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Modeling the Bioclimatic Range of *Musa ingens* (Giant Highland Banana) under Conditions of Climate Change Scenarios

Septianto Aldiansyah[1*] and Risna[2]

[1]Department of Geography, Faculty of Mathematics and Natural Sciences, University of Indonesia, Jalan Margonda Raya, Depok 16424, Jawa Barat, Indonesia

[2]Department of Microbiology, Faculty of Mathematics and Natural Sciences, IPB University, Jalan Merantil, Bogor 16680, Jawa Barat, Indonesia

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*** Corresponding author:**
E-mail:
septianto.aldiansyah@ui.ac.id

ABSTRACT

Climate change significantly impacts living organisms, leading to alterations in their range, distribution, and abundance. This study estimates the potential distribution of representatives of the family *Musaceae*, noted for their large size and importance to tropical ecosystems. We focus on *Musa ingens* Simmonds 1960 and employ bioclimatic variables and in situ datasets to model its species distribution. We differentiate potential distribution areas for *M. ingens* and present a prognostic map of its distribution under four climate change scenarios. Precipitation during the warmest quarter emerges as the primary factor influencing the spatial distribution of *M. ingens*. Under the RCP (Representative Concentration Pathway) 6.0 scenario, the potential distribution shows an initial decrease, followed by a significant increase by 2070. Meanwhile, the RCP 8.5 scenario indicates an increase in 2050, with a subsequent six percent decrease in 2070. Under the RCP 4.5 scenario for 2050, the species distribution shifts regionally, particularly around the Osua Trikora Mountains and the highlands of the Giluwe Mountains to Mount Victoria. By 2070, the feasible area is expected to expand. Notably, the RCP 2.6 scenario for 2070 predicts a dramatic reduction in habitable area around Mount Bintang Lestari, on the border between Indonesia and Papua New Guinea, rendering the entire lowland region of Papua uninhabitable. Consequently, a sharp decline in the population of *M. ingens* in this area is predicted.

1. INTRODUCTION

Climate projections indicate that tropical regions are expected to experecience significantly warmer and more severe compared to other part of the world (Gasparrini et al., 2017; Serdeczny et al., 2017; Siyum, 2020). According to the IPCC's recent multi-model mean, Northeastern United States, Central America, West and South Africa, and Southeast Asia are projected to become drier by 2100, while other already wet tropical regions will become even wetter (Lee et al., 2021). Studies by Feng and Zhang (2015) and Greve and Seneviratne (2015) suggest that wet areas will experience increased precipitation, whereas dry areas will see reduced rainfall. However, Knutti and Sedláček (2013) and McSweeney and Jones (2013) have noted that tropical regions show the lowest consensus among climate models regarding future weather changes. This uncertainty is compounded by smaller-scale assessments (Platts et al., 2015; Rahn et al., 2018). Given the projected increase in temperatures, reduced rainfall intensity represents a potential worst-case scenario for future crop growth.

Climatic factors have long been recognized as influential in ecological studies (Thiele, 1977). Determining optimal temperature and humidity across season is crucial for understanding species habitats predicting changes in their distribution area. *Musa ingens* Simmonds 1960 is an important component of tropical ecosystems, producing over 125 million tons annually and ranking among the world's most

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important fruit crops (FAO, 2018). Every parts of the plant is utilized in daily life (Kennedy, 2009). *M. ingens* can reach heights of 15 m (Argent, 1976; WCSP, 2018), thriving in the highlands of Papua New Guinea's main island within primary montane rainforest and exhibiting intolerance to high temperatures (Simmonds, 1960; Argent, 1976). Such topographic conditions are influenced by biotic and abiotic stresses, including climate factors such as salinity (8.0), relative humidity (15%), heat stress (>15°C), and cold temperature stress (<0°C). As a native plant of tropical regions, *M. ingens* thrives best at temperature between 31°C and 32°C with adequate nutrient and water availability (Kallow et al., 2020; Joshi et al., 2023), facilitating early flowering and higher yields in favorable environments (Ravi and Vaganan, 2016). Recorded collections indicate its presence predominantly in the Central Range montane rainforests ecoregion, with occurence also noted in the Huon Peninsula montane rainforests and Southeastern Papuan rainforests ecoregions (Olson et al., 2001). Studies have additionaly documented its presence in the Arfak Mountains, Indonesia (Sadsoeitoeboen et al., 2021).

The population of *M. ingens* significantly surpasses the threshold for threatened status, owing to its widespread distribution ascross numerouslocations. While specific population trends remains unclear, it is believed to be abundant in the central highlands of Papua New Guinea (Plummer et al., 2020), thus classified as Least Concern by conservation standards. However, habitat fragmentation poses a significant threat to this species (Butler, 2006; WWF, 2019; Mongabay, 2019). Factors such as timber extraction, subsistence, and industrial agriculture expansion, mining activities (Butler, 2006; WWF, 2019; Mongabay, 2019), along with local cultural practices (Sterly, 1997; Kennedy, 2009; Lentfer, 2009) contribute to this fragmentation. Furthermore, while *M. ingens* holds holticultural value, its cultivation outside its native climate presents considerable challenges (Plummer et al., 2020).

Although the anthropogenic factors mentioned are a concern for the survival of this species (Plummer et al., 2020), it appears that climate change has significantly altered the distribution of species such as bananas in the wild and has the potential to affect interactions between plants, pests, and diseases and the humans, animal, and plants hosts (Bebber, 2019; Watts et al., 2023; Abdoussalami et al., 2023). Empirical studies show that competition for water resources between trees may worsen under increasingly hot and dry climate conditions, thereby impacting distribution and productivity (Lott et al., 2009; Abdulai et al., 2018; Blaser et al., 2018). Bebber's (2019) in-depth study found that the increase in risk to the survival of banana species over the last 60 years was influenced by temperature. Therefore, little is known about the influence of climate change on the distribution of bananas, especially *M. ingens*.

Climate change is seen to affect the cycle and habitat range of the *M. ingens* species. In this contex, investigating the potential distribution of species becomes interesting, although some rare species are no less important. The species studied in this research has Least Concern (LC) status according to the IUCN Red List. It is very interesting to predict changes in the potential distribution of this species range in the next 30-50 years due to the influence of global climate change. This research aims to predict trends in changes in the potential distribution of *M. ingens* under various global climate change scenarios for 2050 and 2070.

2. METHODOLOGY

Research material was obtained from the Global Biodiversity Information Facility (GBIF) open database, initially comprising data from 37 sites. However, only 19 sites were used after eliminating duplicate data, coordinate errors, and data without coordinates (GBIF, 2023). We then validate these data with our colleagues through the framework of the Scientific Collaboration Agreement. The data collection covered the time range from 1963 to 2023, with occurences distributed in Indonesia (5 occurrences) and Papua New Guinea (14 occurrences) (Figure 1).

Bioclimatic modeling (Aldiansyah and Wahid, 2023; Aldiansyah and Wahid, 2024) uses 2.5 km resolution WorldClim data from the global climate database (www.worldclim.org) with 19 bioclimatic variables. The model is built from the Community Climate System Model 4 (CCSM 4). This data was chosen considering the development of all CCSM components from the previous version, particularly in the annual water storage cycle in tropical regions which is much improved (Gent et al., 2011). To enchance the prediction quality of the CSSM dataset, we first reduce the long-term bias and then compare it with the adequate Climate Forecast System Reanalysis (CFSR) dataset. Bearing in mind that varying degrees

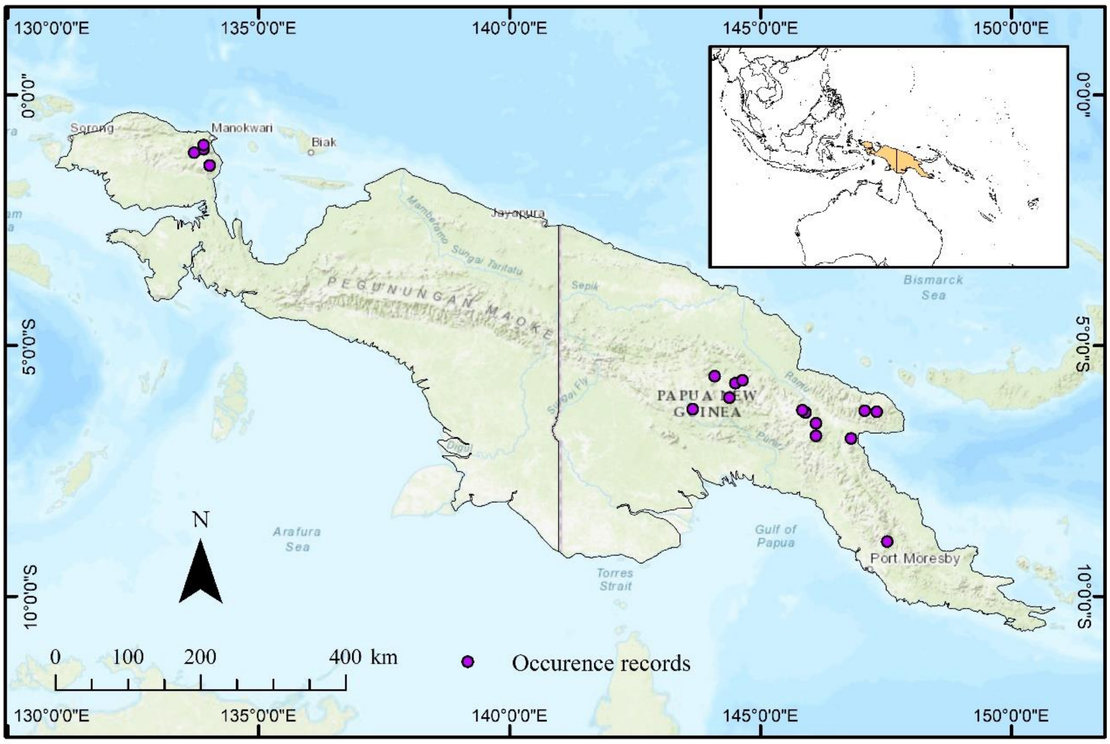

Figure 1. Study area

of bias can be found throughout the atmosphere at the study location for each of these variables, both spatially and temporally. This is due to the CCSM grid being too coarse, which produced significant biases for surface variables such as temperature, relative humidity, geopotential height, wind, and meridionality, especially in complex orographic conditions. We found consistency between CCSM and CFSR mixing ratio climatologies, particularly over complex terrain across the study area. Although it did not directly correct the mixing ratio data, the temperature and relative humidity corrections and subsequent mixing ratio calculations produce a climatology consistent with CFSR. This research calculates future climate predictions through representative concentration pathway (RCP) scenarios. The model provides four scenarios by dividing the radiation dose based on greenhouse gas concentrations: RCP2.6 (implies temperature increase on the planet to 0.9ºC on an average); RCP4.5 (increase to 1.9ºC); RCP6.0 (increase to 2.4ºC); RCP8.5 (increase to 4.1ºC). This model was chosen considering the resulting statistical similarity of the current climate compared to previous climate models (Lee et al., 2014; Ruosteenoja et al., 2016). We selected historical periods according to the latest recommendations of the World Meteorological Organization (WMO, 2017). Applying timeline scales in the past, we modeled for the 2050s and 2070s in each scenario and compared them with the present time model.

This research uses ArcGIS 10.4.1 for layer work and estimated potential reach using the SDM package in R (RStudio Team, 2020), identifying the most influential variables in each scenario. Several R packages were employed in bioclimatic modeling. Package "dismo" is used to load climate variables, while "mapview" is used to see the point of occurrences. Package "usdm" to test collinearity among the climatic variables by providing functions "vifstep" and "vifcor". We use the Variance Inflation Factor (VIF) to overcome the collinearity problem between predictor variables. Therefore, we did not include highly correlated variables to obtain an accurate model (Aldiansyah and Wahid, 2023; Aldiansyah and Wahid, 2024). A total of 19 bioclimatic variables were selected using VIF values. VIF reflects how much the standard error increases due to the multicollinearity of the variables included in the model. The correlation threshold was set at 0.7 (Table 1). Library "sdm" is used to run the algorithm of species distribution models. This package combines different parallel implementations of niche ecology and machine learning models on a single platform and uses an object-oriented, reproducible, and extensible approach in R (Naimi and Araújo, 2016). To predict species probabilities, the “sdmData” package was used to generate 200 pseudo-absence records which were used against 19 presence-only records to calibrate the model. The algorithm is run using bootstrap with two replications and applied to all scenarios. We used the Learning Vector Quantization (LVQ) algorithm to determine the most important factors from each selected predictor variable. LVQ is a supervised classifier that was introduced by Kohonen (1995). LVQ has been used in various studies for environmental sciences (Pourghasemi and Kerle, 2016), flood susceptibility mapping (Termeh et al., 2018; Aldiansyah and Wardani, 2023), landslide susceptibility mapping (Rahmati et al., 2016; Aldiansyah and Wardani, 2024), wildfire mapping (Aldiansyah and Madani, 2024) species distribution mapping (Aldiansyah and Risna, 2023; Aldiansyah et al., 2024). The LVQ was worked by searching for the shortest distance to the value and eliminating the noise, which could potentially interfere with the process of convergence in the forecasting system in large data (Kohonen, 1995).

Table 1. Bioclimatic variables and their computed variance inflation factor (VIF) obtained from the Worldclim database for modeling the bioclimatic range of *Musa ingens*

Bioclimatic variable	Variable description	Unit	VIF
Bio1	Annual mean temperature	ºC	304.41
Bio2	**Mean diurnal range [mean of monthly (maximum temp.-minimum temp.)]**	**ºC**	**1.82**
Bio3	Isothermality (Bio2/Bio7) (× 100)	ºC	17.33
Bio4	Temperature seasonality (standard deviation × 100)	ºC	51.69
Bio5	Maximum temperature of the warmest month	ºC	11.12
Bio6	Minimum temperature of the coldest month	ºC	28.13
Bio7	Temperature annual range (Bio5-Bio6)	ºC	66.07
Bio8	**Mean temperature of wettest quarter**	**ºC**	**1.45**
Bio9	**Mean temperature of driest quarter**	**ºC**	**2.43**
Bio10	Mean temperature of warmest quarter	ºC	521.09
Bio11	Mean temperature of coldest quarter	ºC	80.91
Bio12	Annual precipitation	mm	19.32
Bio13	**Precipitation of wettest month**	**mm**	**2.78**
Bio14	**Precipitation of driest month**	**mm**	**2.08**
Bio15	**Precipitation seasonality (coefficient of variation)**	**mm**	**1.94**
Bio16	Precipitation of wettest quarter	mm	117.25
Bio17	Precipitation of driest quarter	mm	242.24
Bio18	**Precipitation of warmest quarter**	**mm**	**1.84**
Bio19	**Precipitation of coldest quarter**	**mm**	**2.13**

Note: The variables in bold text are those that were selected based on VIF for predicting the bioclimatic range of *Musa ingens*.

Model verification in this study employs several metrics includin Receiver Operating Characteristics-Area Under Curve (ROC-AUC) (Shabani et al., 2016), Correlation (COR), True Skill Statistics (TSS) (Fourcade et al., 2018) Deviance (Agresti, 2018), Prevalence (Allouche et al., 2006), and Calibration (Fieberg et al., 2018). The ROC-AUC evaluates the model’s ability to distinguish between presence and absence data, with values ranging from 0 to 1; an AUC>0.7 indicates good model performance. COR assesses the strength of the relationship between climate variables and species presence. TSS measures relationship between observations and predictions, with values ranging from-1 to +1; a TSS closer to +1 indicates stronger the relationship between the two variables. Deviance represents model error, with values closer to 0 indicating lower error rates. Prevalence measures the proportion of sites where the species is present. Calibration tests the accuracy of model estimates, with values closer to 1 indicating better model calibration. Model accuracy was verified using a random split of presence data: 70% for model training and 30% for testing. A binarization prediction threshold was set based on model performance, considering predictions above the 10^{th} percentile threshold as potential distribution for species. This approach identifies 90% of analyzed presence point within the “potential” range, while disregarding 10% classified as unpotential for climate niche modeling.

3. RESULTS AND DISCUSSION

AUC is used to estimate the model's performance in recognizing the presence or absence of a species in a location. The obtained maps reliably characterize the peculiarities of the distribution of the studied species. In this research model, the average AUC obtained was 0.96, indicating a high model significance with a 97% probability of correctly predicting the presence of the studied species at the recorded points (Table 2). Meanwhile, the average values of COR, TSS, Deviance, Prevalence, and Calibration are 0.91, 0.93, 0.13, 0.14, and 0.80 respectively.

Table 2. Evaluation model of *Musa ingens* according to each scenario

Scenario	AUC	COR	TSS	Deviance	Prevalence	Calibration
Present time	0.98	0.95	0.92	0.09	0.16	0.79
RCP2.6 2050	0.97	0.96	0.93	0.21	0.10	0.89
RCP2.6 2070	0.94	0.93	0.92	0.11	0.10	0.80
RCP4.5 2050	0.97	0.93	0.93	0.10	0.19	0.81
RCP4.5 2070	0.96	0.81	0.96	0.17	0.05	0.74
RCP6.0 2050	0.97	0.79	0.97	0.13	0.21	0.77
RCP6.0 2070	0.93	0.92	0.92	0.09	0.02	0.91
RCP8.5 2050	0.97	0.95	0.91	0.08	0.17	0.81
RCP8.5 2070	0.96	0.93	0.95	0.15	0.27	0.66

Modeling problems generally suggest supplementing the constructed model with points of absence. In this study, the number of absence points was randomly selected as 200 points. According to Phillips et al. (2017), model adequacy will be determined by the choice of traits. This method used all bioclimatic parameters from the WorldClim dataset for this purpose. In case of limited species presence, resampling techniques are generally applied to duplicate the presence data, for example, N=100. However, this is greatly influenced by regional coverage in different cases. Thus, there is considerable variation depending on the type of modeling approach, species, and regional coverage. Modelers therefore need to be aware that the results obtained will include some degree of uncertainty, particularly due to climate (Thuiller et al., 2004; Araújo et al., 2005; IPCC, 2013; Casajus et al., 2016; Quillfeldt et al., 2017). Casajus et al. (2016) proposed an objective approach to selecting climate scenarios for a species. However, there are no definite guidelines for choosing the best type of setting or climate variable, which also depends on the specific periods to be considered and the magnitude of environmental changes (Araújo et al., 2004). This implies that when climate change occurs, the dynamics of the home range can be influenced by intrinsic population dynamics (Lawton, 1993). However, if strong environmental changes occur, species distribution dynamics will be strongly influenced by these changes (Araújo et al., 2004). Many invasive plant species have characteristics that can increase their dominance in transitional climate scenarios (Dukes and Mooney, 1999), as seen in several relatives of the *Musa* species. Additionally, potential new areas may emerge in previously unsuitable or marginal areas, while previously suitable areas may become unsuitable or marginal habitats (Araújo et al., 2004; Hirzel et al., 2002; Hirzel et al., 2006).

This research found that only in the RCP6.0 2070s scenario was the bio13 variable used along with other variables. Meanwhile, other present-time and future scenarios ignore Bio13 variables. The contributing variables in the present time variables are precipitation of warmest quarter, precipitation of driest month, and precipitation of coldest quarter. This contribution analysis remains the same in RCP2.6 and RCP8.5 in 2070, and RCP6.0 in 2070.

Analysis of variables contributions to the 2050 projections across all scenarios highlights the highest significance of precipitation in the warmest quarter, particularly under RCP6.0. Precipitation in the driest month also show significant influence across all scenarios for 2050, whereas in RCP4.5, precipitation of coldest quarter becomes more significant compared to other scenarios. Moving to 2070, precipitation of warmest quarter emerges as most significant under RCP2.6, RCP6.0, and RCP8.5, alongside continued significant of precipitation in the driest month. Notably, precipitation in the driest month takes precendence in importance under RCP4.5. Overall, the contribution of bioclimatic variables is likely to vary in shaping the future spatial distribution of *M. ingens*. Nonetheless, across all models, precipitation of warmest quarter and driest month consistently emerge as crucial variables, except in RCP4.5 where the driest month takes precedence (Figure 2).

This research models nine bioclimatic regions, including projection for 2050 and 2070 under four climate scenarios. Each model identifies four regions with varying probabilities of species presence: 0.8-1.0 -the most probable presence likelihood; 0.6-0.8 -high presence likelihood; 0.5-0.6 -moderate presence likelihood; 0.3-0.5 -low presence likelihood; and value below 0.3 -indicatingno presence likelihood. The threshold value 0.3 corresponds of the 10 percentiles.

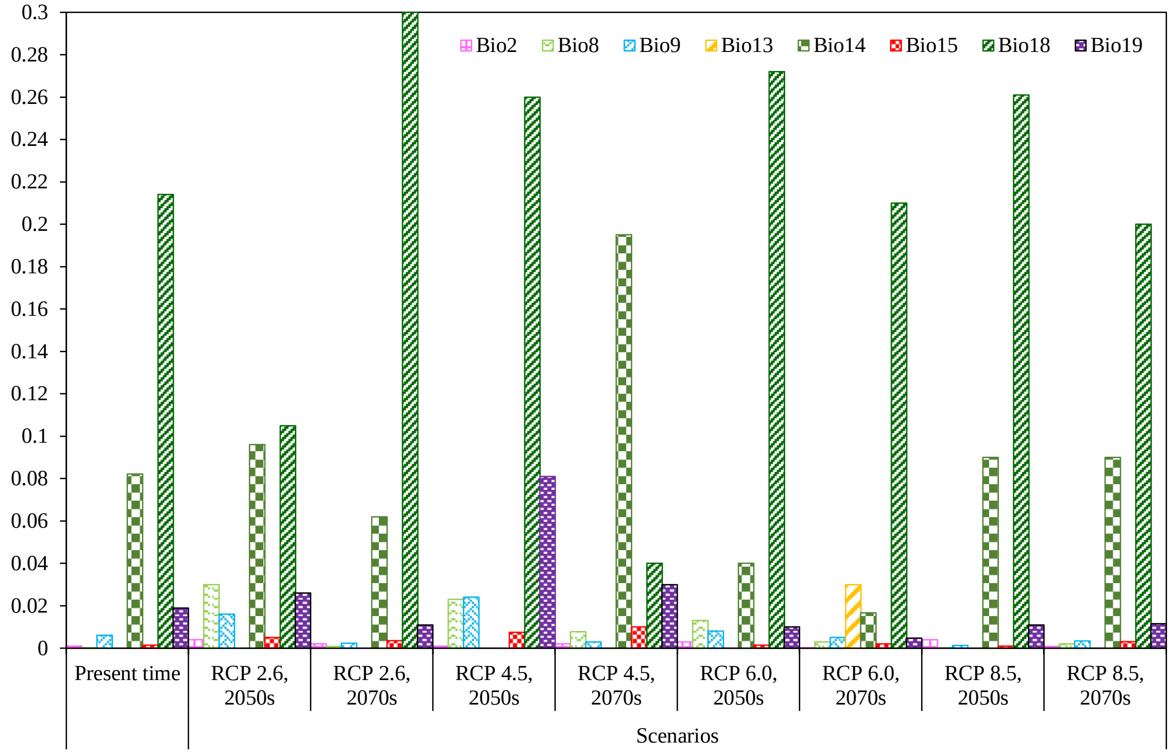

Figure 2. Variable importance

The current bioclimatic model of *M. ingens* identifies several key areas with high likelihood of species presence, including the Arfak mountains (2,955 m.a.s.l.), the Weyland mountains (3,891 m.a.s.l.), from Angemuk Peak (3,949 m.a.s.l.) to Osua Trikora Peak (4,750 m.a.s.l.) in Indonesia, as well as Mount Kabangama (4,104 m.a.s.l.), Mount Wilhelm (4,509 m.a.s.l.), Mount Michael (3,647 m.a.s.l.), Mount Piora (1,722 m.a.s.l.), Mount Victoria (4,038 m.a.s.l.), Mount Sibium (2,295 m.a.s.l.), Mount Suckling (3,676 m.a.s.l.), Mount Simpson (2,883 m.a.s.l.), including McAdam National Park (1.18 km^2) in Papua New Guinea. This area zones with a high probability of species presence (Figure 3). The Gauttier Mountains (2,230 m.a.s.l.), Cyclops Mountains (2,160 m.a.s.l.), and Wondiwoi Mountains (2,251 m.a.s.l.) are area with a moderate probability of species presence. The bioclimatic area with the highest probability of species presence covers 233,628 km^2, with moderate presence covering 97,653 km^2, and with low presence covering 447,407 km^2.

In the context of the RCP 2.6 scenario, there is a notable shift in the zone of high probability of species presence towards the western part of the region, centered around Weyland and Undundi-Wandandi (3,640 m.a.s.l.) (Figure 4). While the area with a very high probability remains with in the contemporary model, there is regional expansion into the high probability zone, notably across the temperate zone. Changes from McAdam National Park to the Simpson Mountains are expected to reduce the bioclimatic range of the region. Areas classified as high and medium probability of species presence have expanded to 341,840 km^2 and 107,874 km^2 respectively, while those with a low probability have decreased to 328,975 km^2.

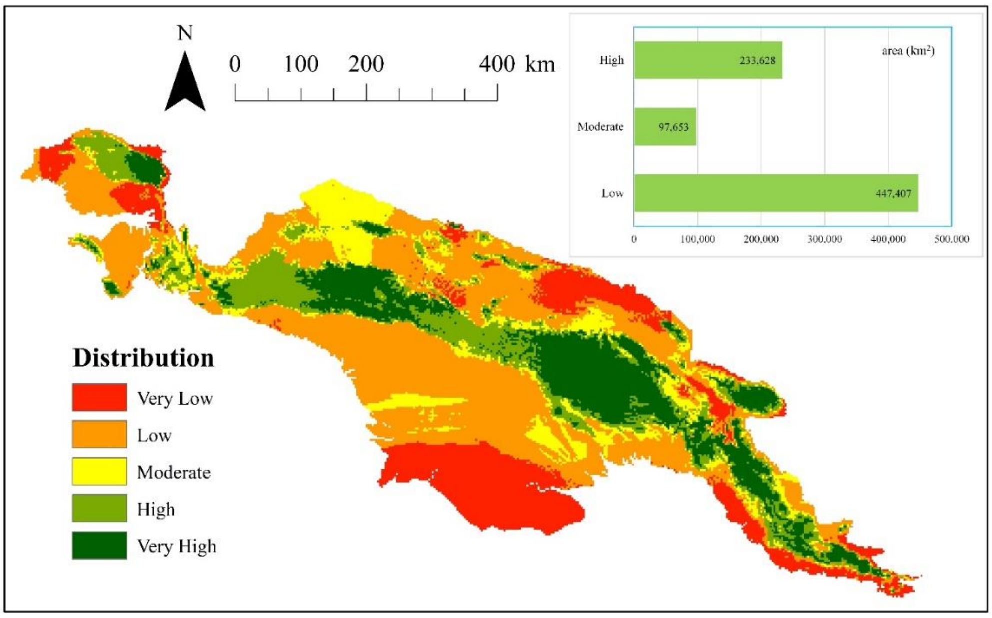

Figure 3. Present bioclimatic area in *Musa ingens*

According to the RCP 2.6 model scenario in 2070, the total area of the bioclimatic area significant changes, resulting in a notable shift in the ratio of area to potential distribution (Figure 4). Areas with high probability decreased by half to 161,091 km^2, while areas with low probability increased nearly double to 594,596 km^2 (Table 3). This change is driven by the RCP 2.6 climate scenario, which predicts rising temperatures due to increased greenhouse gas emissions until 2070. The bioclimatic conditions in 2070 are anticipated to differ significantly from current conditions, with a marked decline in potential area. This decrease is influenced by varying emissions scenarios, predicting a reduction in CO_2 levels from 380 to 100 ppm (IPCC, 2013). This reduction is associated with temperature increases ranging from 0.3ºC to 2.6ºC and 0.9ºC to 6.8ºC by 2100. Extreme low CO_2 levels (<100 ppm) can threaten plant growth, leading to slow growth and increased drought susceptibility even under optimal conditions near the equator. Consequently, only a few plant species may thrive even in the best conditions.

According to the scenario 4.5 projections for 2050, adecline in areas of moderate potential probability is observed compared to the contemporary model. This indicates changes in bioclimatic parameters and deteriorating environmental conditions in most areas, except around Puncak Jaya (4,884 m.a.s.l.). These changes may result from increased seasonal temperature contrasts. The most potential area for the studied species have decrease significantly compared to the current distribution, now covering only 55,482 km^2, with some regions becoming unsuitable (Figure 5). High potential probability is now primarily confined to the Osua Trikora Mountains and the highlands of the Giluwe Mountains (4,367 m.a.s.l.) to Mount Victoria. This scenario represents the most severe changes, with the sharpest decline in potential area.

In the 2070 scenario 4.5, the potential area expands compared to 2050 (high: 139,169 km^2) and the current distribution area (moderate: 307,264 km^2) (Figure 5). The area with low potential decreases to 332,254 km^2, extending its probability to the eastern and southern sides of the region. The most significant changes were observed in the amplitude of the driest monthly temperatures and the average precipitation during the warmest and coldest months. Compared to the current climate, future projections (PACCSAP, 2011) suggest a warmer and wetter, with the rainfall expected to change by ±25%, temperature increase by 1.4ºC to 3.1ºC, and sea level rising by 19 cm to 85 cm. These changes imply an increase in surface temperature of 1.0ºC to 4.2ºC, contributing to a sea level rise of 1.0ºC to 3.0ºC. Additionally, sea water is predicted to become more acidic, dropping by 0.3 to 0.4 pH units due to the increasing CO_2 absortion. Many plant and animal species may struggle to adapt to the impacts of RCP 4.5 (IPCC, 2014). In this scenario, carbon levels are estimated to reach 600 ppm by 2070. Small plants are predicted to decompose and released CO_2 while larger plants may survive longer by absorbing carbon from decaying vegetation. This dynamic explains the observed improvement in this scenario.

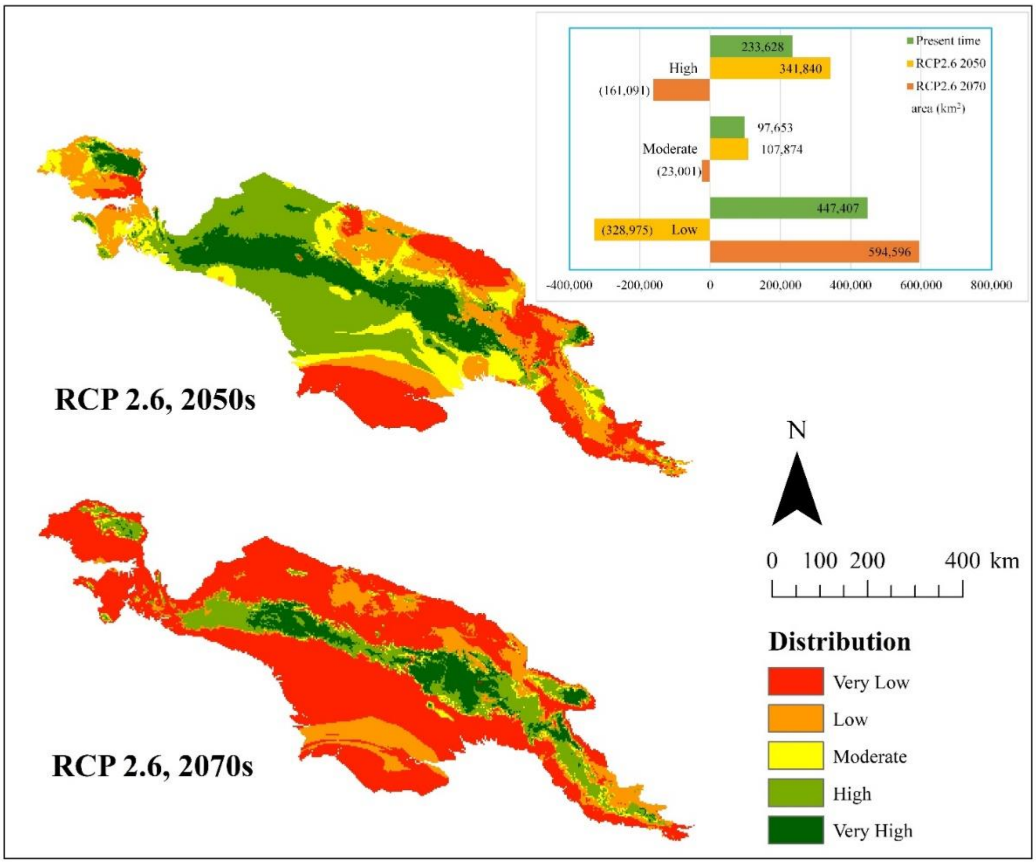

Figure 4. Bioclimatic range of *Musa ingens* to 2050 and 2070 according to RCP 2.6 scenario

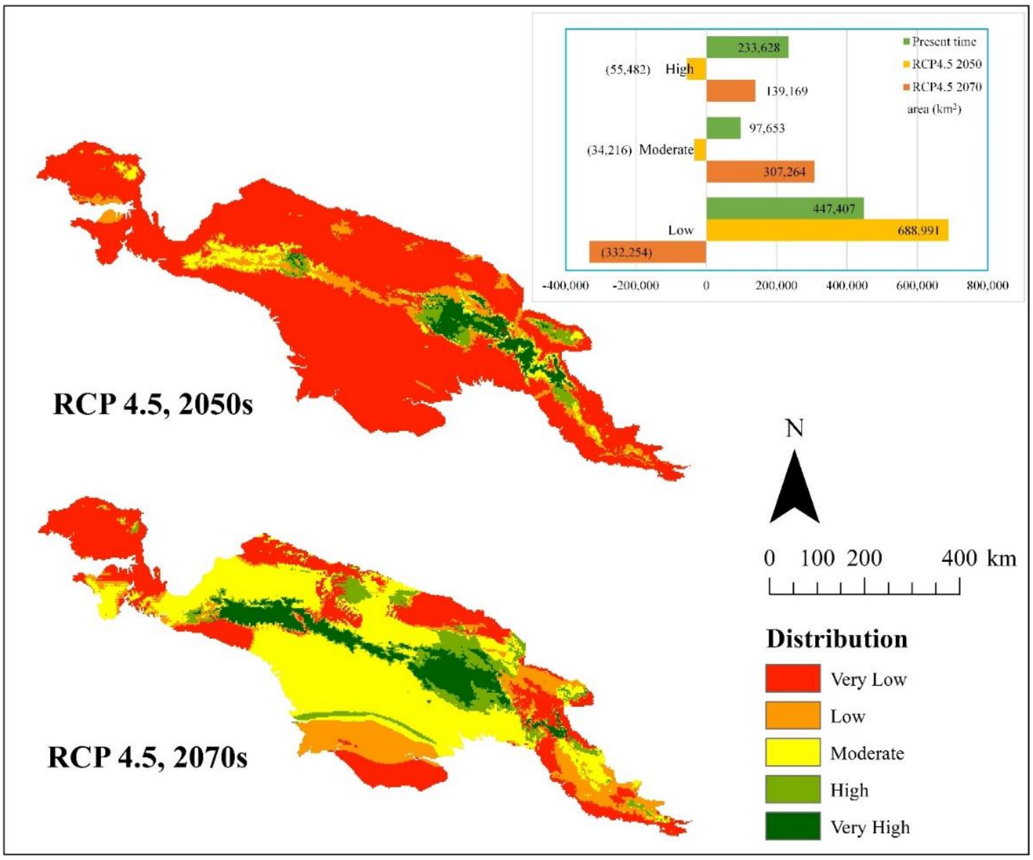

Figure 5. Bioclimatic range of *Musa ingens* to 2050 and 2070 according to RCP 4.5 scenario

According to the prognostic model of the RCP.6.0 scenario, areas with a marginal distribution index of 0.5-0.6 will decrease by 2050 (Figure 6). The area with the highest potential distribution index covers 124,294 km^2, which is 2.5 times lower than the previous model. In contrast, the area with marginal index has decreased significantly, covering only 28,312 km^2. The main contribution to this significant change is influenced by three factors, namely precipitation of warmest quarter, mean temperature of wettest quarter, and precipitation of driest month. The territorial reach is very limited, concentrated around Mount Bintang Lestari (3,745 m.a.s.l.) on the border of Indonesia and Papua New Guinea. Therefore, there is a trend similar to the RCP 4.5 scenario for 2050, where the high potential area decreases, but recovers by 2070 (Figure 6). A similar pattern is observed in areas with marginal potential; however, this is inversely proportional to the RCP 6.0 scenario for 2070, which shows a decrease in probability, covering 26,323 km^2. The difference in altitude, coupled with a gradual but significant increase in temperature from highlands to lowlands, indicates that *M. ingens* doest not grow well. This observation is supported by Argent (1976), who reported a very high intolerance to continuous temperature changes. However, with even sunlight as projected, the canopy of *M. ingens* will receive prolonged shade from largertrees in lowland areas. Unlike other banana subspecies that struggle in low light conditions (Simmonds, 1962), *M. ingens* is relatively shade tolerant.

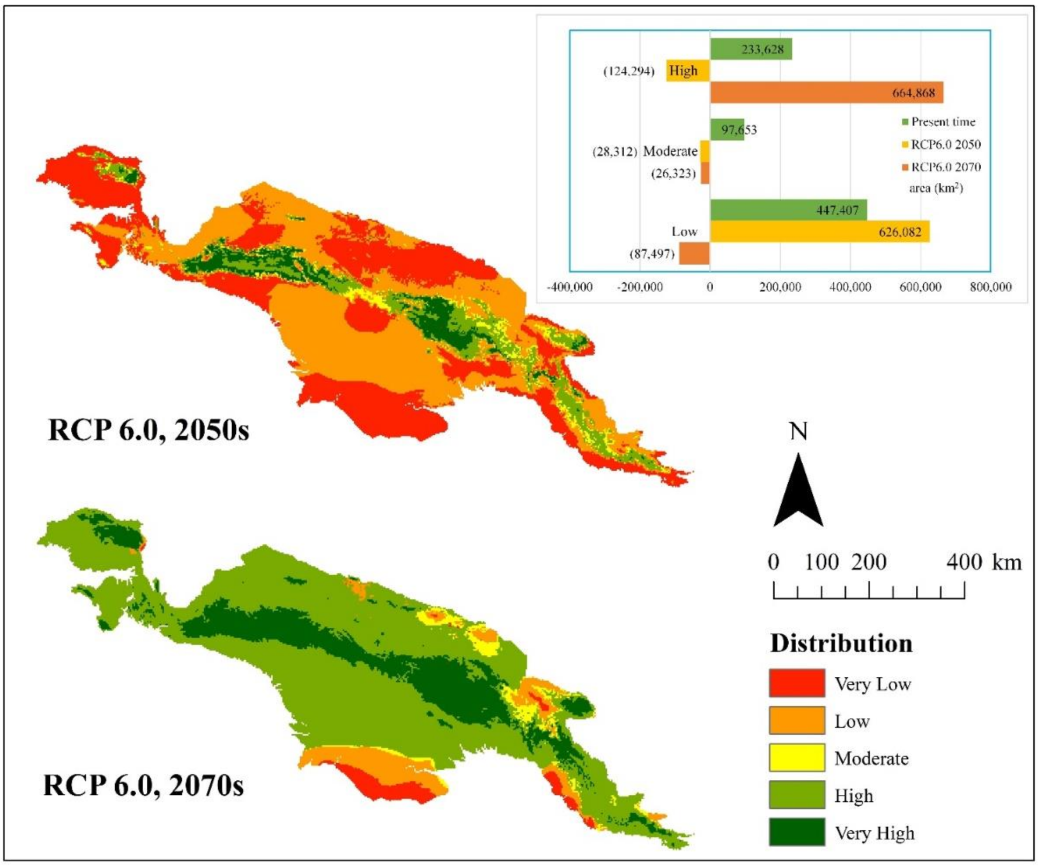

Figure 6. Bioclimatic range of *Musa ingens* to 2050 and 2070 according to RCP 6.0 scenario

The RCP 8.5 scenario shows the most favorablechanges, with minimal significant changes occurring in each region, and an expansion of the bioclimatic area. The highland areas along the island of Papua significantly influence the surrounding lower land areas (Figure 7).

The model in this study shows that the total range does not change significantly. Some factors also show a higher level of importance, and regional distribution is improving. In the “lower” scenario, the area with conditions that have the potential to worsen decrease significantly. However, this area is larger than areas with high potential. This means that by 2070, the average annual temperature for inland, and higher mountain areas will increase by 28.10ºC to 30.20ºC, and 25.10ºC to 37.2ºC respectively. This implies that spatial and temporal variability in temperature will be small (>1.2ºC) compared to current variability, supporting an average annual temperature of around 30±2ºC throughout the region. The temperature increase is estimated at 0.32ºC by 2050 and 0.46ºC by 2070. This change is expected to continue due to increasing greenhouse gas emissions (Canadell and Raupach, 2008; Rahmstorf et al., 2007). Annual and seasonal rainfall is expected to increase consistently with the intensification of the rainy season and the convergence of inter-tropical zones. This suggests that higher areas will receive more than 280 cm of rainfall per year in the current climate, reaching 1,000 cm per year by 2070 until environmental stability is achieved. The temperature required for optimal leaf growth and development is 31.6ºC with a relatively humid climate, which can be achieved year round in tropical areas.

In this study, areas with a high level of probability indicate regions with the most potential and tend to be stable. This stability is influenced by the location's altitude above 1,000 m.a.s.l. (Argent, 1976). The large size of this species allows it to compete for sunlight from the surrounding trees. However, there are significant changes based on each scenario. Areas with moderate probability tend to be less stable, and their condition worsens when bioclimatic parameters change. This situation is exacerbated by complex topographic conditions, which result in higher hydraulic resistance (Domec et al., 2019) because water needs to be transported over long distances as the temperature increases. It is reasonable to assume that *M. ingens* is limited to the highlands because the relatively low temperatures, frequent fog, and low evaporation requirements create favorable conditions for transporting water 15 m upwards without damaging its xylem vessels. The central part of the island of Papua changed significantly, with an increase in precipitation during the warmest quarter. The continental index may rise due to climate change, and this impact seems to affect the highland areas as well. This suggests that the temperature differences in the region are very pronounced.

Changes in temperature and rainfall, relative humidity will significantly affect terrestrial biodiversity. The biodiversity we see today is the result of co-evolutionary processes and mechanisms that developed to coexist through spatial and temporal climate variability. Future tolerance to climate change will bring significant changes to many species, as it will take a long time for them to adapt. These pressures will also alter the composition of soil microbes, impacting the soil as a growth medium and affecting the soil ecosystem. This is crucial because soil microbes play an essential role in the decomposition of dead organic matter and the cycle of soil nutrients, both of which are vital for soil productivity and sustainable use.

The climate change scenario in this study illustrates that bananas require a warm subtropical climate and sufficient humidity. Adequate rainfall and soil moisture are necessary for plant growth (Pabst et al., 2016). Changes in soil moisture will reduce microbial activity, decreased leading to decomposition, and consequently, a reduction in total soil carbon (Meisner et al., 2021). According to Gunina et al. (2018), soil biota biomass is positively correlated with higher rainfall. However, the results of this research simulated a gradual increase in temperature and an indirect reduction inrainfall. This research indicates that climate changes affecting *M. ingens* plants influencethe distribution of soil nutrients fand changes in groundwater as a growing medium. This finding aligns with Becker (2017), who reported that in warm and dry climates (<1,900 m.a.s.l.), variations in total carbon and total nitrogen content in the soil are determined by climatic conditions, whereas in wet climates (>1,900 m.a.s.l.), these variations arestrongly controlled by tree biomass, which produces nutrients in the soil.

Changes in climate conditions have a significant negative impact on banana distribution. In cooler areas, banana distribution is limited, but higher temperatures caused by climate change can benefit productivity (Ramirez et al., 2011). This indicates that annual precipitation can be beneficial for plants, excessively high annual precipitation can be detrimental. High mean annual precipitation can increase the prevalence fungal diseases in bananas, reducing their ability to survive in the wild and lowering their productivity (Nyombi, 2010; Bebber, 2019). In contrast, some drier areas may experience positive effect. However, Bebber (2019) argues that temperature is a significant driving factor for this increased risk of fungal diseases. Climate change has created air temperatures more favorable for fungal spore growth.

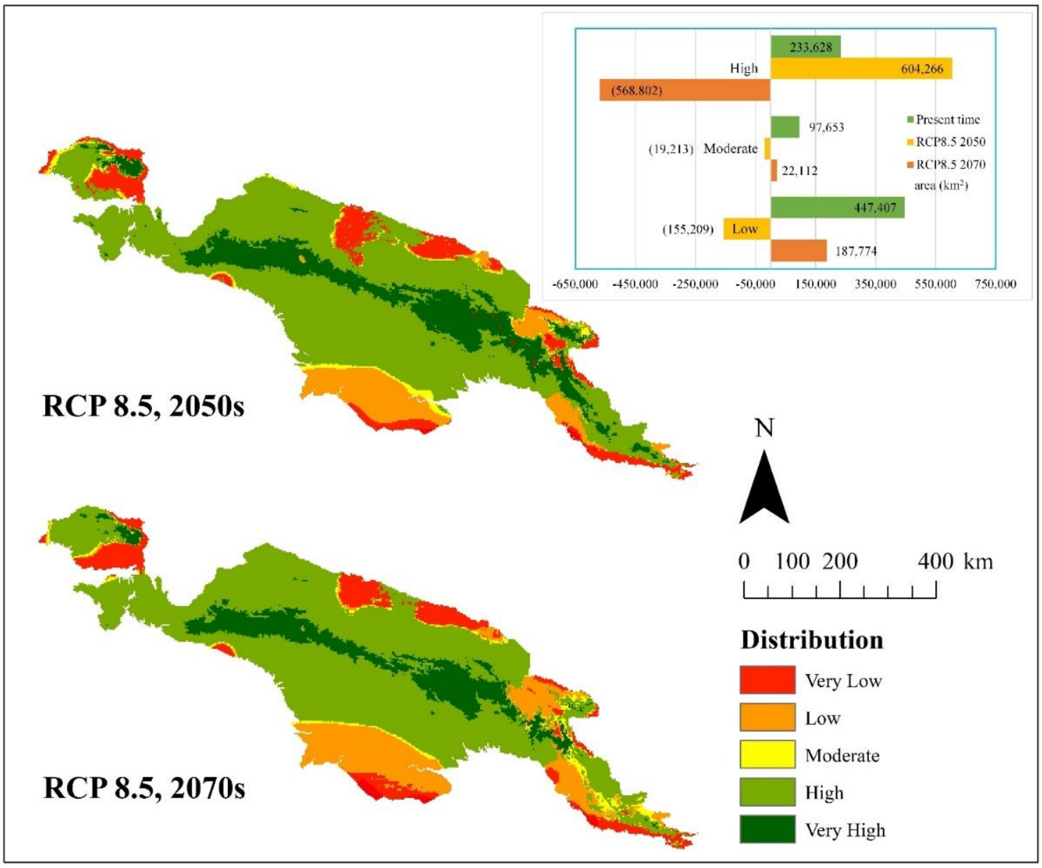

Figure 7. Bioclimatic range of *Musa ingens* to 2050 and 2070 according to RCP 8.5 scenario

Table 3. Bioclimatic area size (km^2) in *Musa ingens* according to RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 scenarios

Period	Bioclimatic range index				
	<0.30	0.30-0.49	0.50-0.59	0.60-0.79	0.80-1.00
Present time	134,980	312,427	97,653	109,037	124,590
RCP2.6 2050	160,626	168,349	107,874	222,497	119,342
RCP2.6 2070	473,667	120,929	23,001	98,796	62,295
RCP4.5 2050	621,765	67,225	34,216	24,609	30,872
RCP4.5 2070	219,937	112,317	307,264	71,478	67,691
RCP6.0 2050	293,193	332,889	28,312	77,340	46,954
RCP6.0 2070	25,561	61,935	26,323	508,813	156,055
RCP8.5 2050	75,732	79,477	19,213	476,925	127,341
RCP8.5 2070	77,890	109,884	22,112	472,926	95,876

Climate change is not the only factor that increases fungal infections in bananas. Diseases that reduce the fruit production tree may also be influenced by other factors. Besides fungal infections, water stress due to inadequate water intake will reduce banana yields. Under water stress, bananas close their stomata to conserve water, reducing carbon assimilation and crop yields (Turner et al., 2007). Most Banana varieties grow best with 12 hours of bright light and high humidity of 50% or higher. The ideal temperature range is around 26 to 30°C. Growth begins at 18ºC, reaches optimal growth at 27ºC, and stops completely when the temperature reaches 38ºC. This suggests that while tropical plants, including bananas, can tolerate temperatures near freezing, the cannot tolerate excessively high temperatures, which they rarely experience in the wild. Although Bananas grow best in bright sunlight, high temperatures will scorch the leaves and fruit, indirectly affecting their survival in the wild.

This research indicates that environmental parameter dynamics within the same distribution across different years can influence the environmental suitability of *M. ingens*, although the long-term population abundance cycle remains unknown. Some scenarios suggest less concerning outcomes; areas to become drier in the future may experience reduce disease infections, but bananas need require amplewater to thrive. Therefore, addressing infection issues through drying out may necessitate effective water management for banana distribution in the future. These factors are crucial in shaping the bioclimatic range of this species. Lastly, this research can inform IUCN about the potential impact of climate change on *M. ingens* in the future. We believe this study is the first report to model the potential bioclimatic range of *M. ingens* across the mainland of Papua Island. Further research on the *Musa* species incorporating biophysical variables, distribution aspects, and habitat history could provide valuable insights for future management of this species.

4. CONCLUSION

The distribution of *M. ingens*, modeled through maximum entropy species distribution modeling, reveals that the key factors influencing its distribution including precipitation of warmest quarter, precipitation of driest month, precipitation of coldest quarter, and mean temperature of wettest quarter. Bioclimatic changes under the RCP 4.5 scenario are projected to result in a fourfold decrease in the current area of high abundance, with a shift towards isolated optimal climate areas in highlands spanning from the Osua Trikora Mountains to the Giluwe Mountains and Mount Victoria. Many areas areas became uninhabitable. Map forecasting species distributions under modeled scenarios ilustrate species-specific responses to potential climate change, indicating a significant reduction in current distribution range and a shift towards the central region, with fewer locations across the island of Papua.

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