Modeling the Current and Future Potential Distribution of Mangkono (Xanthostemon Verdugonianus) in Caraga Region Using Species Distribution Modeling Technique

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Abstract: *Mangkono (Xanthostemon verdugonianus) is a hardwood species indigenous to the Philippines. This study uses the Maximum Entropy model to assess the impact of climate change on the current and future potential distribution of Mangkono in the Caraga region. Five models were produced: ones for current condition, two for 2050 (SSP 245 and SSP 585), and two additional for 2070 (SSP 245 and SSP 585). Evaluation using Area Under Curve (AUC) and True Skill Statistics (TSS) indicated satisfactory performance, with AUC scores ranging from 0.983 to 0.987 and TSS values from 0.750 to 0.832. According to the results, the potential area is expected to increase under SSP 245 for 2050 and decrease with SSP 585. Both SSP 245 and SSP 585 in 2070 will decrease. Our findings suggest that to effectively manage this species, it is crucial to implement preventive environmental measures and include climate change models into land use and forest management plans.*

Keywords: MaxEnt; Species Distribution Model; Mangkono Distribution; Global Climate Model

1. INTRODUCTION

Globally, it is projected that 20-30% of the plant and animal species will encounter an increased risk of extinction due to global warming [6]. The impact of climate change on forests includes heightened vulnerability to disturbances such as insect outbreaks, invasive species, wildfires, and storms. These factors can diminish forest productivity and, in severe cases, lead to the extinction of certain flora species [8].

Mangkono *(Xanthostemon verdugonianus)* is recognized as the most complex timber tree indigenous to the Philippines. The wood of the Mangkono tree is esteemed for its exceptional hardness, rendering it suitable for various applications such as shipbuilding, tool handles, poles, piers, and bridges [4]. Areas abundant in heavy metals are increasingly favored for ironwood cultivation and have been subjected to mining exploitation, concluding that these practices threaten conservation efforts [12]. Additionally, the growing demand for Xanthostemon wood as a commercially viable resource has recently sparked conservation apprehensions. Unsustainable harvesting practices and unregulated activities such as land conversion and mining pose potential threats to the remaining stands and contribute to habitat loss (SIPLAS). The International Union for Conservation of Nature (IUCN) has designated Mangkono as "vulnerable" due to an estimated population decline of more than 30% in the past three generations.

Species Distribution Models (SDMs) are based on the idea that it is possible to measure the link between a certain pattern of interest (like the number of species or absent) and a set of environmental factors [14]. MaxEnt is a widespread species distribution modeling (SDM) method that uses presence-only data based on maximum entropy modeling principles [5]. The main idea of MaxEnt is to find the probability distribution that has the most entropy, which means it is the most spread out, while still following the limits set by the data on species occurrences and the environmental conditions in the study area [2]. MaxEnt is a predominant algorithm for analyzing presence-only data. Presence-only data comprises samples of species occurrences where the target species is confirmed to be present. Models that need presence-only data are more frequently used because presence-only records are the most easily accessible form of species data, whether gathered from fieldwork or museum collection [11].

Climate change is forecasted to affect indigenous hardwood trees in the Philippines. There is a pressing need to employ species distribution modeling techniques for predicting these species' current and future potential distribution. The current and future distribution of Mangkono will provide an understanding of the extent of Mangkono.

The main objective of this study is to model the species distribution of Mangkono in the Caraga region. Specifically, the study aims to identify environmental variables affecting the potential distribution of Mangkono in Caraga region; generate the potential distribution of Mangkono in Caraga region using MaxEnt and model the future distribution of Mangkono under climate change scenarios and global climate model for 2050 and 2070. This study is essential since it will determine the current and future geographical distribution of Mangkono in the Caraga Region. The result of this study will aid in developing targeted conservation strategies to mitigate threats. Integrating the result into land use policies can help prevent further habitat degradation, promoting sustainable practices that balance conservation with economic development.

2. METHODOLOGY

2.1 Study Area

The Caraga Region is located and can be seen in the northeastern part of Mindanao, Philippines, and covers an area of 18,847 square kilometers. It comprises five provinces: Agusan del Sur, Agusan del Norte, Surigao del Sur, Surigao del Norte, and the Dinagat Islands. It hosts the nation's fourth largest established timberland, spanning 992, 131 hectares. The region leads the nation in log production, yielding the highest volume at 573,782.08 cubic meters. This distinction solidifies the Caraga Region`s status as "the timber corridor of the Philippines" [10].

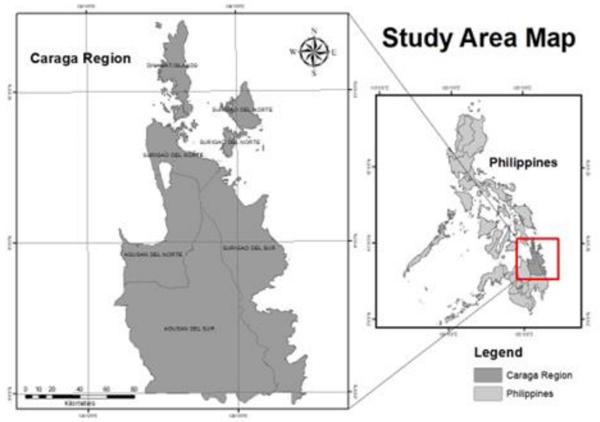

Fig. 1. Study Area

2.2 Methodological Framework

To gain a thorough understanding of the methodological framework of the study, it is crucial to clarify the entire process for better understanding. The research methodology comprises three primary stages: image preprocessing, MaxEnt modeling, and model evaluation.

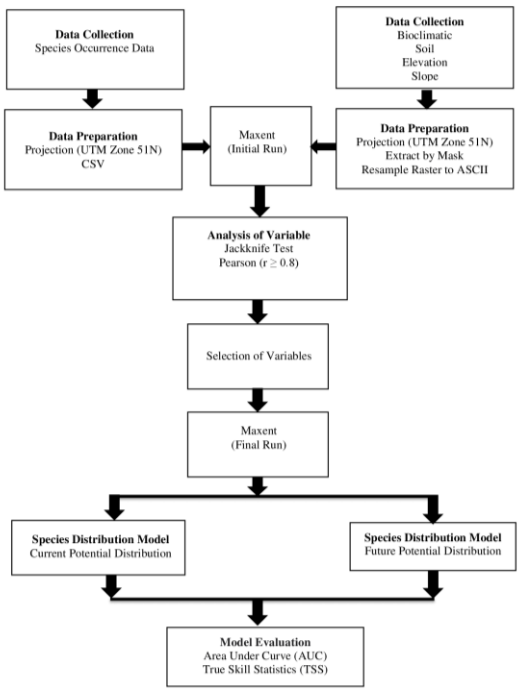

Fig. 2. Methodological Framework of the study

2.3 Mangkono Occurrence Data

The occurrence data of Mangkono *(Xanthostemon verdugonianus)* used in this study came from the Department of Environment and Natural Resources (DENR). The Department disseminates information concerning Mangkono in the Caraga region. Following the collection of occurrence data presented in a polygon feature format, a process is undertaken in ArcGIS using "feature to points" to generate coordinates. As a result, 45 Mangkono occurrence data points were generated. These coordinates are subsequently encoded into a spreadsheet and saved in "comma-separated values" csv format as required by MaxEnt.

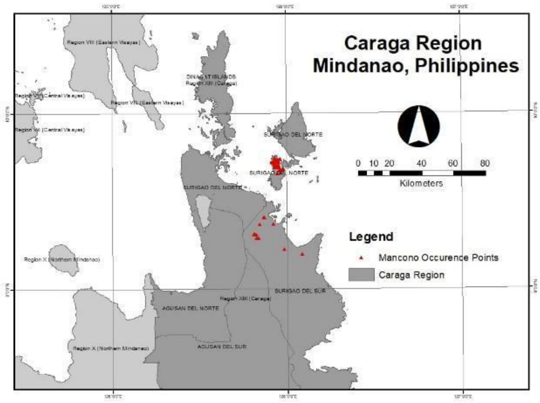

Fig. 3. Mangkono Occurrence Points

2.4 Environmental Variables

The 19 bioclimatic variables were downloaded from the WorldClim https://worldclim.org/ database version 2.1. It has a spatial resolution of 30 seconds (approximately 1 square kilometer) for 1970–2000 as a current period [3]. This database includes monthly minimum, maximum, and mean temperatures, and monthly mean annual precipitation. These datasets have been extensively employed in developing species distribution models [13]. The soil data were downloaded from Geoportal PH (https://www.geoportal.gov.ph/). The Digital Elevation Model (DEM) database on the Shuttle Radar Topography Mission (SRTM) website (http://srtm.usgs.gov/index.php) was downloaded and further analyzed using Spatial Analyst Tools of ArcGIS to derive slope and aspect. All environmental data were processed with uniform extent, cell size, and projection system (WGS_1984_UTM_Zone_51N) within ArcGIS and converted into American Standard Code II (ASCII) format. The overall environmental variables used in this study are summarized in Table1.

Table 1. List of Environmental Variables

CODE	NAME
BIO 1	Annual Mean Temperature
BIO 2	Mean Diurnal Range
BIO 3	Isothermality
BIO 4	Temperature Seasonality
BIO 5	Max Temperature of Warmest Month
BIO 6	Min Temperature of Coldest Month
BIO 7	Temperature Annual Range
BIO 8	Mean Temperature of Wettest Quarter
BIO 9	Mean Temperature of Driest Quarter

CODE	NAME
BIO 10	Mean Temperature of Warmest Quarter
BIO 11	Mean Temperature of Coldest Quarter
BIO 12	Annual Precipitation
BIO 13	Precipitation of Wettest Month
BIO 14	Precipitation of Driest Month
BIO 15	Precipitation Seasonality
BIO 16	Precipitation of Wettest Quarter
BIO 17	Precipitation of Driest Quarter
BIO 18	Precipitation of Warmest Quarter
BIO 19	Precipitation of Coldest Quarter
ELEV	Elevation
SLOPE	Slope
ASPECT	Aspect
SOIL	Soil

2.5 Climate Models and Scenarios

According to IPCC, Global Climate Models (GCMs) are esteemed as the most sophisticated instruments for simulating the response of the global climate system to the ongoing increase in greenhouse gas concentrations. To predict the species' future distribution under various climate emission scenarios and global climate models, bioclimatic variables were gathered with a spatial resolution of 30 seconds for 2041–2060 (2050s) and 2061–2080 (2070s). These were derived from the sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC) from https://worldclim.org/. EC-Earth3-Veg was selected in this study where it gives more accurate uncertainty estimates and a more complete look at the important climate feedback mechanisms compared to global circulation models (GCMs). In order to enhance the reliability and plausibility of the modeling, the scenarios SSP585 (most extreme) and SSP245 (intermediate) were selected for the periods 2050 and 2070.

2.6 Environmental Variables Selection

The selection of variables is the most critical factor in species distribution modeling. Eliminating redundant variables can augment the analytical capability of the model and mitigate multicollinearity among the variables [7]. Given the correlation among environmental variables, it becomes essential to screen them carefully. The initial step involves inputting all environmental variables and occurrence data into MaxEnt for an initial run and those environmental variables with zero contribution will be removed from the final analysis. Then, the remaining variables are then subject to correlation analysis, and if a correlation exceeding 0.8 is detected between variables, variables with higher contribution rate will be included in the final model.

2.7 Species Distribution Modeling

The current and future geographical distribution of Mangkono were built using Maxent version 3.4.1 with Mangkono occurrence points and uncorrelated environmental variables. During the modeling process, 75% of the species occurrence data were utilized as training data to develop species distribution models. In comparison, the remaining 25% were retained as testing data to assess the accuracy of each model. Additionally, the Random Seed option in Maxent was enabled. The maximum number of background points for sampling was maintained at 10,000 and the model was executed in 15 replicates with 5000 iterations to ensure sufficient time for convergence. In each iteration, the presence data is randomly partitioned through subsampling.

Table 2. Mangkono Distribution Models

Model	Period	SSP
1	Current	
2	2041-2060	SSP 245
3		SSP 585
4	2061-2080	SSP 245
5		SSP 585

2.8 Model Evaluation

In the Maxent model, the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) was often used as a default for evaluating the accuracy of the model. As the average AUC value increases, the model's prediction accuracy improves. The performance levels were categorized as follows: excellent (>0.9), good (0.8–0.9), accepted (0.7–0.8), poor (0.6–0.7), and unsatisfactory (<0.6). The closer the AUC value was to 1, the higher the model's performance [9]. Additionally, True Skill Statistics (TSS) was also used as a model evaluation where the TSS score ranges from +1 to −1, where a score near 1 denotes an almost perfect model and a score near zero or less than zero denotes a model that is no better than random [1].

2.9 Mangkono Distribution Model

The outcomes derived from the modeling process were categorized into four classes. Within this classification, the range of <0.2 was deemed low potential, 0.2 to 0.4 was regarded as moderate potential, 0.4 to 0.6 was identified as good potential, and >0.6 was classified as highly potential. These categorizations were established utilizing the Reclassify tool within ArcGIS and were reclassified into four classes [15].

3. RESULTS AND DISCUSSIONS

3.1 Variables Selection

In the initial run of the Maxent model, all 23 environmental variables and occurrence points were incorporated to identify variables with zero percent contribution. The outcome revealed that soil exhibited the highest contribution to the distribution of Mangkono, accounting for 38.6%, followed by precipitation seasonality (Bio15) and mean diurnal range (Bio2) with contributions of 27.5% and 7.7% respectively. Conversely, variables such as Bio1, Bio6, Bio8, Bio10, and Bio11 made 0 contribution to the model and will be removed from further analysis.

Table 3. Percent Contribution of Variables

Variable	Percent Contribution
BIO 1	0
BIO 2	7.7
BIO 3	4.4
BIO 4	0.2
BIO 5	0.5
BIO 6	0
BIO 7	6
BIO 8	0
BIO 9	0.1
BIO 10	0
BIO 11	0
BIO 12	1.8
BIO 13	0.3
BIO 14	2.5
BIO 15	27.5
BIO 16	1.6
BIO 17	2.2
BIO 18	0.1
BIO 19	4.9
ELEVATION	1
SLOPE	0.1
ASPECT	0.7
SOIL	38.6

The remaining 18 environmental variables undergo correlation analysis in RStudio, variables with a coefficient value of $r \geq 0.8$ are deemed correlated. If there are two or more environmental factors with a correlation greater than 0.8, the variable with a higher contribution rate is chosen to be included in the model. Finally, 12 environmental variables will be used for the final modeling.

Table 4. Environmental Variables for Final Model

Soil	Soil
Bio 15	Precipitation Seasonality
Bio 02	Mean Diurnal Range
Bio 14	Precipitation of Driest Month
Bio 17	Precipitation of Driest Quarter
Elevation	Elevation
Aspect	Aspect
Bio 05	Max Temperature of the Warmest Month
Bio 04	Temperature Seasonality
Bio 09	Mean temperature of Driest Quarter
Slope	Slope
Bio 18	Precipitation of Warmest Quarter

3.2 Model Evaluation

AUC (area under the receiving operating curve) is a statistic that is frequently used to assess the prediction effectiveness of species distribution models. However, related research has shown that AUC is not sufficient. Thus, we employed True Skill Statistics (TSS) as an additional measure, which incorporates the advantages of Kappa statistics and has a strong correlation with AUC statistics. TSS scores range from +1 to −1, where a score near 1 denotes an almost perfect model and a score near zero or less than zero denotes a model that is no better than random. Table 5 is the summary for model evaluation of the five models indicating that the result was accurate for current and future projection since AUC and TSS are widely used for evaluating the accuracy of the model.

Table 5. Summary for AUC and TSS

MODELS	**AUC**	**TSS**
Current	0.987	0.832
SSP 245 (2050)	0.983	0.801
SSP 585 (2050)	0.986	0.825
SSP 245 (2070)	0.985	0.821
SSP 585 (2070)	0.984	0.750

3.3 Mangkono Distribution Model

The outcomes derived from the modeling process were categorized into four classes. Within this classification, the range of <0.2 was deemed low potential, 0.2 to 0.4 was regarded as moderate potential, 0.4 to 0.6 was identified as good potential, and >0.6 was classified as high potential. These categorizations were established utilizing the Reclassify tool within ArcGIS and were reclassified into four classes. As shown in the figures are the potential distributions for Mangkono.

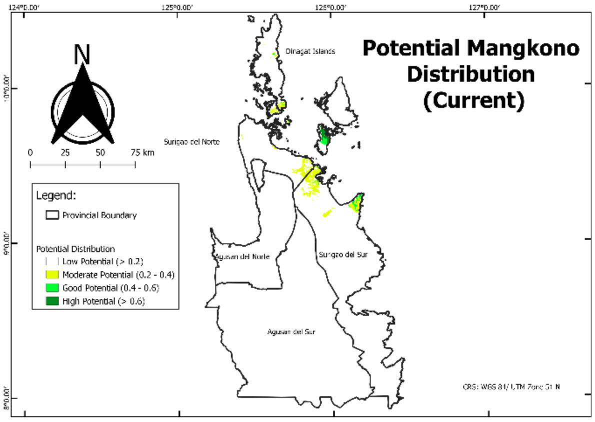

Fig. 4. Current Distribution of Mangkono

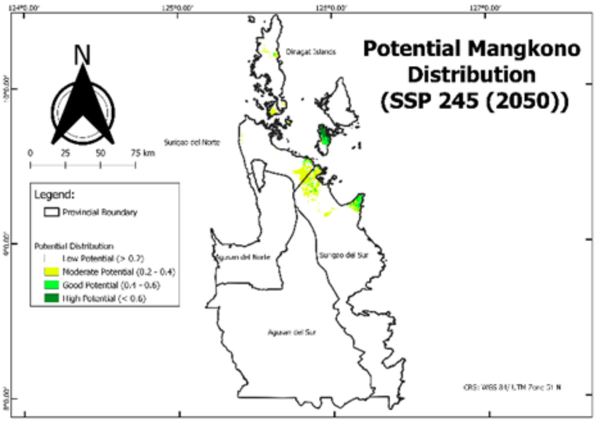

Fig. 5. Maxent Model for SSP 245 (2050)

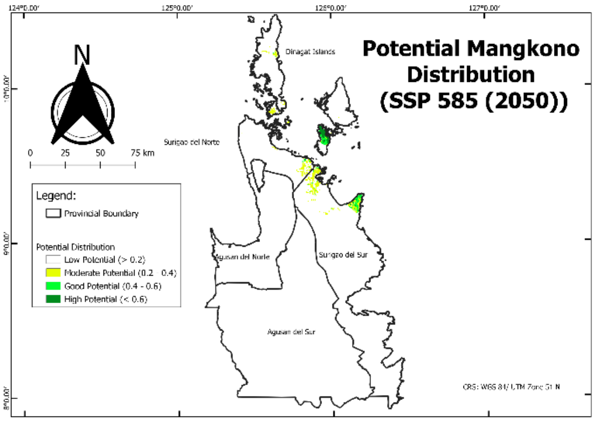

Fig. 6. Maxent Model for SSP 585 (2050)

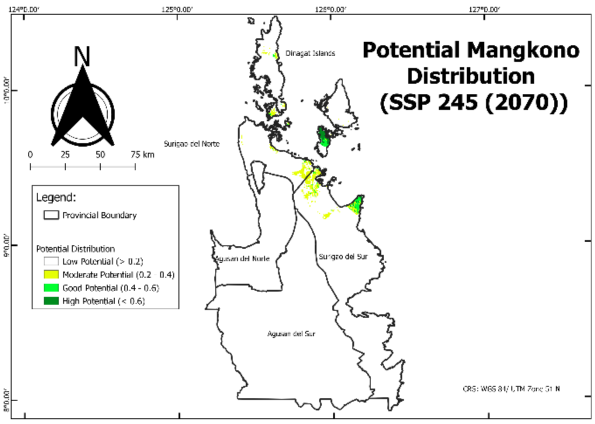

Fig. 7. Maxent Model for SSP 245 (2070)

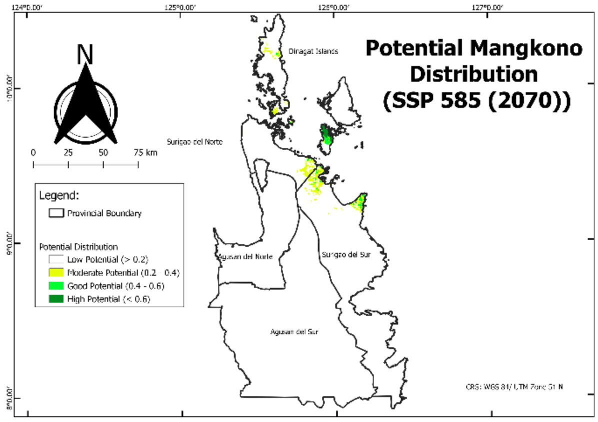

Fig. 8. Maxent Model for SSP 585 (2070)

Based on the result of the MaxEnt modeling, the predicted current and future potential distribution of Mangkono were likely to be affected positively and negatively by future climate. Mangkono potential distribution in the current and future projection shows that the potential areas are concentrated in Surigao del Sur, Surigao del Norte and Dinagat Islands. The variables deemed influential in predicting both the present and future distribution of Mangkono are soil and bio15. Each of the five models demonstrated commendable performance, with AUC values spanning from 0.983 to 0.987 and TSS values ranging between 0.750 and 0.832.

3.4 Comparing Current and Future Models

As shown in Table 6, the current high potential area for Mangkono encompasses 26.52 km2. Projections for SSP 245 (2050) indicate an increased potential area from current which is a sustainable development scenario but decreases the potential area for SSP 585 which is towards the worst-case scenario. According to the model for 2070, there is a decrease of potential area in both SSP 245 and SSP 585 from current distribution.

Table 6. Current and Future Potential Areas

Category (Km^2)	LP (<0.2)	MP (0.2-0.4)	GP (0.4-0.6)	HP (>0.6)
Current	17295.50	256.68	36.09	26.52
SSP 245 (2050)	17305.43	276.58	59.65	28.97
SSP 585 (2050)	17442.59	155.30	47.46	24.94
SSP 245 (2070)	17390.33	196.88	56.60	25.78
SSP 585 (2070)	17390.27	213.42	39.61	25.78

4. CONCLUSION

This study has investigated how climate change affects the geographical distribution of Mangkono, a vulnerable native tree species in the Philippines. Five models were created for present and future scenarios using occurrence points of Mangkono and environmental variables. This study successfully received a limited number of occurrence data sets for Mangkono from the Department of Environment and Natural Resources (DENR). Additionally, a probable distribution model for the Mangkono was built using several variables. The study effectively simulated the potential distribution of Mangkono under two different scenarios (SSP 245 and SSP 585) for the time periods 2041-2060 and 2061-2080. The analysis also identified the key characteristics that influence the spread of this species. To validate the model, the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) was utilized, categorizing performance levels as excellent (>0.9), good (0.8–0.9), accepted (0.7–0.8), poor (0.6–0.7), and unsatisfactory (<0.6). Additionally, True Skill Statistics (TSS) were employed, with scores ranging from +1 to −1, where a score near 1 indicates an almost perfect model. For error analysis, the TSS score near zero or less than zero denotes a model that is no better than random. The model was evaluated using these statistics to ensure accuracy and reliability. The statistical methods employed aimed to enhance the robustness and reliability of the findings by providing a comprehensive assessment of the model's performance under different scenarios.

The study findings suggest that soil, precipitation seasonality, and topography are some of the environmental variables that play crucial roles in determining the distribution of the Mangkono species. This document serves as a guide for safeguarding, introducing, and nurturing Mangkono in environmentally appropriate areas. The current model does not account for biological interactions and human activities, which could significantly affect Mangkono's distribution in the Caraga region. The absence of biological interactions in the model may lead to an oversimplification of the ecosystem dynamics, potentially underestimating or overlooking the true distribution of Mangkono. Human activities, such as deforestation, land-use changes, and urbanization, are crucial factors influencing species distribution. Therefore, it is suggested to incorporate additional environmental and biological data in the model, such as interactions between Mangkono and other plant species or pollinators, as well as human land-use patterns, to enhance the model's precision and accuracy. Additionally, implementing long-term monitoring programs is recommended to validate the model's predictions and track actual changes in Mangkono distribution over time.

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