Evaluating current and future potential distribution of epiphytic orchids in the Congo Basin with ecological niche models

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DEDICATION

I dedicate this piece of work to the Biodiversity Informatics Training Curriculum (BITC) Instructors and the JRS Biodiversity Foundation

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ABSTRACT

The Congo Basin Forest harbors a rich diversity of epiphytic communities, with the Orchidaceae alone making up more than 50% of all epiphytes in the region. Despite the huge diversity of epiphytes, many species, including epiphytic orchids, are at risk to a diverse array of threats. Climate change for instance poses severe threats to epiphytic orchids due to elevated temperatures, prolonged periods of droughts, as well as reduced rainfall across the Congo Basin Forest. In this study, we used ecological niche modeling and GIS techniques to identify spatial patterns of species richness, potential future climate refugia, and novel climatic suitability areas, by estimating future potential climatic suitability for epiphytic orchids in 2021-2040. We also evaluated the overlap of hotspots of climatic suitability for epiphytic orchids with the current network of protected areas in the Congo Basin. Using two Global Circulation Models and moderate and high greenhouse gasses emission scenarios, our results showed that, of the 16 species studied, nine species of epiphytic orchids would lose more than 30% of their current potentially suitable range. Additionally, spatial distribution of epiphytic orchids showed less than 5% overlap of potentially suitable climatic hotspots with the network of protected areas in the Congo Basin. Outside of protected areas our models forecasted stable areas buffering climatic changes ("slow lanes" or climate refugia) and as well novel climatic suitability areas across the biogeographic extent of Africa. Climate refugia and novel areas of climatic suitability may be crucial for long-term persistence and thriving of epiphytic orchids. These findings provide the first estimation to the potential distribution of epiphytic orchids in the Congo Basin and serve as a first step towards a regional effort to protect the biodiversity of the Guineo-Congolian landscape.

Keywords: Congo Basin Forest**,** ecological niche modeling, niche suitability, climate change, climate refugia, conservation and biodiversity

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CHAPTER I: INTRODUCTION

The Orchidaceae (orchids) is one of the largest plant families, with an estimated 25,000 species and 800 genera worldwide. It is a highly diverse taxonomic group, with members thriving in diverse ecological conditions and different niches. Some authors classify the family into life forms (Ellenberg & Mueller-Dombois, 1967) such as Epiphytes, Geophytes, Hemicryptophytes, and Terrestrial herbs, Lithophytic, or Saprophytic (Taylor et al, 2021). Vascular epiphytes mainly grow on trees and globally these plants are distributed across major biomes, although most studies referred to their distribution mainly within the tropical vegetation (Zotz, 2016). They constitute up to 10% of plant diversity and are estimated to make up to 25% of the tropical vascular plant community (Nieder et al, 2001). In this study, we focus on epiphytic orchids in the Congo Basin Forest, an example of a diverse vascular epiphyte group. In the Congo Basin, epiphytic orchids represent about 50% of the vascular epiphyte diversity (Zapfack, & Engwald, 2008; Nfornkah et al, 2019) and are mostly found in the mid canopy and understory tree strata on hosts known as phorophytes (Sodjinou et al, 2019). The success of their establishment on host is highly dependent on the host characteristics and mycorrhizal fungi (Flores-Palacios & Ortiz-Pulido, 2005, Fay & Chase, 2009, Einzmann et al, 2015).

Epiphytic orchids are sensitive to environmental gradients (Fay & Chase, 2009). Hence, the changing climatic conditions in the anthropocene will further exacerbate the already imperiled state of most species of Orchidaceae in the Congo Basin, thereby increasing the risk to local extinction (Benzing, 1986; Zotz & Hietz, 2001; Fay & Chase, 2009; Keppel et al, 2016). Furthermore, some orchids are limited by extreme high temperatures and low precipitation (Gillespie, 2001). Studies have shown that several species of orchids are at risk to a variety of threats (Fay, 2018) such as over-harvesting of wild resources, habitat loss and destruction, fragmentation, deforestation and forest degradation, and recent changes in climate (Cribb & Pollard, 2002; Fay & Chase, 2009; UNEP-WCMC, 2014; Keppel et al, 2016). The survival and success of most epiphytic orchid species also strongly correlate with environmental variables (Benzing, 1986; Zotz & Hietz, 2001). For example, the moisture content of tree trunks or aerial soils (mesh of dead plant materials) on which epiphytic orchids adhere to or grow in are strong determining factors for species' success (Sodjinou et al, 2019 and later Zarate-Garcia et al, 2020).

More broadly, climate is critical in the determination of species' distributions (Woodward & Cramer, 1996; Guisan & Zimmerman, 2000, Nadkarni & Solano, 2002), therefore examining climate as an environmental filter is vital to address future challenges of species' persistence. The changing climate in the Anthropocene is expected to put many species in imperiled circumstances and might even hasten the extinction of some groups with narrow tolerances to environmental variability. Epiphytic species are particularly sensitive to variations in climate (Benzing, 1986; Zotz & Hietz, 2001; Texier et al, 2018) and extreme climatic conditions such as low atmospheric humidity (Zotz, 2016) and prolonged drought (Flores-Palacios & Ortiz-Pulido, 2005; Zarate-Garcia et al, 2020) decrease the fitness of this group of plants. Zotz & Hietz (2001) report that the spatial distribution of epiphytes on forest canopy may be partially due to different germination requirements (e.g., presence of mycorrhizal fungi; McCormick et al, 2018) or eco-physiological characteristics. Moreover, high seedlings and juvenile mortality correlates with drought stress and water-holding capacity of substrates.

Environmental variables such as topography and climate have been used to estimate the ecological niche or distribution of species (Phillips, 2006; Araujo & Peterson, 2012). Superficially, estimating the niche or distribution of species may appear similar, however in-depth evaluation shows conceptual differences separating the two. That is, niche estimation with ecological niche modeling (ENM) is rooted in the niche theory described by Grinnell and later modified by Hutchinson (Araujo & Peterson, 2012). A niche model approximates a species' ecological niche in environmental space and projects it in geographical space (Phillips, 2006). The estimated multidimensional space can be close to the fundamental niche of the species, depending on the species and the data used to train the niche model (Soberón & Nakamura, 2009). By comparison, the goal of species distribution modeling (SDM) is to quantify the occupied geographic distribution of the species that generally is a subset of the fundamental niche, limited by biotic interactions and dispersal abilities (Araujo & Peterson, 2012). The two approaches, ENM and SDM, have been employed to evaluate the effect of climate change on species' distributions to inform conservation management practice and guide decisions to help preserve imperiled populations (Araujo & Peterson, 2012). For example, ENM has been used for (i) discovery of a new population of rare, threatened species (Tang et al, 2018); (ii) discovery of new species (Tang et al, 2018); (iii) conservation planning (Razgour et al, 2016; Qiao et al, 2017); (iv) identifying historic and future refugia for biodiversity (Reina-Rodríguez et al, 2017; Preau, 2018); and (v) assessing potential geographic ranges of invasive species (Konowalik & Kolanowska, 2018; Thiney et al, 2019). ENM has also been used to confirm the IUCN status of species and to update range maps (area of occurrence) built from expert opinion (Droissart et al, 2009).

In biodiversity conservation, sometimes charismatic species (species valued by many or having some important cultural value) are used as candidate species to represent other species for which there are little to no presence records or just expert opinion. Hence, charismatic species are also described as surrogate species, meaning species representing or speaking for other species (Caro & O'Doherty, 1999). However, the use of surrogate species in biodiversity conservation action programs may not be as effective (Game et al, 2013), especially for a group like the epiphytic orchids whose distribution is strongly affected by tree composition, mycorrhiza association, and climatic factors. Many studies on epiphytic orchids have mainly focused on orchid-phorophytes and orchid-mycorrhiza relationships (Li et al, 2021), while climate effects on epiphytic orchid distribution have been seldomly investigated (Kolanowska et al, 2017; Gaskett & Gallagher, 2018; Evans et al, 2020). Moreover, none of these studies have focused on the role of protected areas as a conservation management tool in mitigating deforestation and current-future climatic mismatch for orchids. Climate change for instance poses a severe threat to most species of epiphytic orchids (Nadkarni & Solano, 2002), and this can be exacerbated by extensive deforestation. In this study, we address the potential applications of ENM towards understanding species distributional response to increased temperature and dryness as a result of climate change. Additionally, this study provides insight into the spatial distribution of stable climatic areas (refugia) and novel areas of climatic suitability that may become central for persistence of species and consequently for conservation decisions and management of species and protected areas. Thus, the study was based on the following research questions:

(1) *What is the extent of overlap between the current network of protected areas in the Congo Basin and current or future potential distributions of epiphytic orchids?* This analysis will inform current inclusive strategies to preserve biodiversity i.e., how well the protected areas are doing as a conservation implementation strategy.

(2) What would be the distribution of novel areas of climatic suitability and stable areas (refugia) across Africa? This analysis is vital for landscape conservation and future preservation of epiphytic orchids as it addresses the issues of spatial patterns of climatically suitable areas for the potential dispersal or assisted migration of species.

CHAPTER II: METHODOLOGY

2.1 Study area and focus taxa

This study was conducted in the Congo Basin Forest (otherwise called the Lower Guineo-Congolian Forest), a large area (2 million km^2) of relatively intact humid tropical lowland forest situated within about 7 degrees north and south of the equator on the African continent (Figure 1). The forests extend from the coastline of the Atlantic Ocean from eastern Nigeria across six territorial boundaries (Cameroon, Central African Republic, Democratic Republic of Congo, Equatorial Guinea, Gabon, and the Republic of Congo) into the Albertine rift in eastern Africa (Shapiro et al, 2021).

The forest is characterized by strong precipitation seasonality (Dyer et al, 2017). The regional precipitation predominantly originates from local evaporation and the southern portion of the Indian Ocean. The surrounding land cover contributes via evaporation up to 25% of precipitation in March, April, and May, and 16% in September, October, and November (Dyer et al, 2017). The topography ranges from sea level on the Atlantic coast in West of Africa to more than 1,000 m asl towards the Albertine rift in the Eastern Democratic Republic of Congo (DRC). The annual rainfall ranges from 1,500 mm to about 5,000 mm. The mean annual temperature recorded is between 27 and 30 degrees Celsius (Oyebanji et al, 2021).

Vegetation distribution strongly correlates with rainfall distribution and the severity of the dry season. Drought adapted vegetation is mainly distributed along the northern fringe of the Congo Basin Forest, whereas vegetation adapted to cool and wet conditions is mostly distributed along the western limit of the Congo Basin Forest. Towards the eastern border of the Congo Basin Forest, dryness increases with reduced rainfall as the terrain rises into the mountains of the Albertine rift (CARPE, 2005; Shapiro et al, 2021).

The Congo Basin Forest serves as a global carbon sink, sequestering megatons of atmospheric carbon dioxide (Dargie et al, 2017; Shapiro et al, 2021), thereby playing a key role in mitigating global warming. It also plays an important part in the water cycle by regulating freshwater and weather patterns, as well as providing resources for over 100 million people in the region (CARPE, 2005). It is a biodiversity hotspot and center of high endemicity for both plant and animal species. The forest is estimated to hold up 15% of vascular epiphytes of the floristic composition.

2.2 Biodiversity data and georeferencing

We downloaded occurrence data for epiphytic orchids from the Global Biodiversity Information Facility (GBIF; GBIF.org) in two separate instances: one for Cameroon (11 March 2020) and the other for Gabon, Equatorial Guinea, DR Congo, and the

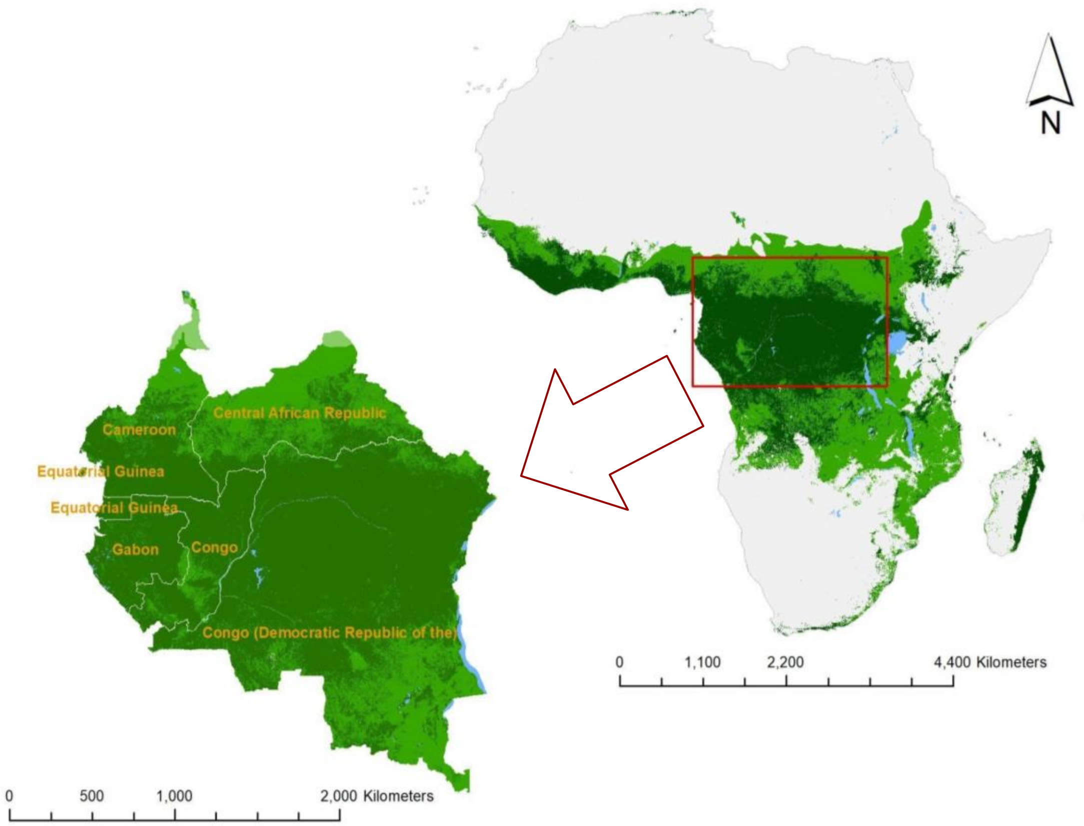

Figure 1: Guineo-Congolian Forest in Africa and the Congo Basin Forest in the red rectangle. Inset map (lower left corner) shows the six countries overlapping with the Congo Basin.

Republic of Congo (4 February 2021). We also used additional occurrence records from a digitization project of West African herbarium specimens. We separated the pooled species records into different orchid lifeforms and selected the epiphytes, totaling 59 orchid species. After a preliminary assessment of the number and spatial distribution of occurrence records, we selected 24 epiphytic orchids, 12 with assigned IUCN threat categories and 12 others, which we separated into narrow range and wide range distributed categories (Table 4 a & b). All 24 species were listed in Appendix II of CITES (Convention on International Trade in Endangered Species), thus trade of any kind with these species is banned by international law because of their threat status (www.cites.org; Cooney et al, 2021).

Some of the occurrence records had data quality issues (vague locality description and imprecise geographic coordinates), and many lacked geographic coordinates (latitude and longitude). Hence, when coordinates were unavailable, we used the locality description to assign latitude and longitude coordinates to species' records (i.e., georeferencing). For the selected 24 species of epiphytic orchids, we georeferenced the occurrence records following best practices by Zermoglio et al, (2020). Using the locality description for each occurrence record, we assigned latitude and longitude coordinates from digital gazetteer (National Geospatial-Intelligence Agency http://geonames.nga.mil) and maps (Google Maps https://www.google.com/maps/place, OpenStreetMap https://www.openstreetmap.org/), and then used Map Developer radius tool (https://www.mapdevelopers.com/draw-circle-tool.php) to determine the radius (spatial extent) of a locality. Finally, the locality's latitude, longitude, and radius were used to estimate the uncertainty associated with each locality description in the georeferencing calculator (Wieczorek, & Wieczorek, 2021).

A total of 1,499 occurrence records was collated from the GBIF orchid occurrence data for Congo Basin countries after we initially identified 24 epiphytic orchid species. The occurrence data were cleaned, georeferenced, and spatially rarified at 4.5 km using SDM Toolbox in ESRI ArcGIS 10.5 to remove duplicate presence records. We selected this spatial resolution to match the occurrence data to the climate data resolution (2.5 arc minutes, about 4.5 km) and to eliminate possible spatial overlap between the training and the testing data sets used in the models (Elith et al, 2006). The number of species incorporated in the modeling process dropped from the initial 24 species to 16; eight species were discarded because they did not meet the minimum number of records (14 for narrow range and 25 for wide range species) needed for Maxent experiment (Proosdij et al, 2016; Hernandez et al, 2006; Papeş & Gaubert, 2007; Elith et al, 2011; Islam et al, 2020). Hence, the rarified procedure retained 569 unique occurrence records for a total of 16 epiphytic orchid species. The sixteen species retained for analysis are: *Ansellia africana* Lindl.; *Angraecum birrimense* Rolfe.; *Angraecum pungens* Schltr.; *Calyptrochilum emarginatum* Schltr.; *Cyrtorchis ringens* (Rchb.f.) Summerh.; *Diaphananthe bidens* Schltr.; *Diaphananthe pellucida* Schltr.; *Podangis dactyloceras* Schltr.; *Polystachya alpina* Lindl.; *Polystachya bifida* Lindl.;

Polystachya calluniflora Kraenzl.; *Polystachya caloglossa* Rchb.f.; *Polystachya victoriae* Kraenzl.; *Polystachya riomuniensis* Stévart & Nguema; *Listrostachys pertusa* Rchb.f.; and *Tridactyle anthomaniaca* (Rchb.f.) Summerh.

2.3 Climate data

We used 19 bioclimatic variables (Table 1) in the modeling process. These are sets of biologically meaningful climate variables generated from monthly temperature and rainfall values. The bioclimatic variables were obtained from the WorldClim database (https://worldclim.org/data/index.html). The database provides both historical climate data and future climate projections. We used historical data (current) from 1970-2000 and future climatic data (climate scenarios) for 2021-2040 at 2.5 arc-minutes resolution (4.5 km). Climatic variables are often used for ENM (Papes & Gaubert, 2007; Qiao et al, 2017; Tang et al, 2018; Dhyani et al, 2018; Tshwene-Mauchaza & Aguirre-Gutierrez, 2019).

We selected two future greenhouse gasses emissions scenarios for the period 2021-2040: the shared-socioeconomic pathway (SSP) 2-4.5 and SSP 5-8.5 that were introduced in the 6th Assessment report by the Intergovernmental Panel for Climate Change (IPCC). The first scenario, SSP2-4.5, represents an optimistic pathway that forecasts a mean increase in global temperature of 3 degrees Celsius while the second scenario, SSP5-8.5, represents a worst-case pathway with no restriction policies to curb carbon emissions, thus projects a mean increase in global temperature of 5 degrees Celsius (Riahi et al, 2017). We selected two global circulation models (GCMs) associated with the two SSPs for future projections of temperature and precipitation, MIROC-ES2L and CNRM-ESM2-1, based on the premise that the Congo Basin Forest is projected to experience reduced rainfall and drought over the next decades and are estimated to be severe in the northern and southern limit of the forest. The two GCMs are known to predict reduced precipitation and severe drought and elevated temperature change (Nashwan & Shahid, 2019).

2.4 The modeling algorithm, training, and testing

The study used maximum entropy (Maxent) approach for estimating species' ecological niches and the corresponding geographic distributions; this is a machine learning algorithm that employs a spatially explicit probability approach (Gibbs probability distribution). The correlative probability values (0-1) estimate the distribution of maximum entropy, subject to a set of environmental constraints that represent our incomplete information about the actual distribution of a species (Phillips et al, 2006). Hence, Maxent uses presence data and a random sample of background locations (or pseudo-absences) to estimate the environmental suitability for a species (Phillips et al, 2006, Phillips & Dudik, 2008). The algorithm has been consistently ranked in recent times as one of the best performing algorithms (Hernandez et al, 2006; Hendricks et al, 2019) and thus frequently used for ENM (Diniz-Filho et al, 2009; Rodriguez-Soto et al, 2013; Harrigan et al, 2014

Table 1: The 19 bioclimatic variables from the WorldClim database used in ecological niche models.

Code	Variable description
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (×100)
BIO4	Temperature Seasonality (standard deviation ×100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

and Hendricks et al, 2019). Its advantage lies in its ability to produce reliable models with small numbers of occurrence records and its strength to incorporate binary, categorical, and continuous environmental predictor variables at the same time (Papeş & Gaubert, 2007; Elith et al, 2011, Islam et al, 2020).

To train the models, we designed five training regions using species occurrence data to identify similar extent of occurrence, then we clipped the current climatic variables to each training region in ESRI ArcGIS 10.5. Then, we buffered each training region by 50 km, assuming that species could disperse maximum 50 km from the outer limit of known occurrences; this extended the training regions ten climatic pixels from known occurrences.

We ran two Maxent experiments. First, to fine-tune model calibration, we used cross validation with five replicates, which split the occurrence data for each species into unique subsets (sampling without replacement) of 80% presences for training and 20% for testing the model; the background sampling was left to default 10,000 random points. We used three levels of regularization multiplier, 0.1, 1, and 2, to identify the best model fitting for each species. The beta regularization multiplier helps to constrain or relax the model, generating a range of overfit (underprediction) or simplified (overprediction) models, respectively. The climatic variables with the strongest influence on the model of each species (i.e., contributing up to 90% to the accuracy of the model) were selected after this calibration run that included the full set of variables (Silva et al, 2015). This selection of a subset of predictor variables for each species was necessary to reduce the high dimensionality of the climate variables dataset (Table 5). The selected set of predictor variables from the calibration run were then used to train the model in the second Maxent experiment (Table 5).

To run the final set of models (second Maxent experiment), we selected the best fitted parameters for each species from the model calibration process (first Maxent experiment). We adjusted the regularization multiplier to 0.1, 1 or 2 based on the best fit for each species from the calibration step. The training/testing split of presence records from the calibration step that produced the best fit was used for each species. Other modeling parameters that were adjusted included maximum iterations (increased from default 500 to 1,000) for model fitting convergence and no extrapolation so that the models did not evaluate suitability outside of the range of the climate variable values from the training region when projecting the model to other climate conditions. The background sampling was set at the default of 10,000 points for the training region. The models for all species were projected on current climatic conditions (1970-2000) for the entire Congo Basin and future climatic conditions (2021-2040) derived from two GCMs and two SSPs (4 future projections total). A 10% training omission error was set as the threshold rule to convert the model outputs from probability of suitability (0 to 1) to binary suitability (yes/no).

The area under the curve (AUC) of the receiver operating characteristic (ROC) was used to evaluate the model performance (Philips et al, 2006; Peterson et al, 2008). An AUC value of 0.5 indicates a poor model (similar to a random model) while an AUC value $\geq$ 0.7 indicates that the model is reliable; highest performance models have AUC values closer to 1 (Swets, 1988). Model performance was also evaluated with omission error, a type 1 error where the model predicted absent known presence records (Phillips et al, 2006; Phillips & Dudik, 2008); to calculate omission error we used testing presence points and the binary model outputs (suitable/unsuitable) at 10% training omission error. Lastly, Maxent calculated cumulative percent contribution of predictor variables to the model accuracy gain, over model iterations. We also visually examined fitted response curves generated by Maxent, to explore the relationship between individual variables and predicted probability of climatic suitability for each species.

2.6 Estimated current and future species richness and degree of overlap with protected areas

We analyzed the binary maps of estimated suitability in ArcGIS to generate species richness maps under current and future climatic conditions, maps of loss of suitable area for each species under future climatic conditions (relative to present suitability), as well as cumulative loss maps. We also analyzed the degree to which the current network of protected areas in the Congo Basin overlaps with areas predicted suitable for epiphytic orchids. We calculated species richness by adding the binary potential suitability maps generated in Maxent for each species to identify hotspots in geographic space.

To evaluate the level of protection of estimated species richness currently and under future climate scenarios, we counted the number of climatically suitable pixels that overlapped with protected areas in the Congo Basin. Protected area information was obtained from the UNEP database of protected areas (UNEP-WCMC and IUCN, 2022). We considered all categories (IUCN I-VI and others) of terrestrial protected areas for this analysis. Species richness pixels overlapping with protected areas were reclassified into quartile categories: unsuitable for all species, suitable for one to four species (low richness, $\leq$ 25% of species), suitable for five to eight species (moderate richness, $\leq$ 50%) and suitable for nine to sixteen species (hotspots, >50% of species).

2.7 Forecasts of climatic suitability loss, refugia, and novel climatic suitability

Potential distribution loss for each species was calculated in ESRI ArcGIS with the aid of map algebra tools by subtracting the current potential distribution from the estimated future distribution within the study extent, for each GCM and each SSP. We calculated the mean relative loss for each species by averaging the binary map output for each species obtained for the two GCMs, by emission scenario (SSP). To identify areas of species richness loss, we selected nine species for which the models estimated at least 30% loss in climatic suitability, and we stacked the mean loss maps of the nine species.

Climate refugia in our study are considered to be stable areas whose climatic conditions are currently suitable for the majority of epiphytic orchids under the current climatic conditions and are forecasted by our models to remain suitable under future climatic conditions. These locations are also known as “slow lanes” because of their buffering capacities (Morelli et al, 2020). By contrast, novel climatic suitability are areas whose current conditions are not suitable for the majority of our studied species but are forecasted as suitable under future climatic conditions by our models. Hotspots under future climatic conditions were considered to contain at least nine species (>50 %) of the sixteen species studied.

To quantify climate refugia, we calculated the difference between the current and future binary distributions of species (presence or absence) as forecasted by our models; pixels that were estimated as suitable both under current and future climatic conditions represent stable areas for each species. All the stable maps (rasters) for the 16 species were summed into a map of species richness using the Mosaic to New Raster tool in ESRI ArcGIS.

We also obtained the novel climatic suitability maps from the difference rasters between the current and future binary distributions of species, by retaining raster pixels that were forecasted as suitable by the models only under future climatic conditions. We summed the individual novel climatic suitability rasters with the Mosaic to New Raster tool in ESRI ArcGIS to obtain the richness raster of 16 species. Both species richness rasters, representing stable climatic suitability (refugia) and novel climatic suitability, were reclassified to identify richness hotspots.

CHAPTER III: RESULTS

3.1 Summary of occurrence records and model calibration experiments

We retained a subset of 1406 records from our GBIF data download for our 16 epiphytic orchid species and georeferenced 994 occurrence records. We could not georeferenced 187 occurrence records because of insufficient information for locality description and in specific cases no link to the database of contributing institutions to access the online digital record for herbarium specimen. We further discarded 425 records after applying the spatial rarefaction of 4.5 km. The average uncertainty of our georeference records was 1.26 km and standard deviation ±3.05.

In the Maxent model calibration experiments, the best model fit with the default regularization multiplier (1) was obtained only for six species. On the other hand, the model of two species of *Angraecum* (*A. pungens* Schltr. and *A. birrimense* Rolfe) used the smaller regularization multiplier value of 0.1 and eight species used the higher regularization multiplier value of 2 (Table 5).

3.2 Performance of the Maxent models

The models for the species included in this study were reliable based on the mean cross-validation test AUC value of 0.915 (± 0.068 SD) for all 16 species. The minimum AUC value of 0.776 was recorded for *Tridactyle anthomaniaca* Rchb. f. Summerh. and the maximum AUC value of 0.994 was recorded for *Angraecum birrimense* Rolfe. Test omission error was zero (0) for fourteen of the sixteen species and 0.062 for *Diaphananthe bidens* Schltr. and 0.167 for *Tridactyle anthomaniaca* Rchb.f. Summerh. These values revealed our models were able to discriminate between suitable and unsuitable climatic conditions for all species (Table 5).

Across all 16 species, a total of 16 out of the 19 bioclimatic variables were used to fit Maxent models. The predictor variable with the highest contribution to model accuracy gain varied across species (Table 5), whereas the most frequently used predictor variables across all the models were bio13 - precipitation of wettest month, bio2 - mean diurnal range (Mean of monthly (max temp - min temp)), and bio12 - annual precipitation (Figure 2). For instance, precipitation of the wettest month contributed to models of 11 species and mean diurnal range (Mean of monthly (max temp - min temp)) contributed to models of 10 species.

3.3 Estimated current and future species richness and degree of overlap with protected areas

Our models of current climatic suitability identified high species richness in three main regions across the biogeographic landscape of Africa (West, Central and

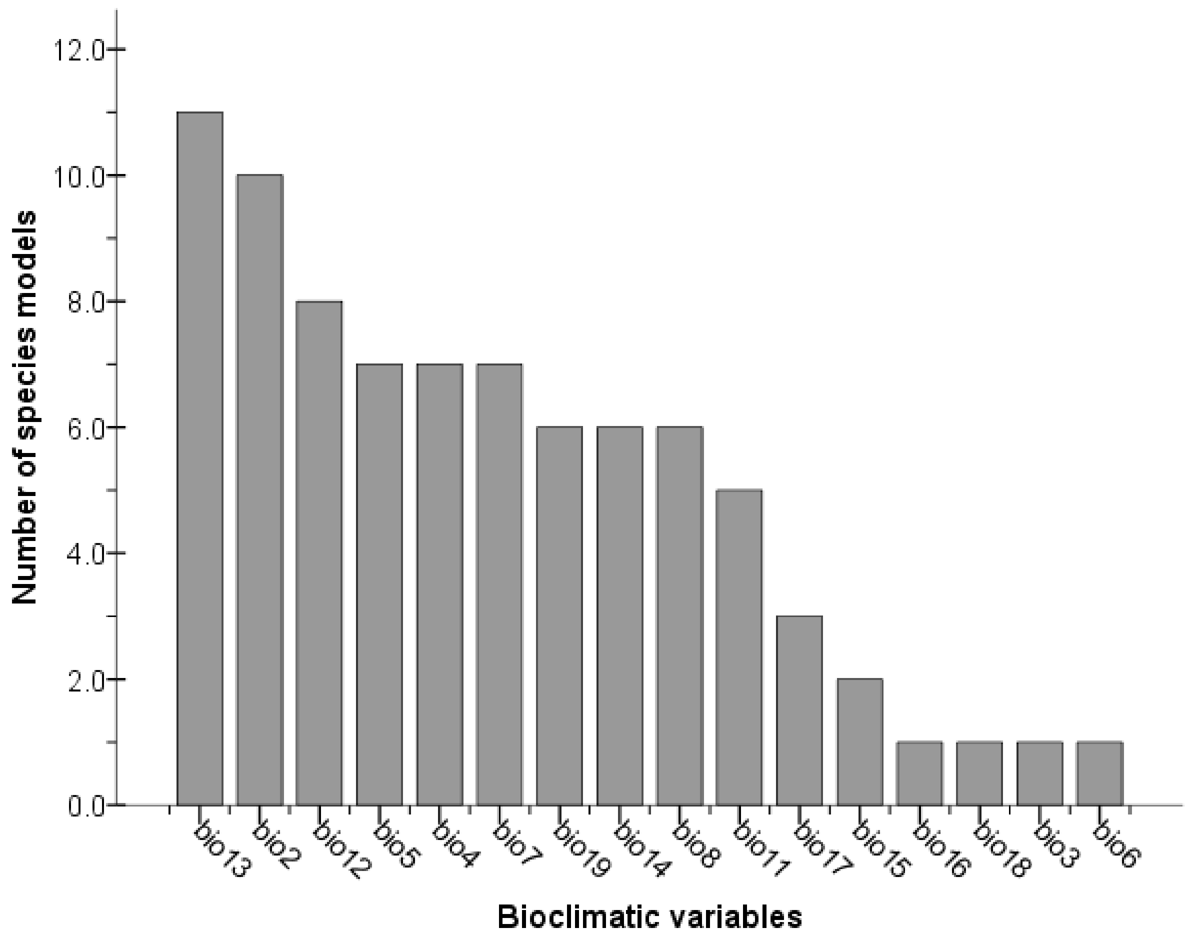

Figure 2: Frequency of 16 bioclimatic variables used in the ecological niche models of 16 epiphytic orchid species from the Congo Basin. See Table 1 for definition of bioclimatic variables.

East; Figure 3). However, the main concentration of species richness was observed in the Central Africa region with a continuous distribution from Western Cameroon along the Cameroon volcanic to Equatorial Guinea island of Bioko, and southward to the mainland Equatorial, Gabon, Congo Republic, and the DR Congo. The future climatic models (four GCMs and SSPs) forecasted reduction in hotspot of species richness in West and Central Africa with greater intensity in Central African but show small increment (novel hotspots) in East Africa. Overall, the four GCMs and SSPs agree in their patterns of forecasting of species richness, however variation is conspicuous in East Africa between the two GCMs and SSPs. Hence, we observed that more moderate suitability (5 - 8 species) were forecasted in East Africa by CNRM compared to MIROC.

Our analysis revealed less than 5% overlap between areas climatically suitable for 9 -16 orchid species (hotspots) under baseline (current) climate conditions and protected areas network in the Congo Basin (Table 2). The current potential distribution estimates showed 53.49% overlap with areas occupied by one to four species, 3.72% overlap with areas that were predicted suitable for five to eight species, and only 3.57% overlap with the majority of the species (9 to 16 species). Unsuitable areas for any species represented 39.22% of the overlap with protected areas. The projected potential distributions on future climatic conditions for 2040 under two emission scenarios (SSPs, moderate and high) and two GCMs were similar and did not differ substantially from the current spatial overlap of species with protected area network in the Congo Basin. Overall, both the moderate and high scenarios for the two GCMs projected small percent reductions in overlap of potential hotspots (9 to 16 species) with protected areas (Table 2) and a small increase in the overlap between protected areas and areas climatically suitable for 1-4 species. Relative to current climate conditions, a small reduction (ranging between 0.5% and 7.9%) in overlap between protected areas and areas climatically unsuitable for any species was forecasted by both GCMs and SSPs.

3.4 Forecasts of climatic suitability loss, refugia, and novel climatic suitability

Overall, the models projected loss in climatically suitable areas for all species, under both SSPs scenarios and GCMs for 2021-2040, with a mean loss of 36.73% (±26.10% SD) and 36.55% (±25.33% SD) for CNRM SSP 2-4.5 and CNRM SSP 5-8.5, respectively, and mean loss of 32.42% (±22.30 % SD) and 31.02% (±20.75% SD) for MIROC SSP 2-4.5 and MIROC SSP 5-8.5, respectively (Table 6). These results indicate that the choice of GCM has a stronger effect on estimating future potential distributions than choice of SSP (emission scenario).

The model projections revealed climatic suitability loss of 30% or more for over half of the species analyzed (9 out of 16; Table 3). The orchid genus *Polystachya* was predicted to be the most affected among all the species, with five of six

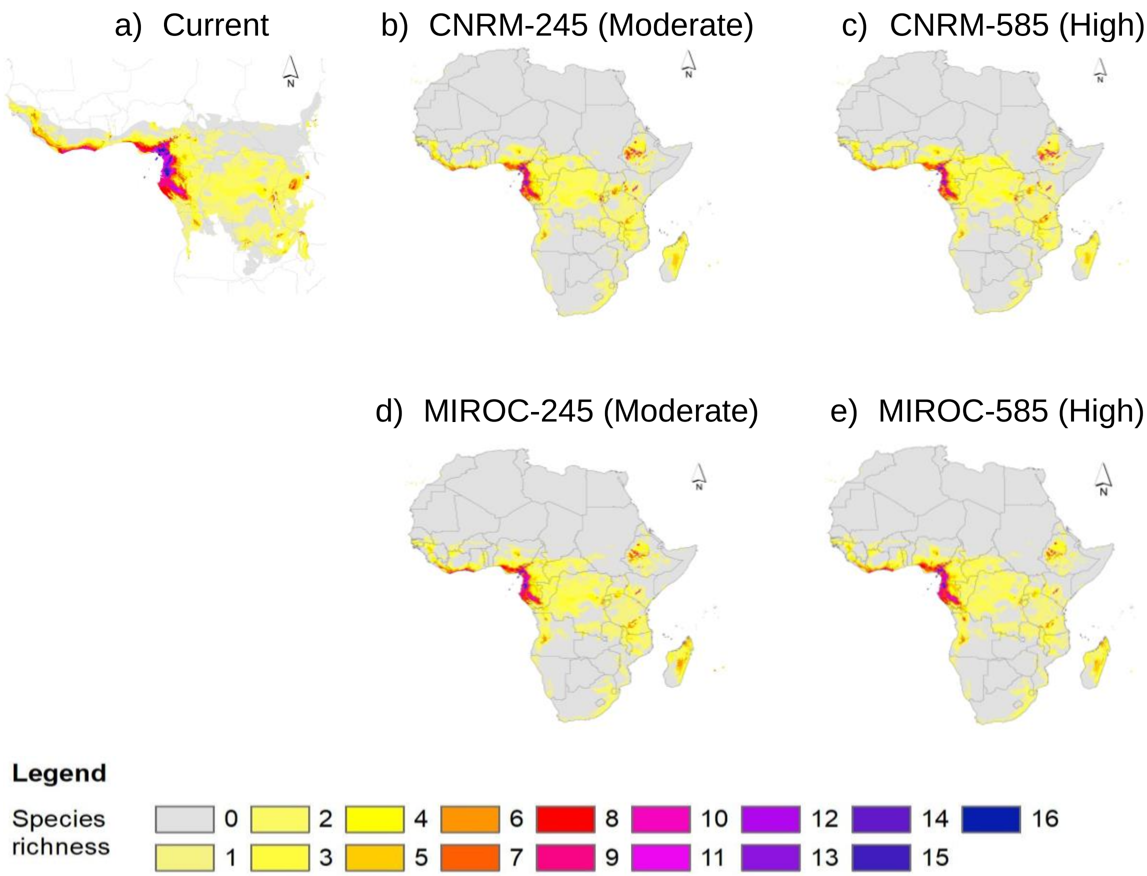

Figure 3: Species richness maps for current climatic conditions and future scenarios (a) Current; (b) Moderate emission scenario projected with CNRM Global Circulation Model; c) High emission scenario projected with CNRM Global Circulation Model; (d) Moderate emission scenario projected with MIROC Global Circulation Model; (e) High emission scenario projected with MIROC Global Circulation Model.

Table 2: Percentage of species overlap by protected areas network in the Congo Basin.

	Low		**Moderate**		**Hotspot**	
	(1 - 4 species)		**(5 - 8 species)**		**(9 - 16 species)**	
Model	**# of pixels**	**%**	**# of pixels**	**%**	**# of pixels**	**%**
Current	29148	53.49	2026	3.72	1944	3.57
CNRM-245	29929	54.92	2311	4.24	1188	2.18
MIROC-245	31034	56.95	1929	3.54	1558	2.86
CNRM-585	33989	62.37	2260	4.15	1195	2.19
MIROC-585	30342	55.68	2030	3.73	1676	3.08

Table 3: Range loss for species with >30% loss projected by two future climatic scenarios for 2040.

A. Moderate (CNRM-245 and MIROC-245 projections 2021-2040)		
Species	**# of Occurrences**	**Mean % loss ± SD**
Tridactyle anthomaniaca Rchb.f. Summerh.	60	30.24 ±9.27
Polystachya caloglossa Rchb.f.	28	41.49 ±9.05
Podangis dactyloceras Schltr.	20	56.98 ±10.49
Angraecum birrimense Rolfe	16	53.66 ±4.37
Polystachya riomuniensis Stévart & Nguema	12	52.54 ±6.99
Polystachya bifida Lindl.	20	52.85 ±9.76
Angraecum pungens Schltr.	14	55.81 ±7.27
Polystachya alpina Lindl.	20	68.28 ±1.51
Polystachya calluniflora Kraenzl.	23	67.16 ±3.54

Table 3: continued

B. High (CNRM 585 and MIROC 585 projections for 2021-2040)		
Species	**# of Occurrences**	**Mean % loss ± SD**
Tridactyle anthomaniaca Rchb.f. Summerh.	60	34.59 ±3.17
Polystachya caloglossa Rchb.f.	28	38.59 ±6.78
Polystachya bifida Lindl.	20	49.83 ±13.45
Angraecum pungens Schltr.	14	48.54 ±9.19
Angraecum birrimense Rolfe	16	46.50 ±6.61
Podangis dactyloceras Schltr.	20	55.17 ±11.17
Polystachya riomuniensis Stévart & Nguema	12	57.17 ±1.66
Polystachya calluniflora Kraenzl.	23	65.38 ±5.75
Polystachya alpina Lindl.	20	68.49 ±3.40

species facing threat of more than 30% contraction in estimated climatic suitability by 2040 (Table 3). We added the 9 species with $\geq$30% climatic suitability loss to map areas of forecasted loss of richness (Figure 4) and observed spatial correspondence with areas of high species richness estimated with current models. A moderate climate change scenario (CNRM SSP 2-4.5) revealed that species estimated to experience climatic suitability contraction are those currently distributed in high elevation in cooler and moist sites, like the range along the Cameroon volcanic line from Bioko Equatorial Guinea, spanning through Western highlands of Cameroon. Also, range contraction spanned from southern Cameroon into mainland Equatorial Guinea, via Gabon and to the Republic of Congo, as well as the southeastern DR Congo extending to the Albertine rift in East Africa. Some range contraction (loss of climatic suitability) was also projected in West Africa (Figure 4).

Our model forecasting showed climate refugia for epiphytic orchids in West and Central Africa only, compared to potentially suitable areas for epiphytic orchids under current climate conditions (in West, Central and East Africa; Figure 5a). We obtained agreement between the two GCMs (CNRM and MIROC) and emission scenarios (moderate and high) which indicate potential stable climatic suitability (refugia) for more than 50% (at least 9 species) of the epiphytic orchids.

Lastly, the model forecasts agreed on the potential formation of novel areas of suitable climate for epiphytic orchids across Africa. The novel suitability areas were distributed across East Africa in Ethiopia, Kenya, Southern Sudan, Uganda, and Tanzania, as well as Nigeria in West Africa, the Comoros Islands and Madagascar (Figure 5b-e).

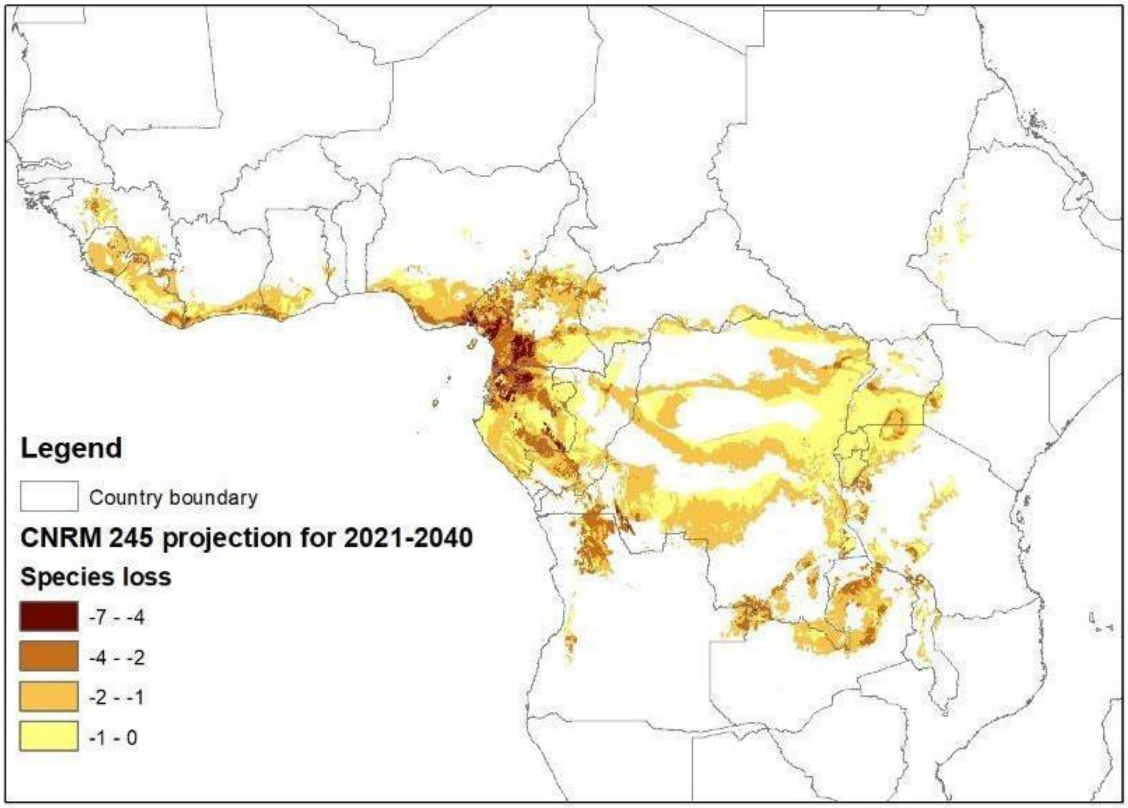

Figure 4: Map of forecasted richness loss of epiphytic orchids in the Congo Basin. Nine species with >30% projected suitability loss were used to generate this map. The highest number of species loss is 7.

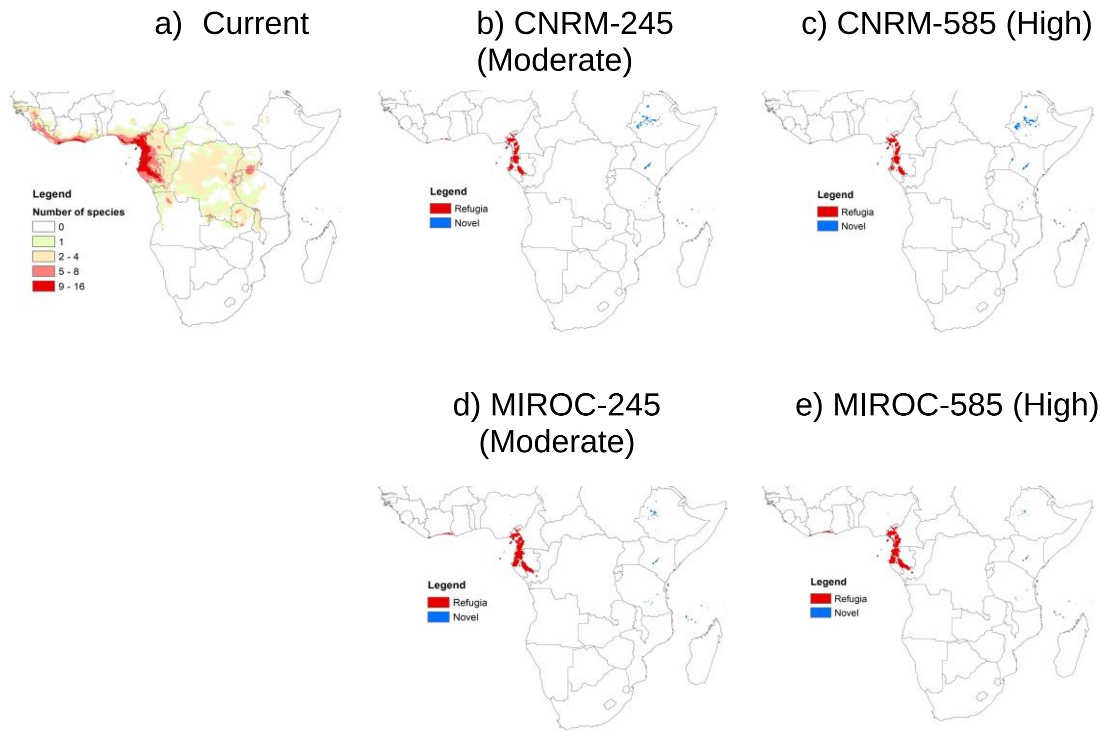

Figure 5: Distribution map showing stable areas (climate refugia) and novel climatic suitability hotspots. (a) Current species richness; (b) Moderate emission scenario projected with CNRM Global Circulation Model; c) High emission scenario projected with CNRM Global Circulation Model; (d) Moderate emission scenario projected with MIROC Global Circulation Model; (e) High emission scenario projected with MIROC Global Circulation Model.

CHAPTER IV: DISCUSSION

The main purpose of this study was to improve our understanding of potential effects of climate change on the distribution of epiphytic orchids in the Congo Basin. Specifically, we sought to gain valuable insight on the spatial distribution of climate refugia and novel areas of climatic suitability for persistence of epiphytic orchids. These areas are critical for conservation decisions and management of epiphytic orchids. We found that changes in rainfall and temperature forecasted by two GCMs and two emission scenarios (SSPs) may adversely affect the distribution of epiphytic orchids. Furthermore, our models projected a southward shift and expansion for areas with highest potential climatic suitability for epiphytic orchids from the northern limit of the Guineo-Congolian forest eastward towards the Albertine rift and north-east in the Ethiopian mountains. Additionally, a suitable climatic area extends southward from the south limit of the Congo-Basin Forest into Angola.

Furthermore, climate refugia and novel areas of climatic suitability were predicted in regions of high altitude and increased rainfall. These regions were located in the western and eastern parts of the Congo Basin Forest and received moisture and precipitation from the Atlantic and Indian oceans, respectively. This finding corroborates the results of Linder, (2001) that showed that plant species richness of the Congo Basin was associated with the regions receiving relatively high moisture and rainfall. The result reinforces the understanding that species' distributions are largely driven by climatic variables such as moisture and temperature. For example, evidence from ecology of epiphytes shows that most epiphytes including orchids are highly sensitive to change atmospheric moisture and temperature (Nadkarni & Solano, 2002; Zotz, 2016), hence their survival and persistence in the geographic space strongly correlate and are limited by environmental variables like low moisture, extreme drought, and high temperatures (Benzing, 1986; Zotz & Hietz, 2001; Fay & Chase, 2009). Therefore, our study provides evidence that epiphytic orchids in the Congo Basin Forest and, more broadly the Guineo-Congolian forest, are at risk due to climate change.

Our models projected species' climatic suitability loss by more than 30% for nine of the sixteen studied species. Moreover, the current network of protected areas (PAs) in the Congo Basin Forest, to a larger extent, did not overlap with hotspots of epiphytic orchids (climatically suitable for 9-16 species), under current and future climatic conditions. Therefore, if biodiversity conservation strategies were to include the majority of species from our study region, currently and in the future, identifying and protecting areas that best represent the diversity of the landscape could be a priority (Leach et al, 2013). Historically, most of the PAs in the Congo Basin were established between the mid-19th and 20th century, with very few recently established PAs (Doumenge et al, 2015). The continuous expansion of human populations is exerting pressure on PAs and biodiversity thereby impeding the creation of new PAs. Moreover, the boundaries of some older PAs are being redrawn, reducing their original size, as a mechanism to yield to the increasing population growth pressure in some regions (Symes et al, 2016; Qin et al, 2019). In this dilemma, a quick and informative approach is to combine the existing datasets for a region and make effective use of modern geospatial tools to redefine priority areas.

Conservation of biodiversity and PAs in the Congo Basin have come a long way; however, the use of forecasting approaches like ENM can improve selection of priority areas for protection, focusing on climate refugia or hotspots with high priority for including the majority of species. This is imperative in situations of sampling gaps and data bias because one can never wait for the entire area to be sampled before acting to preserve or protect species (Grantham et al, 2009). Therefore, ENM serves as a rapid first approximation to estimate climate change risks and to guide the prioritization effort in conservation of biodiversity, even in circumstances of data deficiency like in the case of the majority of epiphytic species of orchids in the Congo Basin. Sampling epiphytic orchids in the Congo Basin Forest, like any other tropical forest, could be a long-term, daunting task, while threats most species are exposed to intensify over time, including logging, wild harvesting, deforestation, and climate change. For example, previous studies show that wild harvesting of orchids for trade (Hinsley et al, 2018) and selective logging of potential host species (Nfornkah et al, 2019) are of major conservation concern to orchids. Other studies indicate that the complexity of life strategies of orchids exposes them to a plethora of threats, and more so, the epiphytic orchids are at greater risk due to the complex interactions with other species during life history stages such as germination, pollination, and growth (Fay, 2018). This complexity of life history strategies underpins one of the main challenges of conserving orchids.

Unlike other life forms like trees, shrubs and lianas, epiphytic orchids have life history that is intertwined with host (phorophytes), mycorrhizal associations, and some even have complex pollination strategy including co-evolution with specific pollinator species. Epiphytic life strategy involves growing in humus crevices, tree fissures, and wet bryophyte mats (Zotz, 2016). A complex stage in orchid life history is that the seeds depend on mycorrhizae for germination in hosts which makes mycorrhizae presence a key determinant factor that can limit orchid distribution. This limitation of orchid distribution by mycorrhizae fungi has only been observed at micro scale thus no studies have observed this effect on the macro scale distribution of orchids (McCormick et al, 2018). However, dispersion success of epiphytic orchids depends on the type of mycorrhizal association and the interaction with prevailing environmental conditions (McCormick et al, 2018; Li et al, 2021). In comparison to other life forms, orchids have long dispersal ability, hence a major factor that can limit dispersal is the distribution of forest and potential hosts.

By comparison, a study on the climate effect on the spatial distribution of endemic legume species by Oyenabji et al, (2021) in the Guineo-Congolian forest found that environmental conditions such as rainfall (precipitation of driest quarter) and temperature ranges are critical factors limiting the distribution of the species. Fayolle et al, 2014 also showed that the distribution and composition of trees across tropical Africa principally correlates with rainfall and to some extent with temperature and altitude. Although previous studies reported seed dispersal and anthropogenic activities as major factors that can affect spatial distribution of species, we suggest that epiphytic orchids are more vulnerable to anthropogenic activities and climate change compared to other life forms. For example, a study by Nfornkah et al, (2019) in Ndelele forest, East Cameroon observed that epiphytic orchids and other epiphytic plant species in a selectively logged forest were rapidly depleted compared to host phorophyte species. Fay, (2018) reported that besides being at greater risk because of their complex lifestyle (interaction with other species), orchids in general are severely affected by anthropogenic activities such as habitat destruction and wild harvesting of orchids. This is congruent with the findings of Hinsley et al, (2018) that elucidated on five key areas to be addressed [(i) trade, (ii) behavior of people involved in trade, (iii) taxonomic complexity of orchidaceae, (iv) gaps in ecological data and conservation status assessment and (v) institutional barriers)] to help strengthen the sustainability and conservation of orchids.

4.1 Model accuracy and estimated spatial species richness for epiphytic orchids

In this study, we used a combination of ENM and spatial data and analyses to estimate potential distributions of epiphytic orchids. Despite the low number of sample points available for some of our studied species, our results were robust and comparable across all species, based on the two model evaluation metrics, AUC, and omission error. Maxent performs well with relatively small presence data in studies predicting distributions of species' niche in geographic space (Proosdij et al, 2016; Hernandez et al, 2006; Papeş & Gaubert, 2007; Elith et al, 2011). Our results provide a baseline potential distribution of epiphytic orchids in the Congo Basin and, more broadly, Guineo-Congolian forest. Hence this first approximation of climatic niches of epiphytic orchid species in the region can assist conservation action programs by guiding future surveys of epiphytic orchids.

We assessed the spatial patterns of epiphytic orchid species richness (hotspots) in our study and observed strong influence of environmental variation on orchids' distributional patterns. The main sources of environmental variation that contributed to the estimated distribution of our studied species came from sixteen bioclimatic variables. Three bioclimatic variables that contributed to the models of most species were precipitation of the wettest month (bio 13), mean diurnal range (mean of monthly maximum temperature to minimum temperature, bio 2) and annual precipitation (bio 12). However, the spatial distribution for individual species was determined by a unique combination of bioclimatic variables, identified during the ENM calibration experiment; additionally, we observed distinct contributions of each bioclimatic variable to model accuracy gain, depending on the species distributional requirements (Table 5). The fitted model of one species (*Podangis dactyloceras* Schltr.) was explained by only two climatic variables probably because this species is restricted to high elevation habitat which is characterized by extremes of climates.

4.2 Loss in climatic suitability for epiphytic orchids

It is apparent that the current potential distribution of epiphytic orchids in our study area is highly influenced by suitable environmental conditions such as atmospheric humidity, rainfall, temperature (Linder, 2001; Fayolle et al, 2014), and as well as ecological variation. For instance, a study by Sodjinou et al, 2019 in the Guineo-Congolian forest observed stratified positioning of epiphytic orchid species, with the majority of the epiphytic orchids occurring in the mid canopy level (8 - 30 m) and the understory vegetation (<8 m). The study also observed stratified positioning of epiphytes in the host tree crown: more than 60% of epiphytic orchids were mostly found in middle and distal position of branches on crown (zone IV and V of Johansson 1974 classification). In another study, Einzmann et al, 2015 observed that host traits determined epiphyte diversity in Panama, such that different species of epiphytes were found on deciduous, semi-deciduous, and evergreen trees, and these differences were consistent in a forest. For example, heliophyte and drought resistant species were mostly observed on semi-deciduous and deciduous tree species while moisture loving and shade species were mostly associated with evergreen tree species, a clear indication that environmental variables drive selection and distribution of epiphytic species.

Our study focused on macroscale environmental conditions (i.e., climate) that influence the distribution of epiphytic orchids, both currently and under climate change scenarios. The study revealed a future potential loss of suitable climatic niche for up to seven species in areas deemed currently suitable for epiphytic orchids. Under the current climatic conditions, species richness of epiphytic orchids in the Congo Basin Forest (Lower Guineo-Congolian forest) and in other forests (Upper Guinea forest) was concentrated in the coastal forest vegetation adjacent to the Atlantic Ocean in Central and West Africa. This pattern of orchid distribution is based on suitable climatic conditions of high rainfall and favorable temperature (Gaskett & Gallagher, 2018). Additionally, we observed a small, isolated concentration of species richness in the eastern part of the Congo Basin Forest towards the Albertine rift in East Africa, similarly explained by climatic suitability. However, few species showed a wider distribution pattern across the Upper Guinea forest in West Africa, the Congo Basin, and toward the Albertine rift in East Africa, partly because of species' wider tolerance to variations in climatic conditions. Our future projections under the four scenarios of climate change estimated that most epiphytic species of orchids in the Congo Basin Forest will experience range contraction and shifting due to changes in potential climatic suitability. This is projected to occur mainly from the species' northern limits in the Congo Basin Forest towards the southwestern and southeastern range limits, with some evidence of potentially suitable climatic niche shifting to higher elevations. For example, mountainous species like *Podangis dactyloceras* Schltr. was forecasted to shift upward, and novel suitability was also observed at higher altitude (Figure 6). In addition, our models also forecasted species' loss in climatic suitability in the Upper Guinea forest in West Africa and the altitudinal shift of suitable climatic conditions towards higher altitude in Ethiopia and across the Albertine rift.

4.3 Protected areas overlap in the Congo Basin

Historically, biodiversity protection in the Congo Basin can be traced back to the pre-colonial era when local traditional communities preserved and protected secret forests for multiple reasons; sometimes preservation of forest resources had the sole purpose of performing traditional rites and/or protecting a natural resource believed to have a cultural value (Fongod et al, 2014; indigenous people of Oku pers. comm. February 2018). This historical evidence is present across countries that make up the Congo Basin, as some of the secret sites/resources are still protected by the ingenious people today. For example, the Bwiti religion in Gabon practiced by the Punu and Mitsogo people and some closely related tribes along the Cameroon-Gabon frontier have ensured the preservation of the plant *Tabernanthe iboga* for centuries because of its religious and cultural value (Tonye et al, 2000; Havel et al, 2021). In addition, there is also evidence of colonial and post-colonial era PAs with various levels of protection under the current administrations across the Congo Basin countries.

Two regional bodies, the Congo Basin Partnership Fund (CBPF) and Central African Regional Program for the Environment (CARPE), have a mandate to protect and preserve the rich biodiversity and cultural heritage as a response to United Nations (UN) resolution 54/214. The strategy of these bodies has been to identify potential landscapes across the region for promoting forest conservation while advancing comprehensive regional conservation strategies (CARPE, 2011). Under the current scheme, the identified landscapes selected for preserving biodiversity resources happen to be the fundamental resources serving millions of inhabitants in the region and the ever-increasing population in the region makes it difficult to achieve a network of connected PAs. The precarious nature of these landscapes provides the basis for the first question which sought to investigate the degree of overlap between the spatial richness of our focal species group and the current extent of PAs of all IUCN categories in the Congo Basin. Our results revealed less than 5% overlap of PAs and hotspots of suitable climatic areas for epiphytic orchids for 2021-2040, a key insight to the understanding of suitable climatic areas of epiphytic orchids and level of protection in the region. Previous studies showed that epiphytic orchids make up more than 50% of the epiphyte diversity in the Congo Basin (Zapfack & Enwald, 2008; Sodjinou et al, 2019) and most are already highly threatened by several factors, including climate change. More broadly, the entire family of orchids (Orchidaceae) is listed in CITES appendix II which prohibits the international trade of any material from the species (Fay and Chase, 2009), a clear indication of the severity of threat to these species. Additionally, faced with increasing human density, many countries in the region will be forced to redefine PA boundaries to accommodate the expansion of human activities, thereby increasing the threat to species and their suitable habitat.

4.4 Stable climate areas (refugia) for species persistence and novel climate suitability

Climate refugia are often described as "slow lanes" because of their capacity to keep the stability of climate in each geographic space (Morelli et al, 2020). While refugia maintain stable conditions that favor the persistence of species, new areas of suitable conditions can also form on the landscape, acting as a haven for species that might escape unfavorable conditions and achieve persistence in time and space. In a 2018 study, Tang et al, used the ENM approach to identify climate refugia that preserved relic lineage of ancient plant species in southeast Asia. In addition, Reina-Rodriguez et al, 2017 and Preau, 2018 both present evidence of historical and future climatic refugia that enable species and communities to persist. Such examples of ENM integration in biogeography studies prompted our second question, which investigated the possibility of future climate refugia and novel climatic suitability across Africa that may contribute to the persistence of epiphytic orchids. Our results identified possible stable climatic niches, refugia or "slow lanes for biodiversity persistence" in West and Central Africa and small, isolated areas of stability in Angola. We also observed small areas of stable climatic suitability in East Africa highlands, specifically in Ethiopia and in countries sharing the Albertine rift. Meanwhile, novel areas of climatic suitability were projected across the Ethiopian mountains and eastern DR Congo, towards the countries of the Albertine rift, and in the Comoros Islands and Madagascar. The two SSPs scenarios (moderate or high greenhouse gas emissions) showed similar patterns of distributions of stable climatic areas ("slow lanes" or refugia) and novel areas of climatic suitability for projections into 2021-2040. Consequently, we propose that climate refugia and novel climatic suitability areas can serve as potential future locations to focus conservation efforts because stability of suitable climatic conditions enables the spatial and temporal persistence of species, communities, and ecosystems (Morelli et al, 2020).

The limitations of our study are inherent to the modeling technique and the study organisms. We use climate-based ecological niche models, so one main limitation of our study is that the potential suitability maps represent only a subset of conditions (abiotic) necessary for species' survival; biotic interactions (presence of host trees, mycorrhizal fungi, and pollinators) and dispersal capabilities are needed to refine (reduce) the extent of these potential distributions and better approximate actual distributions. Thus, our estimates of climate refugia and novel areas of climatic suitability are larger than the on-ground, species-specific details of actual distributions. The complex life history of epiphytic orchids involves a combination of host, mycorrhizae association and pollinators which were not included in our analysis. Thus, our future recommendations to help improve on this type of study is to incorporate distributional information of host and mycorrhizae, as well as other complex interactions like pollinators and dispersal.

4.5 Conclusion

Our results invoke possible near future conversation to reconsider planning decisions to conserve biodiversity in the Congo Basin region, specifically the spatial and temporal use of PAs to preserve biodiversity. It further elucidates on how our efforts to conserve biodiversity in the Congo Basin region and beyond can encompass forecasts of future climate effects on species. Our study contributes to understanding the potential for integration of climate refugia in conservation planning.

REFERENCES

Araujo, M. B., & Peterson, A. T., (2012). Uses and misuses of bioclimatic envelope modelling. *Ecology,* 93(7), 1527–1539.

Benzing, D. H., (1986). The vegetative basis of vascular epiphytism. *Selbyana*, 9(1), 23-43.

Caro, T. M., & O'Doherty, G., (1999). On the use of surrogate species in conservation biology. *Conservation Biology,* 13(4), 805-814.

CARPE, (2005). *The forest of the Congo Basin: A preliminary assessment*

CARPE, (2011). *Accelerating Central Africa's transition to climate-resilient, low emissions development through sustainable management of biodiverse forests*. Central Africa Regional Program for the Environment (CARPE) Regional Development Cooperation Strategy (RDCS) 2011-2020.

Cooney, R., Challender, D. W. S., Broad, S., Roe, D., & Natusch, D. J. D., (2021). Think Before you act: Improving the conservation outcomes of CITES listing decisions. *Frontiers Ecology and Evolution*, 9.

Cribb, P., & Pollard, B. J., (2002). New Orchid discoveries in western Cameroon *Kew Bulletin,* 57(3), 653 – 659.

Dargie, G. C., Lewis, S. L., Lawson, I. T., Mitchard, E. T. A., Page, S. E., Bocko, Y. E., & Ifo, S. A., (2017). Age, extent and carbon storage of the central Congo Basin peatland complex. *Nature,* 542, 86–90.

Dhyani, S., Kadaverugu, R., Dhyani, D., Verma, P., & Pujari, P., (2018). Predicting impacts of climate variability on habitats of *Hippophae salicifolia* (D. Don) (Seabuckthorn) in Central Himalayas: Future challenges. *Ecological Informatics,* 48, 135-146.

Diniz-Filho, J. A. F., Bini, L. M., Rangel, T. F., Loyola, R. D., Hof, C., Nogués-Bravo, D., & Araújo, M. B., (2009). Partitioning and mapping uncertainties in ensembles of forecasts of species turnover under climate change. *Ecography,* 32(6), 897–906.

Doumenge, C., Palla, F., Scholte, P., Hiol Hiol, F. & Larzillière, A., (Eds.), 2015. *Aires protégées d'Afrique centrale – État 2015*. OFAC, Kinshasa, République Démocratique du Congo et Yaoundé, Cameroun: 256 p.

Droissart, V., Sonke, B., Nguembou, C. K., Djuikouo, M-N. K., Parmentier, I., & Stevart, T., (2009). Synopsis of the Genus Chamaeangis (Orchidaceae), Including Two New Taxa. *Systematic Botany*, 34(2), 285-296.

Dyer, E. L. E., Jones, D. B. A., Nusbaumer, J., Li, H., Collins, O., Vettoretti, G., & Noone, D., (2017). Congo Basin precipitation: Assessing seasonality, regional interactions, and sources of moisture. *Journal of Geophysical Research*: *Atmospheres,* 122(13), 6882-6898.

Einzmann, H. J. R, Beyschlag, J., Hofhansl, F., Wanek, W., & Zotz, G., (2015). Host tree phenology affects vascular epiphytes at the physiological, demographic and community level. *Annals of Botany Plants*, 7, plu073.

Ellenberg, H., & Mueller-Dombois, D., (1967). A key to Raunkiaer plant life forms with revised subdivisions. *Berlin Geobotanical Institute ETH, Stiftung,* 37, 56-73.

Elith, J., Graham, C. H., Anderson, R. P., Dudı´k, M., Ferrier, S., Guisan, A., Hijmans, R. J., Huettmann, F., Leathwick, J. R., Lehmann, A., Li, J., Lohmann, L. G., Loiselle, B. A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J. McC., Peterson, A. T., Phillips, S. J., Richardson, K. S., Scachetti-Pereira, R., Schapire, R. E., Soberon, J., Williams, S., Wisz, M. S. & Zimmermann, N. E., (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 29(2), 129-151.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J., (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distribution,* 17(1), 43–57.

Evans, A., Janssens, S., & Jacquemyn, H., (2020). Impact of climate change on the distribution of four closely related *Orchis* (Orchidaceae) Species. *Diversity*, 12(8), 312.

Fay, M. F., (2018). Orchid conservation: how can we meet the challenges in the twenty-first century? *Botanical Studies,* 59, 16.

Fay, M. F., & Chase, M. W., (2009). Orchid biology: from Linnaeus via Darwin to the 21st century. *Annals of Botany*, 104(3), 359–364.

Fayolle, A., Swaine, M. D., Bastin, J.-F., Bourland, N., Comiskey, J. A., Dauby, G., Doucet, J.-L., Gillet, J.-F., Gourlet-Fleury, S., Hardy, O. J., Kirunda, B., Kouamé, F. N. & Plumptre, A.J. (2014). Patterns of tree species composition across tropical African forests. *Journal of Biogeography*, 41, 2320-2331.

Flores-Palacios, A., & Ortiz-Pulido R., (2005). Epiphyte orchid establishment on termite carton trails. *Biotropica,* 37(3), 457-461.

Fongod, A. G. N., Ngoh, L. M., & Veranso, M. C., (2014). Ethno-botany, indigenous knowledge and unconscious preservation of the environment: An evaluation of indigenous knowledge in South and Southwest Regions of Cameroon. *International Journal of Biodiversity and Conservation.* 6(1) 85-99.

Game, E. T., Kareiva, P., & Possingham, H. P., (2013). Six common mistakes in conservation priority. *Conservation Biology*, 27(3), 480-485.

Gaskett, A. C., & Gallagher, R. V., (2018). Orchid diversity: Spatial and climatic patterns from herbarium records. *Ecology and Evolution*, 8(22),11235-11245.

GBIF.org (11 March 2020). GBIF Occurrence Download.

GBIF.org (4 February 2021). GBIF Occurrence Download.

Gillespie, T. W., (2001). Species richness and cover of orchids and bromeliads on an active volcano. *Selbyana* 22(2), 192-196.

Grantham, H. S., Wilson, K. A., Moilanen, A., Rebelo,T. & Possingham, H. P., (2009). Delaying conservation actions for improved knowledge: how long should we wait? *Ecology Letters*, 12(4), 293–301.

Guisan, A., & Zimmermann, N. E., (2000). Predictive habitat distribution models in ecology. *Ecological Modelling* 135(2-3), 147–186.

Harrigan, R. J., Thomassen, H. A., Buermann, W., & Smith, T. B., (2014). A continental risk assessment of West Nile virus under climate change. *Global Change Biology* 20(8), 2417–2425.

Havel, V., Kruegel, A. C., Bechand, B., McIntosh, S., Stallings, L., Hodges, A., Wulf, M. G., Nelson, M., Hunkele, A., Ansonoff, M., Pintar, J. E., Hwu, C., Abi-Gerges, N., Zaidi, S. A., Katritch, V., Yang, M., Javitch, J. A., Majumdar, S., Hemby, S. E., & Sames, D., (2021). Novel Class of Psychedelic Iboga Alkaloids Disrupts Opioid Addiction States, bioRxiv 2021.07.22.453441.

Hendricks, S. A., Schweizer, R. M., Harrigan, R. J., Pollinger, J. P., Paquet, P. C., Darimont, C. T., Adams, J. R., Waits, L. P., vonHoldt, B. M., Hohenlohe, P. A. & Wayne, R. K. (2019). Natural re-colonization and admixture of wolves (*Canis lupus*) in the US Pacific Northwest: challenges for the protection and management of rare and endangered taxa, *Heredity* 122, 133–149.

Hernandez, P. A., Graham, C. H., Master, L. L., & Albert, D. L. (2006). The effect of sample size and species characteristics on performance of different species distribution modelling methods. *Ecography*, 29(5), 773–785.

Hinsley, A., de Boer, H. J., Fay, M. F., Gale, S. W., Gardiner, L. M., Gunasekara, R. S., Kumar, P., Masters, S., Metusala, D., Roberts, D. L, Veldman, S., Wong, S., & Phelps, J., (2018). A review of the trade in orchids and its implications for conservation. *Botanical Journal of the Linnean Society*, 186(4), 435–455.

Islam, K., Rahman, M. F., Islam, K.N., Nath, T. K., & Jashimuddin, M., (2020). Modeling spatiotemporal distribution of *Dipterocarpus turbinatus* Gaertn. F in

Bangladesh under climate change scenarios. *Journal of Sustainable Forestry*, 39(3), 221-241.

Keppel, G., Gillespie, T. W., Ormerod, P., & Fricker, G. A., (2016). Habitat diversity predicts orchid diversity in the tropical south-west Pacific. *Journal of Biogeography,* 43(12), 2332–2342.

Kolanowska, M., Kras, M., Lipińska, M. Mystkowska, K., Szlachetko, D., & Naczk A. M., (2017). Global warming not so harmful for all plants - response of holomycotrophic orchid species for the future climate change. *Scientific Reports,* 7, 12704.

Konowalik, K., & Kolanowska, M., (2018). Climatic niche shift and possible future spread of the invasive South African orchid *Disa bracteata* in Australia and adjacent areas. *PeerJ,* 6, e6107.

Leach, K., Zalat S., & Gilbert, F., (2013). Egypt's protected area network under future climate change. *Biological Conservation* 159, 490–500.

Li, T., Wu, S., Yang, W., Selosse, M-A., & Gao, J., (2021). How mycorrhizal associations influence orchid distribution and population dynamics. *Frontiers in Plant Science*, 12, 647114.

Linder, H. P., (2001). Plant diversity and endemism in sub-Saharan tropical Africa. *Journal of Biogeography*, 28(2), 169-182.

McCormick, M. K., Whigham, D. F., & Canchani-Viruet, A., (2018). Mycorrhizal fungi affect orchid distribution and population dynamics. *The New Phytologist*, 219(4), 1207–1215.

Morelli, T. L., Barrows, C. W., Ramirez, A. R., Cartwright, J. M., Ackerly, D. D., Eaves, T. D., Ebersole, J. L., Krawchuk, M. A., Letcher, B. H., Mahalovich, M. F., Meigs, G. W, Michalak, J. L., Millar, C. I., Quinones, R. M, Stralberg, D., & Thorne, J. H., (2020). Climate-change refugia: biodiversity in the slow lane. *Frontiers in Ecology Environment,* 18(5), 228–234.

Nadkarni, N. M., & Solano, R., (2002). Potential effects of climate change on canopy communities in a tropical cloud forest: An experimental approach. *Oecologia*, 131(4), 580-586.

Nashwan, M. S., & Shahid, S., (2019). A novel framework for selecting general circulation models based on the spatial patterns of climate. *International Journal of Climatology*, 40(10), 4422–4443.

Nfornkah, B. N., Tchamba, M., Zapfack, L., Djomo, C. C., Mairong, N. F. & Sonke, B., (2019). Vascular epiphytes loss in exploited trees of the semi deciduous managed forest of Ndelele, East Cameroon. *Journal of Sustainable Forestry*, 38(7), 670-685.

Nieder, J., Prosperi, J., & Michaloud, G., (2001). Epiphytes and their contribution to canopy diversity. *Plant Ecology,* 153, 51–63.

Oyebanji, O. O., Salako, G., Nneji, L. M., Oladipo, S. O., Bolarinwa, K. A., Chukwuma, E. C., Ayoola, A. O., Olagunju, T. E., Ighodalo, D. J., & Nneji, I. C., (2021). Impact of climate change on the spatial distribution of endemic legume species of the Guineo-Congolian forest, Africa. *Ecological Indicators,* 122, 107282.

Papeş, M. & Gaubert, P., (2007). Modelling ecological niches from low numbers of occurrences: assessment of the conservation status of poorly known viverrids (Mammalia, Carnivora) across two continents. *Diversity and Distributions,* 13(6), 890–902.

Peterson, A. T., Papeş, M. & Soberon, J., (2008). Rethinking receiver operating characteristic analysis applications in ecological niche modeling. *Ecological Modelling* 213(1), 63–72.

Phillips, S. J., Anderson, R. P., & Schapire, R. E., (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190(3-4), 231–259.

Phillips, S., & Dudik, M., (2008). Modeling of species distributions with Maxent: New extensions and a comprehensive evaluation. *Ecography*, 31(2), 161–175.

Preau, C., Trochet, A., Bertrand, R., & Isselin-Nondedeu, F., (2018). Modeling potential distributions of three European amphibian species comparing ENFA and Maxent. *Herpetological Conservation and Biology,* 13(1), 91-104.

Proosdij, A. S. J. v., Sosef, M. S. M., Wieringa, J. J., & Raes, N., (2016). Minimum required number of specimen records to develop accurate species distribution models. *Ecography,* 39(6), 542–552.

Qiao, H. J., Peterson, A. T., Ji, L. Q., & Hu, J. H., (2017). Using data from related species to overcome spatial sampling bias and associated limitations in ecological niche modelling. *Methods in Ecology and Evolution,* 8(12), 1804-1812.

Qin, S., Kroner, R. E. G., Cook, C., Tesfaw, A. T., Braybrook, R., Rodriguez, C. M., Poelking, C., & Mascia, M. B., (2019). Protected area downgrading, downsizing, and degazettement as a threat to iconic protected areas. *Conservation Biology,* 33(6), 1275–1285.

Razgour, O., Rebelo, H., Di Febbraro, M., & Russo, D., (2016). Painting maps with bats: species distribution modelling in bat research and conservation. *Hystrix, Italian Journal of Mammalogy,* 27(1).

Reina-Rodriguez, G. A., Mejia, J. E. R., Llanos, F. A. C., & Soriano, I., (2017). Orchid distribution and bioclimatic niches as a strategy to climate change in areas of tropical dry forest in Colombia. *Lankesteriana: International Journal of Orchidology,* 17(1), 17-47.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Samir, KC, Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L. A., Smith, S., Stehfest, E., Bosetti,V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J. C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., & Tavoni, M., (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, 42, 153-168.

Rodríguez-Soto, C., Monroy-Vilchis, O., & Zarco-González, M. M., (2013). Corridors for jaguar (*Panthera onca*) in Mexico: Conservation strategies. *Journal for Nature Conservation,* 21(6), 438– 443.

Shapiro, A. C., Grantham, H. S., Aguilar-Amuchastegui, N., Murray, N. J., Gond, V., Bonfils, D., & Rickenbach, O., (2021). Forest condition in the Congo Basin for the assessment of ecosystem conservation status. *Ecological Indicators,* 122, 107268.

Silva, L., Dias, E. F., Sardos, J., Azevedo, E. B., Schaefer, H., & Moura, M., (2015). Towards a more holistic research approach to plant conservation: the case of rare plants on oceanic islands, *Annals of Botany Plants*, 7, plv066.

Soberón, J., & Nakamura, M., (2009). Niches and distributional areas: Concepts, methods, and assumptions. *Proceedings of the National Academy of Sciences,* 106(2), 19644-19650.

Sodjinou, K. E., Radji, R. A., Adjonou, K., Quashie, M. A., Adjossou, K., Abotsi, K. E., & Kokou, K., (2019). Ecological characterization of epiphytes orchids in the meridional zone of Mount Togo. *Journal of Horticulture* 6(1), 252.

Swets, J. A., (1988). Measuring the accuracy of diagnostic systems. *Science*, 240(4857), 1285-1293.

Symes, W. S., Rao, M., Mascia, M. B., & Carrasco, L. R., (2016). Why do we lose protected areas? Factors influencing protected area downgrading, downsizing and degazettement in the tropics and subtropics. *Global Change Biology,* 22(2), 656–665.

Tang, C. Q., Matsui, T., Ohashi, H., Dong, Y-F., Momohara, A., Herrando-Moraira, S., Qian, S., Yang, Y., Ohsawa, M., Luu, H. T., Grote, P. J., Krestov, P. V., LePage, B., Werger, M., Robertson, K., Hobohm, C., Wang, C-Y., Peng, M-C., Chen, X., Wang, H-C., Su, W-H., Zhou, R., Li, S., He, L-Y., Yan, K., Zhu, M-Y., Hu, J., Yang, R-H., Li, W-J., Tomita, M., Wu, Z-L., Yan, H-Z., Zhang, G-F., He, H., Yi, S-R., Gong, H., Song, K., Song, D., Li, X-S., Zhang, Z-Y., Han, P-B., Shen, L-Q., Huang, D-S, Luo, K. & López-Pujol, J., (2018). Identifying long-term stable refugia for relict plant species in East Asia. *Nature Communications,* 9, 4488.

Taylor, A., Keppel, G., Weigelt, P., Zotz, G. & Kreft, H., (2021). Functional traits are key to understanding orchid diversity on islands. *Ecography*, 44(5), 703-714.

Texier, N., Deblauwe, V., Stevart, T., Sonke, B., Simo-Droissart, M., Azandi, L., Bose, R., Djuikouo, M.-N., Kamdem, G., Kamdem, N., Mayogo, S., Zemagho, L., & Droissart, V., (2018). Spatio-temporal patterns of orchids flowering in Cameroonian rainforests. *International Journal of Biometeorology,* 62(11), 1931-1944.

Thiney, U., Banterng, P., Gonkhamdee, S., & Katawatin, R., (2019). Distributions of Alien Invasive Weeds under Climate Change Scenarios in Mountainous Bhutan. *Agronomy*, 9(8), 442.

Tonye, M. M., Asaha, S., Ndam, N., & Paul, B., (2000). *State of knowledge study on Tabernanthe iboga Baillon: a report for the Central African Regional Program for the Environment.* https://pdf.usaid.gov/pdf_docs/Pnads957.pdf

Tshwene-Mauchaza, B., & Aguirre-Gutierrez J., (2019). Climate drivers of plant species distributions across spatial grains in southern African tropical forests. *Frontiers in Forest and Global Change* 2, 69.

UNEP-WCMC (Comps.), (2014). *Checklist of CITES species*. CITES Secretariat, Geneva, Switzerland, and UNEP-WCMC, Cambridge, United Kingdom.

UNEP-WCMC and IUCN, (2022). Protected Planet: The World Database on Protected Areas (WDPA) and World Database on Other Effective Area-based Conservation Measures (WD-OECM) [Online], March 2022, Cambridge, UK: UNEP-WCMC and IUCN. Available at: www.protectedplanet.net.

Wieczorek, C., & Wieczorek, J., (2021). *Georeferencing Calculator*. Available: http://georeferencing.org/georefcalculator/gc.html. Accessed [2021-10-20]

Woodward, F. I., & Cramer, W., (1996). Plant functional types and climatic change: introduction. *Journal of Vegetation Science,* 7(3), 306–308.

Zarate-Garcia, A. M., Noguera-Savelli, E., Andrade-Canto, S. B., Zavaleta-Mancera, H. A., Gauthier, A., & Alatorre-Cobos, F., (2020). Bark water storage capacity influences epiphytic orchid preference for host trees. *American Journal of Botany* 107(5), 726–734.

Zapfack, L., & Engwald, S., (2008). Biodiversity and spatial distribution of vascular epiphytes in two biotopes of the Cameroonian semi-deciduous rain forest. *Plant Ecology*, 195(1), 117-130.

Zermoglio, P. F., Chapman, A. D., Wieczorek, J. R., Luna, M. C., & Bloom, D. A., (2020). *Georeferencing Quick Reference Guide. Copenhagen: GBIF Secretariat.*

Zotz, G., (2016). Biogeography: Latitudinal and Elevational Trends. In: *Plants on Plants – The Biology of Vascular Epiphytes,* pp 51-66*.* Fascinating Life Sciences. Springer, Cham.

Zotz, G., & Hietz, P., (2001). The physiological ecology of vascular epiphytes: current knowledge, open questions. *Journal of Experimental Botany*, 52(364), 2067–2078.

APPENDIX

Table 4a: Epiphytic orchid species selected based on IUCN threat categories (all listed in CITES appendix II)

No.	Scientific Name	Occurrence records	IUCN category
1	*Ancistrorhynchus serratus* Summerh.	18	NT
2	*Angraecum pungens* Schltr.	45	VU
3	*Ansellia africana* Lindl. (Leopard orchid)	36	VU
4	*Bulbophyllum fayi* J.J.Verm.	15	VU
5	*Bulbophyllum bifarium* Hook.f.	22	VU
6	*Bulbophyllum calvum* Summerh.	11	VU
7	*Polystachya bicalcarata* Kraenzl.	15	VU
8	*Genyorchis platybulbon* Schltr.	13	CR
9	*Polystachya victoriae* Kraenzl.	33	CR
10	*Bulbophyllum porphyrostachys* Summerh.	3	NT
11	*Polystachya bifida* Lindl./*Polystachya farinosa* Kraenzl	58	EN
12	*Polystachya kupensis* P.J.Cribb & B.J.Pollard	1	CR

Table 4b: Epiphytic orchid species selected for this study, based quality of occurrence data & range (all listed in CITES appendix II)

No.	Scientific name	Occurrence records	Spatial distribution of records
1	*Polystachya caloglossa* Rchb.f.	77	Narrow
2	*Cyrtorchis ringens* (Rchb.f.) Summerh.	112	Narrow
3	*Polystachya alpina* Lindl.	56	Narrow
4	*Listrostachys pertusa* Rchb.f.	168	Narrow
5	*Podangis dactyloceras* Schltr.	43	Narrow
6	*Polystachya riomuniensis* StÃ©vart & Nguema	41	Narrow
7	*Diaphananthe bidens* Schltr.	206	Wide
8	*Calyptrochilum emarginatum* Schltr.	147	Wide
9	*Diaphananthe pellucida* Schltr.	111	Wide
10	*Polystachya calluniflora* Kraenzl.	72	Wide
11	*Tridactyle anthomaniaca* (Rchb.f.) Summerh.	141	Wide
12	*Angraecum birrimense* Rolfe	55	Wide

Table 5: Summary of Maxent model inputs (training presences, variables), regularization parameter (beta), and model evaluation for each species, with two evaluation metrics (test omission error and AUC). Also shown are cumulative contributions of bioclimatic variables to gain in model accuracy.

Species	Training	Testing	Beta	Variables selected	Cumulative % contribution	Test Omission error	AUC
Ansellia africana Lindl.	16	3	1	bio2, bio8, bio13, bio7, & bio19	90.4	0	0.907
Calyptrochilum emarginatum Schltr.	57	15	2	bio13, bio7, bio2, bio19, & bio18	91.6	0	0.946
Diaphananthe bidens Schltr.	61	16	2	bio2, bio13, bio12, & bio14	94.1	0.062	0.888
Angraecum pungens Schltr.	12	2	0.1	bio19, bio12, bio17, bio2, bio5, bio11, bio14, & bio7	92.7	0	0.954
Polystachya calluniflora Kraenzl.	19	4	1	bio5, bio19, bio8, & bio4	90.4	0	0.946
Polystachya caloglossa Rchb.f.	22	6	1	bio12, bio5, bio19, bio2, bio4, bio15 & bio17	92.4	0	0.983
Angraecum birrimense Rolfe	13	3	0.1	bio12, bio7, bio3, bio14, bio11, bio5, bio15 & bio6	93.1	0	0.994
Podangis dactyloceras Schltr.	16	4	2	bio8, bio13	90.6	0	0.965

Table 5: continued

Species	Training	Testing	Beta	Variables selected	Cumulative % contribution	Test Omission error	AUC
Polystachya alpina Lindl.	16	4	1	bio11, bio13, bio8 & bio5	93.5	0	0.992
Listrostachys pertusa Rchb.f.	47	11	2	bio13, bio7, bio16, bio14, bio19, & bio4	90.7	0	0.779
Polystachya riomuniensis Stévart & Nguema	10	2	1	bio5, bio14, bio11	91.6	0	0.964
Polystachya victoriae Kraenzl.	14	4	2	bio12, bio2, & bio13	90.1	0	0.888
Cyrtorchis ringens Rchb. f. Summerh.	34	9	2	bio13, bio4, bio8, bio2 & bio12	92.6	0	0.89
Diaphananthe pellucida Schltr.	45	11	1	bio13, bio12, bio14, bio2, bio4, bio8, bio7 & bio17	91.5	0	0.849
Polystachya bifida Lindl.	16	4	2	bio13, bio2, bio5, & bio4	93	0	0.912
Tridactyle anthomaniaca Rchb. f. Summerh.	48	12	2	bio2, bio7, bio12, bio13, bio4 & bio11	91.9	0.167	0.776

Table 6: Loss in area suitable by species shown in moderate and high scenarios

Moderate		
Species	**GCM-SSP**	**% loss**
Polystachya caloglossa Rchb.f.	CNRM-245	47.89
Polystachya caloglossa Rchb.f.	MIROC-245	35.10
Angraecum birrimense Rolfe	CNRM-245	50.57
Angraecum birrimense Rolfe	MIROC-245	56.75
Podangis dactyloceras Schltr.	CNRM-245	64.39
Podangis dactyloceras Schltr.	MIROC-245	49.56
Polystachya alpina Lindl.	CNRM-245	69.35
Polystachya alpina Lindl.	MIROC-245	67.22
Polystachya riomuniensis Stévart & Nguema	CNRM-245	57.48
Polystachya riomuniensis Stévart & Nguema	MIROC-245	47.59
Diaphananthe pellucida Schltr.	CNRM-245	23.51
Diaphananthe pellucida Schltr.	MIROC-245	20.47
Polystachya bifida Lindl.	CNRM-245	59.75
Polystachya bifida Lindl.	MIROC-245	45.95
Tridactyle anthomaniaca Rchb.f. Summerh.	CNRM-245	36.79
Tridactyle anthomaniaca Rchb.f. Summerh.	MIROC-245	23.69
Ansellia africana Lindl.	CNRM-245	17.33
Ansellia africana Lindl.	MIROC-245	15.81
Calyptrochilum emarginatum Schltr.	CNRM-245	5.32
Calyptrochilum emarginatum Schltr.	MIROC-245	12.10
Cyrtorchis ringens Rchb. f. Summerh.	CNRM-245	17.28
Cyrtorchis ringens Rchb. f. Summerh.	MIROC-245	17.24
Polystachya victoriae Kraenzl.	CNRM-245	3.47
Polystachya victoriae Kraenzl.	MIROC-245	4.23
Diaphananthe bidens Schltr.	CNRM-245	1.06

Table 6: continued

Moderate		
Species	**GCM-SSP**	**% loss**
Diaphananthe bidens Schltr.	MIROC-245	2.53
Listrostachys pertusa Rchb.f.	CNRM-245	2.87
Listrostachys pertusa Rchb.f.	MIROC-245	5.20
Polystachya calluniflora Kraenzl.	CNRM-245	69.67
Polystachya calluniflora Kraenzl.	MIROC-245	64.66
Angraecum pungens Schltr.	CNRM-245	60.95
Angraecum pungens Schltr.	MIROC-245	50.67

High		
Species	**GCM-SSP**	**% loss**
Polystachya caloglossa Rchb.f.	CNRM-585	43.38
Polystachya caloglossa Rchb.f.	MIROC-585	33.79
Angraecum birrimense Rolfe	CNRM-585	51.18
Angraecum birrimense Rolfe	MIROC-585	41.83
Podangis dactyloceras Schltr.	CNRM-585	63.06
Podangis dactyloceras Schltr.	MIROC-585	47.27
Polystachya alpina Lindl.	CNRM-585	70.89
Polystachya alpina Lindl.	MIROC-585	66.09
Polystachya riomuniensis Stévart & Nguema	CNRM-585	58.34
Polystachya riomuniensis Stévart & Nguema	MIROC-585	55.99
Diaphananthe pellucida Schltr.	CNRM-585	24.48
Diaphananthe pellucida Schltr.	MIROC-585	17.56
Polystachya bifida Lindl.	CNRM-585	59.33
Polystachya bifida Lindl.	MIROC-585	40.32
Tridactyle anthomaniaca Rchb.f. Summerh.	CNRM-585	36.83

Table 6: continued

High		
Species	**GCM-SSP**	**% loss**
Tridactyle anthomaniaca Rchb.f. Summerh.	MIROC-585	32.35
Ansellia africana Lindl.	CNRM-585	17.52
Ansellia africana Lindl.	MIROC-585	16.24
Calyptrochilum emarginatum Schltr.	CNRM-585	8.32
Calyptrochilum emarginatum Schltr	MIROC-585	13.02
Cyrtorchis ringens Rchb. f. Summerh.	CNRM-585	19.18
Cyrtorchis ringens Rchb. f. Summerh.	MIROC-585	14.88
Polystachya victoriae Kraenzl.	CNRM-585	3.79
Polystachya victoriae Kraenzl.	MIROC-585	5.24
Diaphananthe bidens Schltr.	CNRM-585	1.69
Diaphananthe bidens Schltr.	MIROC-585	4.05
Listrostachys pertusa Rchb.f.	CNRM-585	2.36
Listrostachys pertusa Rchb.f.	MIROC-585	4.30
Polystachya calluniflora Kraenzl.	CNRM-585	69.44
Polystachya calluniflora Kraenzl.	MIROC-585	61.31
Angraecum pungens Schltr.	CNRM-585	55.04
Angraecum pungens Schltr.	MIROC-585	42.04

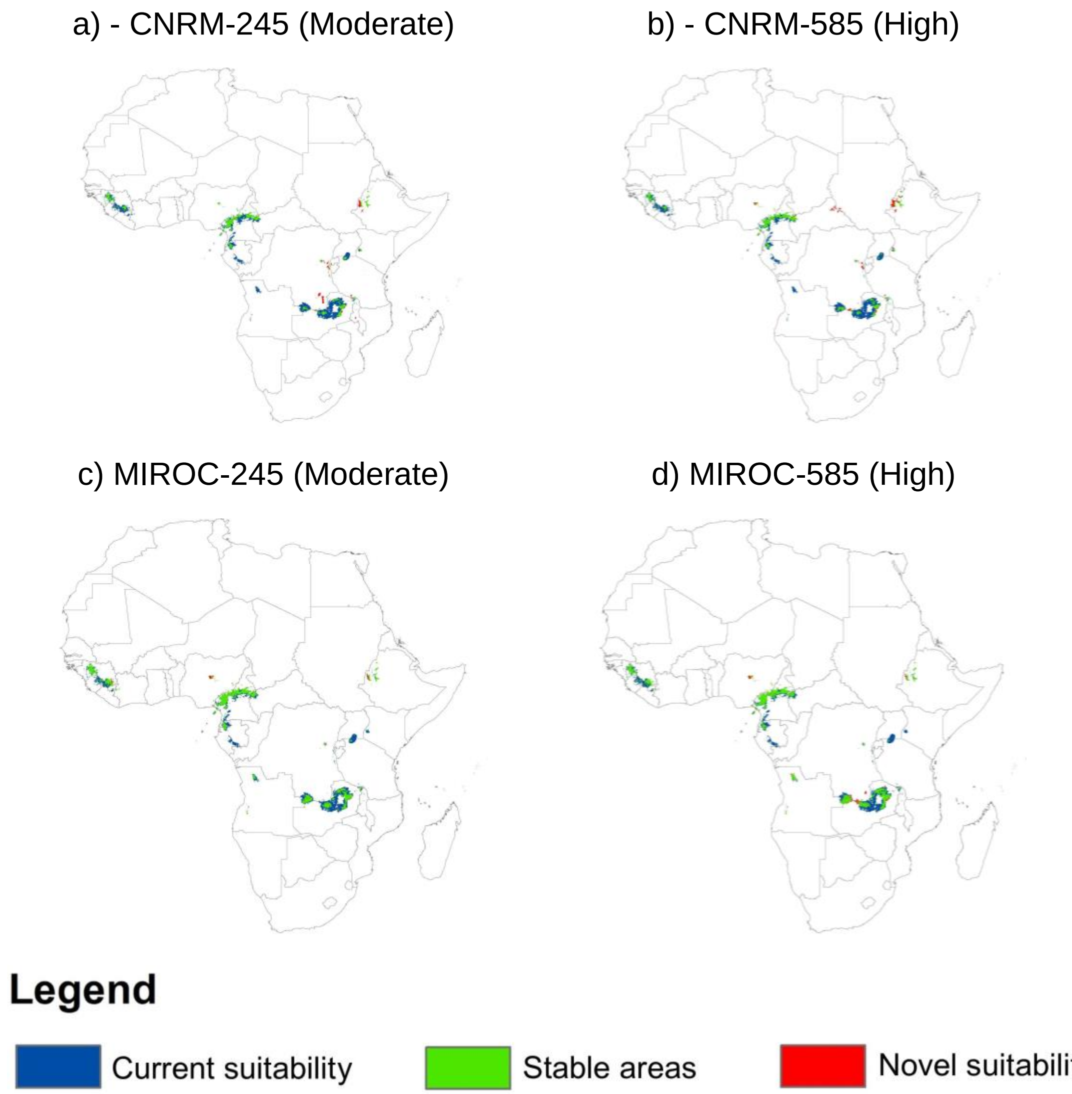

Figure 6: Distribution map of *Podangis dactyloceras* Schltr. showing current suitability, forecasted stable areas for the species and novel climatic suitability. Difference between forecasted stable areas and current suitability indicate range contraction. Noticed an altitudinally movement of suitability loss for the species. (a) Moderate emission scenario projected with CNRM Global Circulation Model; (b) High emission scenario projected with CNRM Global Circulation Model; (c) Moderate emission scenario projected with MIROC Global Circulation Model; (d) High emission scenario projected with MIROC Global Circulation Model.

VITA

Michael Lyonga Ngoh is an international student from Buea, Southwest, Cameroon. He grew up and attended most of his education in the hospitable city of Buea. While studying at the University of Buea, Cameroon, he obtained a BSc in Botany with a minor in Horticulture and an MSc in Botany. Afterwards, Michael became passionate about forest ecology and conservation as a volunteer for local NGO/research institutions. Michael joined the University of Tennessee/EEB Graduate School to pursue a Master of Science degree in Ecology with focus on using ecological niche modeling to address conservation questions relating to plant diversity. After his graduation, he will continue with his fundamental goal to obtain a PhD from the University of Tennessee, Knoxville. Haven been inspired by the incredible research training he obtained at EEB, Michael is grateful to all at the Department of Ecology and Evolutionary Biology, for creating the opportunities and a conducive learning environment. He also expresses gratitude to his lab mates and cohort for the knowledge shared, to his family for the love and support and to his creator for the grace throughout his studies.