academicJournals

Vol. 8(1), pp. 1-8, January 2016
DOI: 10.5897/JENE2015. 0525
Article Number: 7E8F16357002
ISSN 2006-9847

http://www.academicjournals.org/JENE

Journal of Ecology and the Natural Environment

Full Length Research Paper

Using ecological niche models to plan conservation in a changing environment: A case for the plant *Chasmanthera dependens* Hochst (Menispermaceae) in West Africa

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Received 13 May, 2015; Accepted 6 October, 2015

Climatic envelope modeling techniques implemented in two algorithms, Genetic Algorithm for Rule-set Production (GARP) and bioclimatic variables (BIOCLIM) were used to assess effects of climatic conditions on distributions of plants and anticipate how climate would have delimited their distribution under future conditions using a liana species *Chasmanthera dependens* as a case example. In all, 120 geo-referenced plant records generated from fieldwork and drawn from data served by the Global Biodiversity Information Facility (GBIF). Environmental variables were derived from monthly temperature and rainfall data from WorldClim; eliminating environmental variables with correlations of 0.75 and left eight (8) variables for analysis. Results show that the current suitable range (ecological niche) of the model plant was broad across the tropical rain forest regions. Predictions to future climate scenarios (2050), predicted a significant reduction of suitable distributional areas for the species suggesting possible loss of plant species. Indeed, *ex-situ* conservation may be the most appropriate conservation tool for this species and others in similar situations.

Key words: Bioclimatic variables (BIOCLIM), climate change, conservation, ecological niche models, genetic algorithm for rule-set production (GARP).

INTRODUCTION

Viéet al. (2008) have reported that the numbers of threatened species are on the increase every year; and more attention needs to be given to them in the light of emerging issues of climatic change. According to McCarty (2001) and Hughes (2000), climate change at global and regional scales is predicted to alter species distributions, life histories, community composition and ecosystem function.

In particular, population losses caused by climate change threaten both species diversity and the delivery of critical ecosystem services (Hughes, 2000). Climate change is now seen to be one of the major causes of biodiversity loss; these impacts are further weakening already fragile ecosystems, for example, the continuous

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expansion of deserts in the northern Nigeria (CBD, 2007). The effects of climate change on biodiversity require and demand detailed assessment especially in developing countries like Nigeria and across West Africa more generally.

Lianas (woody vines) according to Schnitzer and Bongers (2002), are non-self-supporting epiphytic plants that uses the architecture of trees to ascend to the forest canopies. They are particularly abundant and diverse in lowland tropical forests, where they constitute up to 40% of the woody biomass representing more than 25% of the woody species (Schnitzer and Bongers, 2002), and contribute substantially to forest leaf area and biomass (Gerwing and Farias,2000; Chave et al.,2001).

Interestingly, Martin et al. (2004) reports that they are more prevalent in areas of secondary forest succession and are often able to compete effectively against tree and shrub species in specialized environmental conditions such as areas of both acute and chronic disturbance. Furthermore, with increases in global temperatures due to climate change, it has been projected that vine growth rates will further increase (Phillips et al., 2002).

*Chasmanthera dependens*a liana can provide information on liana roleas important structural components and key species richness indicators of tropical forests; where they are important physiognomic and structural components (Gentry, 1991; Schnitzer and Bongers, 2002).It belongs to the family Menispermaceae and is reported as the only Chasmanthera species in West Africa. Ortiz et al. (2007) reported that Chasmanthera and other Menispermaceae are poorly known for lack of a comprehensive phylogenetic hypothesis. Since *C. dependens* is mainly wild, genetic erosion owing to over-exploitation could occur.

This risk may increase owing to effects of climate change, resulting in population decline. Moritz et al.(2008) have reported the impacts of a century of climate change on small-mammal communities in Yosemite National in the USA while Rubidge et al. (2012) has reported that climate-induced range contraction drives genetic erosion in alpine mammals. These changes in environmental conditions can rapidly shift allele frequencies in populations of species with relatively short generation times thus causing a decrease in their populations (Hoffmann and Willi, 2008). Therefore, an understanding of how plants will fare in the present changing climate would provide information essential to effectively protecting the species.

The most important tools in conservation planning with respect to climate change according to Elith and Leathwick (2009) should be the deployment of species distribution models which will evaluate present and potential future species ranges in relation to climate, soils and other predictive variables. These models according to Thuiller et al. (2005), can highlight individual species that may be at risk because of climate change, and geographic areas that may face substantial shifts in diversity and species composition (Williams et al., 2005; Loarie et al., 2009). In some cases, models suggest that protected areas may no longer maintain populations of key species, possibly the very ones that the reserves were created to protect (Araújo et al., 2004).

Thorn et al. (2009) and Marini et al. (2009b) have also reported its usefulness in targeting conservation efforts for threatened species. Conversely, shrinking distributions and range shifts could create new refugia - areas where threatened species would be concentrated in the future (Loarie et al., 2009).This according to Marini et al.(2009a) will provide frameworks for identifying spatially optimal conservation strategies which includes designing networks for these priority areas.

Using model plant *C. dependens* Hochst (Menispermaceae) in West Africa, we present ecological niche models (ENM) which were used to determine the potential distribution of the species across West Africa, predict future distribution patterns and thus use these models to develop conservation planning priorities.

MATERIALS AND METHODS

Input data

Two types of data were used as the basis for this study: geographic location records of occurrence of the species and geospatial data sets describing environmental variation across the region. According to Peterson et al. (2012), occurrence records should be from sites spread over the range such that a species' occurrence patterns can be assessed in the light of its influenced major environmental dimensions of variation. Such broad sampling of occurrence is known to increase the accuracy of ecological niche model results (Peterson et al., 2012).

Hence, the entire African range of the liana was taken into account in model calibration, but results were presented only for West Africa. Occurrence data were obtained from field collections across five West African countries; Ghana; Togo, Benin, Nigeria and Cameroun. Additional occurrence data were acquired from data mediated by the Global Biodiversity Information Facility (GBIF), from the Census of the flora of Benin, Naturalis Biodiversity Centre (NL) - Botany Wageningen, Missouri Botanical Garden, National Herbarium Nederland, University of Ghana - Ghana Herbarium, Real Jardín Botánico (Madrid), Vascular Plant Herbarium (MA), Botany (UPS), Vascular Plant Collection at the Botanische Staatssammlung München, Herbarium Togoense, Herbier du Bénin, Herbarium Senckenbergianum (FR) and TAIF (Taiwan e-Learning and Digital Archives Program, TELDAP). In order to have single occurrence information from the various herbaria data collected, duplicate records were removed from the data set.

All data were then displayed in relation to country boundaries and examined visually to detect and remove records in incorrect locations that are outliers that did not fall within the country boundaries which may be due to improper geo-referencing from the herbarium records.

Environmental data

In order to generate more biologically meaningful variables, bioclimatic variables (BIOCLIM) derived from the monthly temperature and rainfall values were used as climatic data from these experiments. Current and future climate data in the form of 19 "bioclimatic" variables were obtained (http://www.worldclim.org) at a 2.5' spatial resolutions. These variables represent annual trends (for example, mean annual temperature, annual precipitation) seasonality (for example, annual range in temperature and precipitation) and extreme or limiting environmental factors (for example, temperature of the coldest and warmest month, and precipitation of the wet and dry quarters).

Current data were from the WorldClim data set (Hijmans et al., 2005) while the 2050, were from the General Circulation Model (GCM): CCCMA climate model, A2 scenario generated by the Intergovernmental Panel on Climate Change (IPCC, 2007).

GCMs depict the climate using a three dimensional grid over the globe, typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and sometimes as many as 30 layers in the oceans. Their resolution is thus quite coarse relative to the scale of exposure units in most impact assessments. Moreover, many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modelled. Instead, their known properties must be averaged over the larger scale in a technique known as parameterization. This is one source of uncertainty in GCM-based simulations of future climate. Others relate to the simulation of various feedback mechanisms in models concerning, for example, water vapour and warming, clouds and radiation, ocean circulation and ice and snow albedo. For this reason, GCMs may simulate quite different responses to the same forcing; simply because of the way certain processes and feedbacks are modelled. However, these differences in response are usually consistent with the climate sensitivity range.

The A2 marker scenario (A2-ASF) was developed using Atmospheric Stabilisation Framework Model (ASF), an integrated set of modelling tools that was also used to generate the first and the second sets of IPCC emission scenarios (SA90 and IS92).

Overall, the A2-ASF quantification is based on the following assumptions (Sankovski et al., 2000): Relatively slow demographic transition and relatively slow convergence in regional fertility patterns; Relatively slow convergence in inter-regional GDP per capita differences; Relatively slow end-use and supply-side energy efficiency improvements (compared to other storylines); Delayed development of renewable energy as well as no barriers to the use of nuclear energy.

ENM approaches

Several studies have advised consensus approaches in ENM development (Pearson et al.,2007). We applied two algorithms GARP (Stockwell, 1999) and BioCLIM (Busby, 1991) to construct ENMs. Present day ENMs were developed based on occurrences within the mask appropriate to the model species; in this case, the mask area was the 5 West African countries from where we sampled its populations.

The climate envelope techniques BioCLIM is a classic bioclimatic modelling approach. It fits a minimal envelope in a multidimensional climate space and use presence-only instead of presence/absence data, which can be highly advantageous: many data sets provide presence-only data, and even if absence points are available, they are not always reliable, especially for areas that are not thoroughly inventoried or for species that are difficult to detect. On the other hand, if information on absence points is available and reliable, it is to a model's disadvantage not to employ it (Jeschke and Strayer, 2008).

GARP (Genetic Algorithm for Rule-set Production) does not need presence/absence data for its application, but presence-only data are sufficient. GARP includes multiple, non-deterministic iterative procedures that incorporate various model distribution methods such as logistic regression and range envelopes, producing with each run predicted binary maps of presences and absences. Multiple optimal models are produced for each data set, which can be converted into presence likelihoods. However, BioCLIM (envelop algorithm) is less complex than GARP, and often perform poorly in simulations (Wisz et al., 2008). Different algorithms produce different outputs, but in general convey presence probabilities, or some arbitrary value that could be interpreted in similar fashion.

Table 1. Bioclimatic variables, derived from temperature and precipitation, used in the analysis.

S/N	Parameter	Meaning
1	Bio 1	Annual mean Temperature
2	Bio 2	Mean monthly Temperature
3	Bio 5	Max temp of warmest month.
4	Bio 6	Minimum temp of coldest month
5	Bio 12	Annual precipitation
6	Bio 13	Precipitation of the wettest month
7	Bio 14	Precipitation of the driest month
8	Bio 15	Precipitation seasonality

For Desktop GARP (version 1.1.6) to construct ENMs, 100 random replicate models were developed using the default parameters of convergence limit (0.01) and maximum iterations (1000). The GARP was run on the OpenModeller platform (1.10) (Muñoz et al., 2011). Also using the OpenModeller software, the BIOCLIM was calculated by disregarding the lower and higher 5% to reduce the impact of outliers (Muñoz et al., 2011).

Prior to this, we performed a two-tailed spearman correlation analysis between all pairwise combinations of 19 variables based on their values at 1000 points selected randomly from across West Africa. Eliminating environmental variables with correlations of 0.75 and less, that is, variables that least likely limited geographic distributions, for example, removing mean values rather than maxima or minima (Wiens et al., 2006; Paz, et al., 2015), we were left with eight (8) bioclimatic variables used to construct the models (Table 1).

The Niche A software was also used to provide an improved method to calculate the Area Under Curve (AUC) by calculating the AUC value of the partial area of the Receiver Operating Characteristic (ROC). This was run on the E value of 0.5.

RESULTS

Results from the model construct are presented in Figures 1A and 1B for ENM of *C. dependens* using BIOCLIM and Figures 2A and 2B forENM of *C. dependens* using GARP.

Figures 1A (BIOCLIM) and 2A (GARP) predicted current highly suitable area for the species across the tropical forest belt of West Africa, this is in line that the model plant is wildly distributed in the tropical forest regions of West Africa. Models do not clearly show accurately the distribution from the Camerouns, this was understandable as the presence-only data used from the Camerouns was limited. However, both models showed a possibility of plant survial and distribution in the tropical region of the Camerouns. The models also showed some marginally suitable areas on the maps of Nigera, Benin, Togo and Ghana which were likely to be the sudan

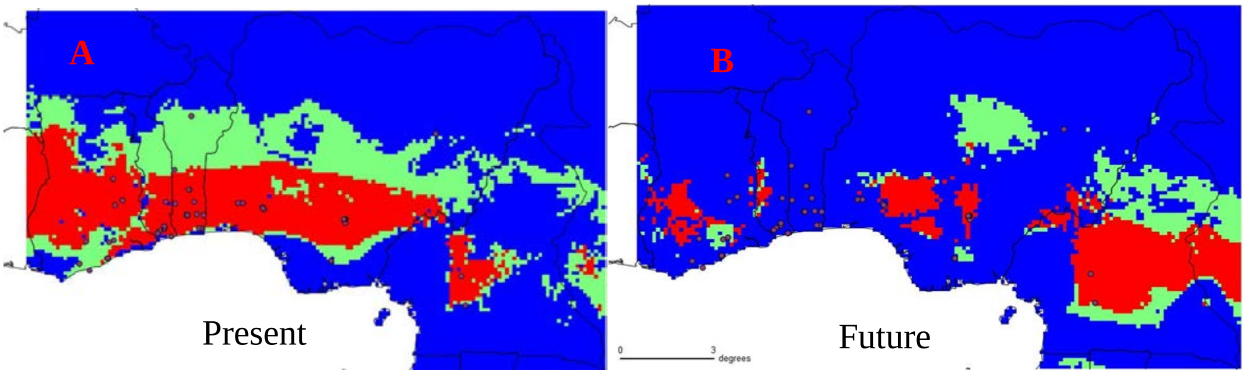

Figure 1A-B. Ecological niche models for *Chasmanthera dependens* using BIOCLIM and showing West African potential distribution at present and projected to 2050.

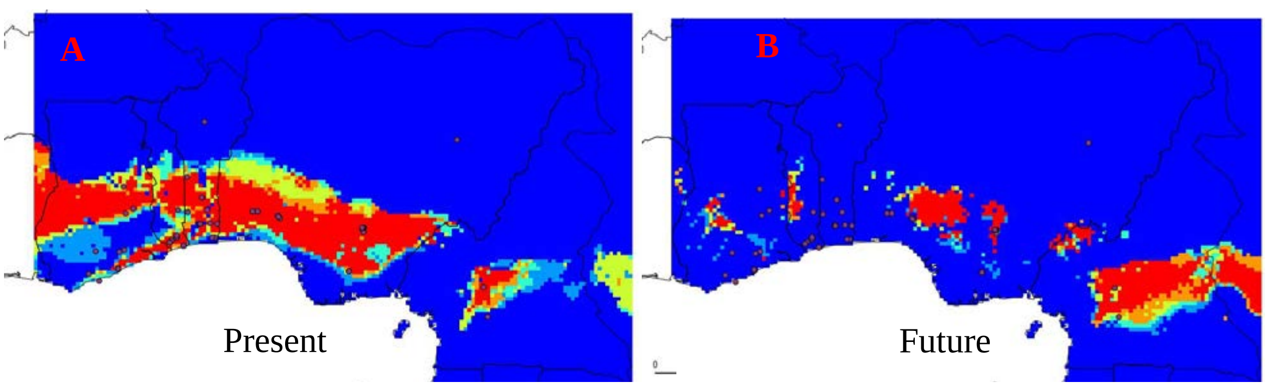

Figure 2A-B. Ecological niche models for *C. dependens* using GARP and showing West African potential distribution at present and projected to 2050.

regions. This could be defined as the plant's fundamental niche that is; the range of environmental conditions in which the species survives. Areas above the sudan (sahel) as well as the magrove regions were not suitable for plant growth as analysed by the models.Models showed a pseudo-probability surface of the test plant distribution.

Figures 1B and 2B presents future distirbution areas of the species across the tropical belt of West Aftrica. Models were able to show a contraction in niche from the present distribution to the future distribution. This contraction in niche could clearly be seen in Nigeria, Benin, Togo and the Ghana. Maximum suitable areas on the 2050 maps were mainly in the South-Western parts of Nigeria and majorly in the Cameroun s. Interestingly, there was little or no contraction in this area.

DISCUSSION

In this study, a total of 120 geo-reference plant records were used in the model calibration. According to Hernandez et al.(2006), the ability to estimate ecological niches effectively is influenced strongly by species' ecological characteristics independent of sample size and models built with few points, while not as accurate as those based on large data sets and potentially not appropriate for all applications, can still be useful (Hernandez et al., 2006). The Bioclimatic variables used to run the models had correlations below 0.75 according to Peterson et al. (2011) variables, a correlation below 0.75 give best model results.

Both algorithms used had an area under the curve (AUC) of the partial area of the receiver operating characteristic (ROC) of BIOCLIM0.94 and GARP0.95, respectively. The use of partial-area ROC approaches to provide a firmer foundation for evaluation of predictions from ecological niche models (Peterson et al., 2008). This is because models evaluated favorably by traditional ROC, AUCs are not necessarily the best when niche modeling considerations are incorporated into the design of the test thus a recommendation that a modification of ROC that remedies these problems is used (Lobo et al., 2008; Peterson et al., 2008).

The model predicted current suitable area for the species across the tropical forest belt of West Africa. Our present model results showed an ecological niche representation which coincides with the geographic distribution based on herbarium specimens and field work of the plant species corroborating that niche conditions of the species are represented in the known geographic range, that is; a realized niche that is the range of environmental conditions in which a species is really found. This result is in line with many studies that indicate that a species' fundamental niche is almost always larger than its realized niche in terms of geographic footprint (Pearson and Dawson, 2003; Peterson, 2003a). Cuni-Sanchez et al. (2010), for example, used ecological niche modeling to estimate the fundamental niche of the tree *Adansonia digitata* (baobab) and have considered this area to reflect the global cultivation potential or invasive potential of the species.

As these models have proven to identify potential distribution areas of species it is important to note that geographical distribution of species are influenced by biological interactions and historical factors which are not taken in to account in the modeling algorithms (Illoldi-Rangel and Escalante, 2008). Hence, ENMs are ecological niche modeling interpreted as the geographical representation of environmental conditions required by the species (Martínez-Meyer, 2005).

As reported in Rojas-Soto et al.(2003), Sánchez-Cordero et al.(2005), predicted distributions of species from ENM approaches provides clear gains as well as offer a number of opportunities over raw existence data. Whereas, as raw occurrence data may be bias in detectability and sampling efforts, Soberón and Peterson (2004) reports that modeled distributions as input information for these models can overcome these biases to an impressive degree. These methods according to Pressey and Cowling, (2001) help to compensate for the lack of comprehensive distributional data in regional conservation planning.

Pittock (2009) has reported that estimated variables and process applied in a model construction are likely to influence the outcome of the model hence increasing the range of uncertainty in climate projection. Therefore, rather than projecting what will happen really in the future, climate projection is a procedure for providing insights into what may happen. As such, reports will enable a robust decision-making in the face of uncertainty as well as how much to offer conservation planning (Araújo and New, 2007).

Our ENMs were able to demonstrate the likely climate change effects on species'potential distributions across West Africa, these effects of climate change agree well with reports from parallel studies in other regions (Peterson, 2003b; Peterson, 2003c; Peterson et al.,2002, Thuiller, 2004; Araújoand New, 2007; Christensen et al., 2007). Again, Williams et al. (2003) has reported that these findings are in contrast with the severe losses predicted for more diverse environments, such as tropical rainforest.

Models were also able to show massive loss of potential habitat in Benin Republic. Gouwakinnou (2013) has also reported this in the tree species *Sclerocarya birrea* in Benin Republic. Interestingly, in the Camerouns, there was little or no contraction in this area, is there a possibility that the refugia hypothesis which suggests that the current diversity in the tropics could be attributable to successive isolation and subsequent expansion of populations in response to frequent oscillations of the climate during the quaternary period (Mittelbach et al., 2007). Since fundamental niche might be lost, there is a possibility that areas in the Cameroun might just be point of refugia for West African plants where conditions might be favorable for their existence.

In presenting the results of this study, it should be taken into account that changes in the environment brought about by the effects of climatic change under emission scenarios are only hypotheses of the changes in the environmental requirements (niche) of the species. This according to Pearson and Dawson (2003) takes into account the reactions individual species exhibits to climatic change and therefore, these possibilities may not be considered in the bioclimatic models (Pearson and Dawson, 2003).

The ability for species to adapt to new conditions or move to new places where conditions are favorable is crucial survival (Pearson and Dawson, 2003). However, it is also possible that species do not adapt to new changes, and that the range lost automatically represents the total disappearance, minimally or in part, of its geographical range. The reduced potential habitat in this study may poses these challenges hence, if plant species is not able to adapt to the new changes, it might automatically lose their current distribution.

Conservation concerns

Our understanding of plant distributions is precursors to effective protection of our forest especially in Africa. However, these practices will be greatly set aback with the issues of climate change. The ENMs of this study were able to demonstrate the likely climate change effects on species' potential distributions across West Africa and thus maintaining diversity under the present climatic scenarios is likely not to be sustained due to the possible reduction in ecological niche in future. Indeed, *ex-situ* conservation may be the most appropriate conservation tool for this species and others in similar situations across West Africa.

Conflict of interests

The author(s) did not declare any conflict of interest.

ACKNOWLEDGMENTS

Special thanks to Prof. A. Townsend Peterson for granting the first author the opportunity to attend the ENM course organized by the Biodiversity Informatics Training Curriculum, University of Kansas, USA. We also thank him for all the discussions and useful comments regarding this manuscript. I also thank the reviewers of this manuscript, they provided a lot of questions and suggestions that have made this work a better one. Thank you so much.

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