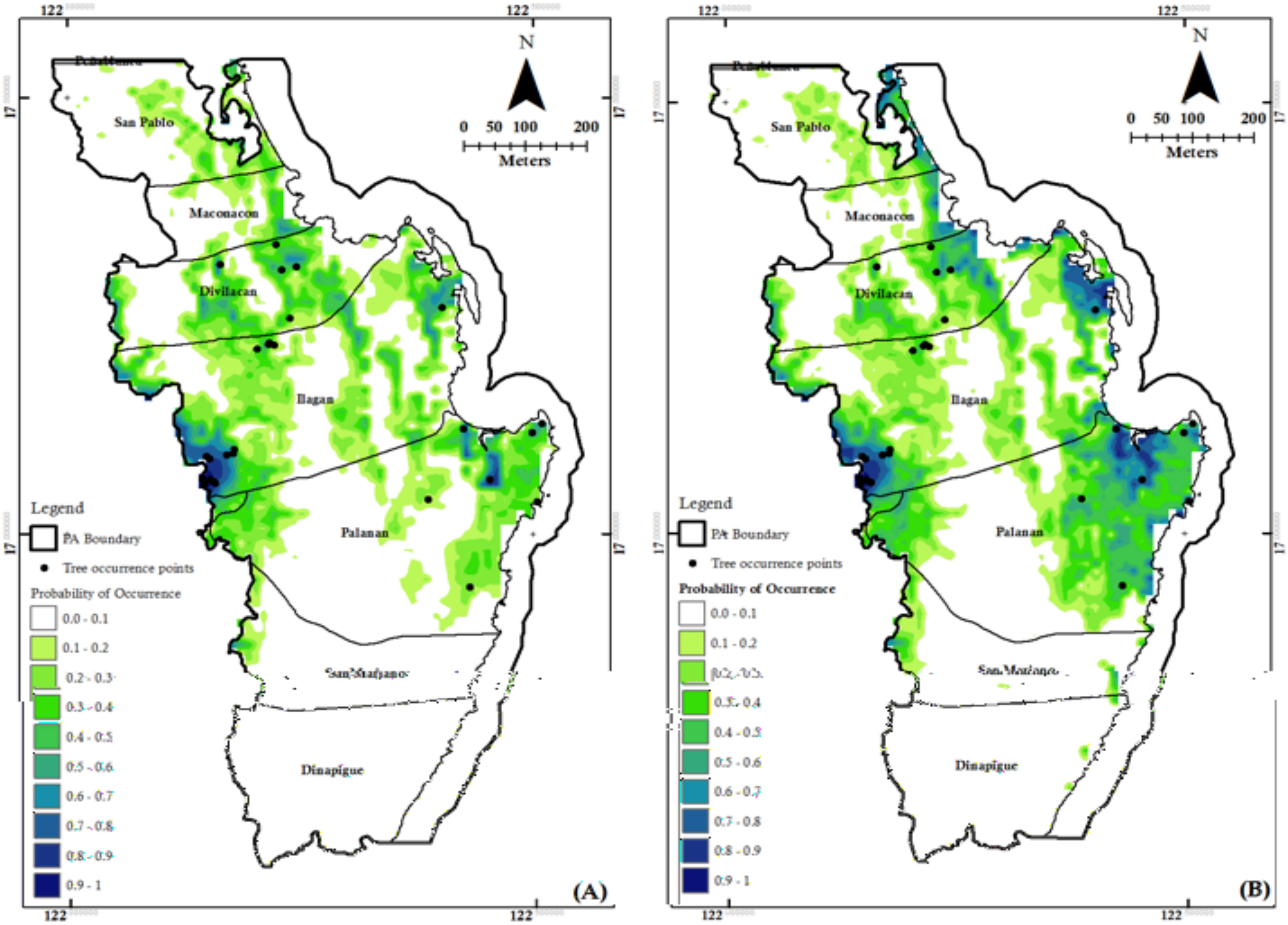


S. palosapis

Koordersiodendron pinnatum, *Mangifera altissima*, *Shorea contorta*, *Shorea palosapis*, *Shorea polysperma* and *Vitex parviflora*, will likely benefit from future climate change.

CONCLUSIONS AND RECOMMENDATIONS

Each species responds differently to a changing environment. Thus, species composition, communities and even ecosystems vary in different ways from one place to another, in response to climate change (*IPCC 2014*). The impacts of projected climate changes on the vegetation of the lowland tropics are currently poorly understood. Hence, this study evaluated the consequence of climate change on the geographical distribution of *S. palosapis* and *S. polysperma* in the NSMNP. The study also explored which species distribution model performed best by evaluating and comparing the relative predictive performance of seven probability models for each species. The environmental variables with the highest contribution in the geographic distribution of *S. palosapis* and *S. polysperma* were determined based on the selected best performing model. The assessment of model predictive accuracy is one fundamental issue in the development of SDMs *(Guisan and Thuiller 2005; Barry and Elith 2006*). Thus, this study used to two statistics measures to assess the model performance: (1) the Area under Receiver Operating Characteristics (ROC) Curve Analysis (AUC) and (2) True Skill Statistics (TSS). Using the proposed AUC classification by *Swets* (*1988*), all seven probability models for both *S. palosapis* and *S. polysperma* showed performance that are better than random mode as indicated by the AUC values greater than 0.5. The Final model performed best both for *S. palosapis* (AUC = 0.8763; TSS = 0.8176) and *S. polysperma* (AUC = 0.8626; TSS = 0.8332). The ranking of all seven models based on TSS values are not exactly the same as the AUC-based index except for the Final model that always ranked on top for both species and Climatic-only model that always placed sixth. This suggests that the model's relative predictive performance improves as the number of variables increase but only up to a certain extent. For instance, the Full model with all 30 original variables performed worse compared to the Final model with only 18 variables. This



S. polysperma

explained that a series of variable reduction methods (e.g Multi-collinearity and Jackknife tests) led to the best performing model that has few variables. Homer and *Lemeshow* (*2000*) suggested that patterns or relationships between variable may be more stable when fewer variables are involved, thus, easier to make generalizations.

In general, analysis of variable importance using the Final model revealed that predicting the occurrence of the two tree species was largely determined by climatic variables (34.35%) followed by anthropogenic variables (27.25%) and topographic variables (24.15%) Vegetation-related and edaphic variables had relatively lesser contribution with 7.58% and 6.67%, respectively. On the average, the top fve predictors with the highest contribution are: distance to roads, slope, precipitation of driest quarter, isothermality and distance to rivers. However, it is important to reiterate that forest tree species distribution or "species habitat requirement" is defned by the environmental variables where they occur and optimal combination of these factors allows a particular forest tree species to persist in certain areas. This set of environmental variables for plants may directly or indirectly affect its patterns of abundance and distribution in NSMNP. Thus, the study emphasized the interplay of forces between environmental variables that affect the overall suitability of species in a particular region. The model affrms the relationship between species known range and environmental factors and uses this relationship to identify species distribution.

In terms of potential distribution, results also showed that the probability of occurrence of the species studied changed under the projected climate scenario. Since this study was focused on the potential effects of present and future climates on natural system by evaluating the behavior of *S. palosapis* and *S. polysperma* in terms of their geographical distribution under different climate scenarios, all variables were treated as constant except climatic variables. The comparison of Maxent logistic predictions for present and future distributions showed that both species were found to beneft from future climate with increasing suitable habitat range. Moreover, it is important to note that the distributions of dipterocarps in Asia particularly in the southeast asia are being controlled by climatic conditions at different elevation gradient. Furthermore, the conjunction of altitude and other natural barriers obstructed its distribution. The dipterocarps occupy several phytogeographical regions that mainly conform to climatic and ecological factors.

Species probability distribution maps will provide conservation practitioners with estimates of the spatial distributions of species requiring more attention. Furthermore, this will greatly contribute to decision-makers especially in mainstreaming climate change in the NSMNP management plan to better conserve potential suitable habitats of priority species. The identification of potential suitable habitat is also beneficial in strategic planning, particularly in the light of inadequate funds and resources. Predictive distribution maps are also prerequisite to many aspects of resource management, conservation planning such as biodiversity assessment, reserve design, population, community and ecosystem modeling, invasive species, risk assessment, and predicting the effect of climate change on species and ecosystem, which was the focused of this study. The potentials of species distribution modeling (SDM) have already been set and a lot of research gaps on the aforementioned fields are already identified as well. With those in mind, hopefully, conservation practitioners and other stakeholders must be capacitated on the use of SDM tools especially the user-friendly, free and open source application like Maxent modeling software (*Phillips et al. 2006*).

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