Spatial distribution and ecological niche modelling of *Brachytrupes membranaceus* under climatic incidence in Kinshasa, DRC

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Abstract

Species distribution modeling has become a very popular tool for anticipation and decision-making in biological resource conservation. This study aims to assess changes in the future distribution of *Brachytrupes membranaceus* habitats in Kinshasa between 2055 and 2100.

Three variables contributed most to the model: rainfall in the driest month (38.4%), soil (28.9%) and rainfall in the coldest quarter (13.9%). Currently, 89.3% of Kinshasa's surface area is highly favorable to the development and conservation of *B. membranaceus*, compared with 69.5% and 47.5% in 2055 (optimistic and pessimistic scenarios respectively) and 61.5% and 39.2% in 2100 (optimistic and pessimistic scenarios respectively), mainly in the urban zone. From the current to the future climate,

the areas potentially favorable to the development and conservation of *B. membranaceus* shift from the periphery to the urban center of Kinshasa (for all scenarios for the years 2055 and 2100).
This shows that threats to the development and conservation of *B. membranaceus* are mainly due to anthropogenic activities (anarchic construction and slash-and-burn agriculture) and less to climatic/environmental factors (rainfall and soil). These results contribute to Sustainable Development Goals 11 and 15 by 2030.
Keywords: Ecological niche, sustainable development, *Brachytrupes membranaceus*, Kinshasa, MaxEnt.

1. Introduction

In cities, the ecological services provided by biodiversity are fundamental to urban sustainability. This sustainability requires knowledge and rational long-term management of available resource. The exploitation of non-timber forest products, and in particular edible insects, plays an important role in the dietary habits and local economies of populations in the Congo Basin. Understanding their spatio-temporal distributions under climatic conditions seems essential today.
Species distribution models are currently the main tools used to obtain spatially explicit predictions of the correspondence between habitats and conditions favorable to species (Mavunda et al., 2022). They use computer programs to predict the distribution of a species in geographical space and time, based on environmental data. These data are most often climatic data (e.g. temperature, rainfall), to which other variables such as soil type, geomorphology, water depth and vegetation can be added. Species distribution models became very popular in the scientific community around the turn of the century, as a means of projecting the impact of climate change on the spatial distribution of biodiversity across the globe (Elith & Leathwick, 2009; Ramirez-Villegas et al., 2014). Over the past two decades, they have become a key tool for mapping the current distribution of species and projecting their spatio-temporal variation in relation to projected climate change.
Climate change results from the concentration of greenhouse gases (GHGs) in the atmosphere, and generates more or less stable changes in factors such as temperature, rainfall, drought, etc. (Kumar et al., 2021; Ramanathan & Feng, 2009). These changes

can have adverse consequences for plant and animal species, particularly in terms of distribution and abundance (Hall et al., 1992; Van Der Putten et al., 2010). Given the proven and potential magnitude of the effects of climate change, their impacts on the distribution and abundance of plants and animals has become a major concern for biological resource managers (Weiskopf et al., 2020). In the past, species have responded to climate change by adapting, migrating or perishing (Pitelka & Group, 1997; Visser, 2008; Winkler et al., 2014). Modelling the distribution of species in relation to projected climate change has rightly attracted the interest of researchers around the world.

In the Democratic Republic of Congo, certain studies have been carried out on ecosystems and landscape modelling. These include work by (Kombate et al., 2022; Mavunda et al., 2022) to determine the influence of demographics and climate change on biotopes and biocenoses. They have shown that human population growth and climate change play an important role in landscape dynamics and the distribution of biodiversity. However, very little research has been done on ecological niche modelling, particularly for edible insects, for example in the city of Kinshasa.

The study assumes that the geographical distribution of *B. membranaceus* in Kinshasa is linked to the dynamics of bioclimatic, environmental and demographic factors over time. The main question for this study is to define the direction of *B. membranaceus* dynamics and the climatic variables that most influence these dynamics. The aim of this study is to determine the variables that contribute most to the modeling and prediction of the habitat and spatial distribution of *B. membranaceus* in Kinshasa for the horizons 2055 and 2100, with a view to its conservation.

2. Materials and Methods

Presentation of the study area

The City-Province of Kinshasa covers an area of 9 965 km^2 (De Saint Moulin & Kalombo, 2005). It stretches along the southern bank of the "Pool Malebo", forming a huge crescent covering a low, flat surface with an average altitude of around 300 m. Located between 4° and 5° south latitudes and between 15° and 16°32' east longitude (Figure 1). Kinshasa is bordered to the east by the provinces of Mai-Ndombe, Kwilu

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and Kwango; to the west and north by the Congo River, forming a natural border with the Republic of Congo; and to the south by the province of Kongo Central (Mavunda et al., 2022).

The climate is tropical, hot and humid. The average annual temperature is 25°C and average annual rainfall is 1,400 mm, with an average of 112 rainy days per year, peaking in April with 18 rainy days (Kinyamba et al., 2015). Vegetation used to consist of Guinean-Congolian ombrophilous gallery forests in the wet valleys and grassy formations, but is now characterised by heavily degraded, intensively exploited pre-forest fallows in the form of forest recruits of various ages. In addition, a small group of typically ruderal vegetation grows along a strip a few metres wide along the railroad (Habari, 2009).

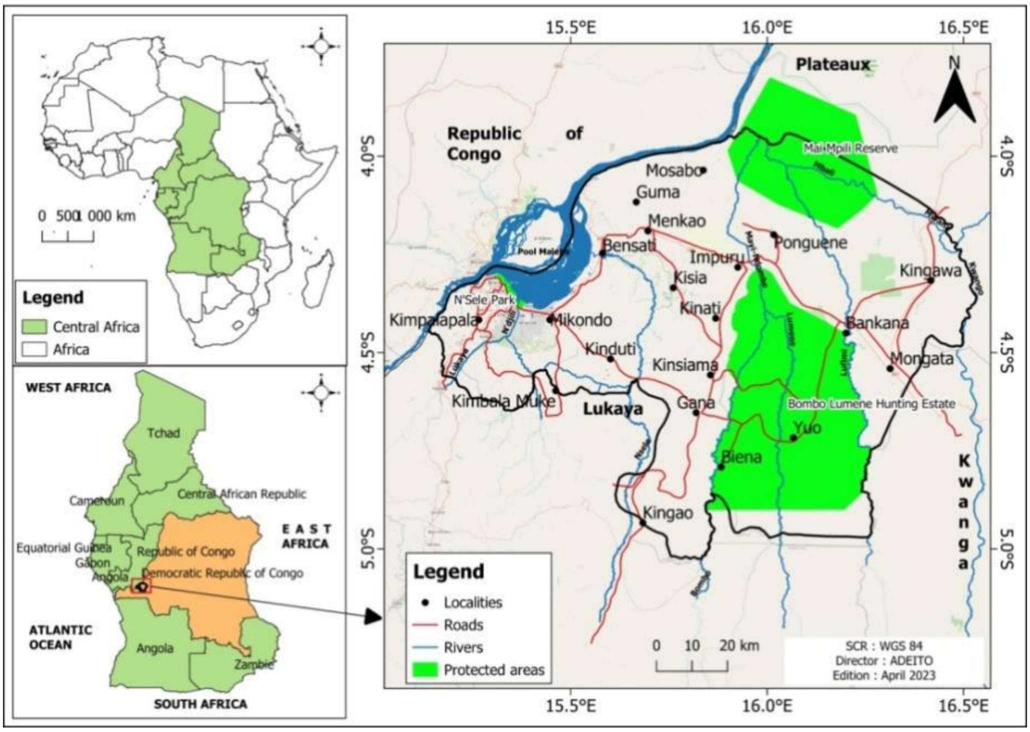

Figure 1. Location of the City-Province of Kinshasa in the DRC and situation in Central Africa.

Collect and Data analysis

Presence data

Data on the presence of *B. membranaceus* in Kinshasa were recorded using a GPS (Global Positioning System) receiver and the MAPS.ME mobile application. In order to maximise the accuracy of the models, it is recommended that the presence data for the species studied should cover as much of the region as possible, where it is influenced by the same climatic factors (Fitzpatrick & Hargrove, 2009). For this reason, points of presence of the species outside Kinshasa were completed in other provinces of the country, and even in Central African countries, by exploring the GBIF database (Global Biodiversity Information Facility: www.gbif.org). The visualisation of points of presence enabled a purging process to be carried out, involving the removal of erroneous points and duplicates. A total of 2446 points of presence were used to model ecological niches, including 789 points collected in the field (Table 1).

Table 1. Sources of data on the presence of *B. membranaceus*.

Species	Source	Number of points	Type of presence	Geographical location
B. membranaceus	Adeito (Personal observation)	789	Personal observation	Kinshasa
	GBIF (02 08 2022)	2446	Personal observation	DRC and Central Africa

Environmental variables

For the modelling, 21 environmental variables were exploited (Table 2). These included 19 bioclimatic variables, most directly related to the physiological aspects of species growth, altitude and soil data. Soil data were extracted from the Harmonised World Soil Database (HWSD) (http://www.data.tpdc.ac.cn/en/data/84410ba-d359-4020-bf76-2b58806f9205/), while altitude data were downloaded from WorldClim2.1 (https://www.worldclim.org/data/worldclim21.html). Current climate data from the 1970-2000 averages of 19 bioclimatic variables, WorldClim2.1 version, come from the Chelsa.V.2.1 platform (Karger et al., 2021).

For future climate projections to 2055, representing the average for the periods 2041-2070, bioclimatic variables are taken from the same platform. Two scenarios of the five (5) Shared Socio-economic Pathways (SSPs) were considered. The optimistic scenario (SSP126) corresponds to a gradual but global change towards a sustainable socio-economic context with a decrease in demography and consumption, and the pessimistic

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scenario (SSP585) estimates a rapid and global growth of the economy, coupled with the abundant exploitation of fossil fuels (O'Neill et al., 2017). The resolution of all data is 30 seconds (approximately 1 km^2).

Tableau 2. Ecological predictor variables selected for habitat suitability modelling of *B. membranaceus*, their code and units of measurement.

Climatic variables	**Variable definition**	**Unity**
bio 1	Mean annual temperature	°C
bio 2	Mean diurnal amplitude	°C
bio 3	Isotherm	%
bio 4	Seasonal temperature	°C
bio 5	Maximum temperature of warmest month	°C
bio 6	Minimum temperature of coldest month	°C
bio 7	Annual thermal amplitude	°C
bio 8	Mean temperature of wettest quarter	°C
bio 9	Mean temperature of driest quarter	°C
bio 10	Mean temperature of warmest quarter	°C
bio 11	Mean temperature of coldest quarter	°C
bio 12	Annual precipitation	mm
bio 13	Precipitation of wettest month	mm
bio 14	Precipitation of driest month	mm
bio 15	Seasonal precipitation	%
bio 16	Precipitation of wettest quarter	mm
bio 17	Precipitation of driest quarter	mm
bio 18	Precipitation of warmest quarter	mm
bio 19	Precipitation of coldest quarter	mm
hwsd	Soil	
elev	Altitude	m

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Model execution and validation

The modelling of potential areas for *B. membranaceus* was extended to the scale of Central Africa in order to increase the accuracy of the models at the scale of Kinshasa. Modelling was carried out using the MaxEnt (Maximum Entropy) principle. This algorithm uses an optimisation procedure comparing species presence with environmental parameters (Phillips et al., 2006). In conservation ecology, MaxEnt represents an important predictive tool (Phillips et al., 2006) and is widely used in species distribution (Dimobe et al., 2020). The mean resulting from the repetition of 10 crossed models is used in habitat mapping. This model was calibrated with 1503 points, i.e. 75% of presence points, and 25% of these points were used for testing. A general-purpose machine learning method, Maximum Entropy (MaxEnt v. 3.4.4) (Mugiyo et al., 2022) was applied to model the habitat suitability of *B. membranaceus* according to the selected predictors.

In addition to the default MaxEnt parameters, the following parameters were used, such as combinations of linear, quadratic, product and hinge feature classes and 10 times replicate with "subsample" as the replicate run type to reduce model overfitting (Phillips & Dudık, 2008). Ten of the thousands of base locations were also randomly generated from the entire study area to model the habitat quality map. In addition to the default MaxEnt parameters, the following parameters were used, such as linear, quadratic, product and hinge feature class combinations and 10 times replicate with "subsample" as the replicate run type to reduce model overfitting (Moukrim et al., 2020; Phillips & Dudık, 2008). Ten of the thousands of base locations were also randomly generated from the entire study area to model the habitat quality map.

The jackknife test was used to determine the predictive power of each variable and to identify those that contribute most to the generation of the distribution model produced by MaxEnt. Therefore, the contribution of each variable to the realisation of the models was evaluated using the Jackknife test (Bradie & Leung, 2017; Martens & Martens, 2000). Model evaluation was completed by projecting the presence points on the generated model in order to provide accuracy.

Based on the training dataset, we evaluated our models using the evaluation metric called Area Under the ROC (Receiver Operating Characteristic) curve (AUC: Area Under Curve) (Bekkar et al., 2013; Wang et al., 2015). It is a threshold-independent measure and is used to evaluate the predictive ability of the models for generating the habitat suitability map (Hirzel et al., 2006). ROC curves are mostly applied to validate habitat suitability models and are being used to judge the discrimination ability of various statistical methods (Ottaviani et al., 2004). It portrays the relationship between the proportion of correctly predicted observed presence (sensitivity) and the proportion of wrongly predicted observed absence (1 – specificity) (Phillips & Dudık, 2008; Wouyo et al., 2022). A model that predicts correctly will generate a ROC curve that follows the left axis and the top of the figure, whereas a model that is unable to reliably categorize places where the species is present and missing will generate a ROC curve that follows the 1:1 line. The AUC value varies from 0.5 to 1.0, in which AUC values above 0.90 is 'high accuracy'; 0.70< AUC <0.90 'good accuracy'; 0.50< AUC <0.70 'low accuracy' and AUC <0.50 'no better than random' (Kufa et al., 2022).

Habitat mapping and identification of priority areas

The MaxEnt model for cricket is a representation of the probability of presence of the species at each pixel in the study area. This model is used to produce the distribution map for cricket (*B. membranaceus*).

Habitat mapping for *B. membranaceus* was carried out with QGIS 2.18 software, using information from MaxEnt modelling. Two habitat classes were defined, based on the 10 percentile threshold (S) required to transform continuous probabilities of occurrence into binary presence/absence values (Phillips & Dudık, 2008). Values above "S" are considered favourable habitats, while values below are considered unfavourable. Based on the threshold value, three classes of favourable habitats were redefined (Moukrim et al., 2020) : highly favourable habitats ($p \geq S$), moderately favourable habitats ($S/2 \leq p < S$) and lowly favourable habitats ($S/4 \leq p < S/2$) (Moukrim et al., 2020). Determination of the species' current potential ranges and those for 2055 and 2100 according to each climate scenario (SSP125 and SSP585) enabled us to deduce potential habitat dynamics for 2055 and 2100, using the spatial analysis tool in QGIS 2.18 software.

Priority habitats were identified and classified using ArcMap/ArcGIS 10.8 (Moilanen et al., 2011). For this software, which is a conservation planning tool, the input files are the results of modelling in MaxEnt. These are: (i) current potential habitats, (ii) habitats at horizon 2055 according to the SSP126 and SSP585 scenario, and (iii) habitats at

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horizon 2100 according to the SSP126 and SSP585 scenario. These files are converted to a TIFF (Tagged Image File Format) format compatible with QGIS 2.18 software.

Description of study species

Made up of four subspecies including*: B. m. colosseus Saussure*, *B. m. hoggarensis Chopard*, *B. m. mauritanicus Chopard* and *B. m. membranaceus* (Lakhdari et al., 2015). Adult has a plump brown body, a broad blunt head, long antennae and powerful legs. It has a long head and body measuring 4 to 5 cm (Hill, 2008) (Figure 2).

Figure 2. Field image of a *B. membranaceus* individual (**Source**: Adeito, 2022).

B. membranaceus is nocturnal. It digs a burrow that can be 50 to 80 cm deep, with chambers in which it stores food. The burrow is dug by the mandibles, and the front legs are used to move loose earth and push it out of the entrance. An adult cricket can form a mound up to 30 cm high next to the burrow entrance (Lakhdari et al., 2015).

Crickets live almost entirely underground, each in its own burrow. Mating takes place in the male's burrow, and the female may remain there until the eggs are laid, in an enclosed side tunnel (Fayard, 2022). In Zimbabwe, breeding takes place in February and March. The female lays around two hundred eggs, which hatch about a month later. The nymphs crawl out of the burrow and disperse, each digging its own burrow. At first, the nymphs grow rapidly, but growth slows during the dry season from June to October. When young succulents become available in November, growth rates accelerate, with adults emerging from December onwards. There is only one generation per year (Fayard, 2022).

The diet consists of grasses, succulent plant parts and tree shoots such as *Brachystegia* and *Isoberlinia*. In cultivated areas, foodstuffs may include seedlings, transplants, vegetables, tobacco, maize and faba beans. Plant material is transported underground

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and packed in storage chambers. It does not ferment, so it is likely to be cut and left to wilt before being transported underground. Material that is too dry may soften with dew before storage (Lakhdari et al., 2015; Nsevolo, 2012).

3. Results

Variable contribution and model validation

The variables that contributed most to the models were the soil variable (hwsd), followed respectively by precipitation in the driest month (bio14), precipitation in the driest trimester (bio17) and precipitation in the coldest trimester (bio19) (Figure 3). Table 3 shows all the variables that contributed to the realization of the models.

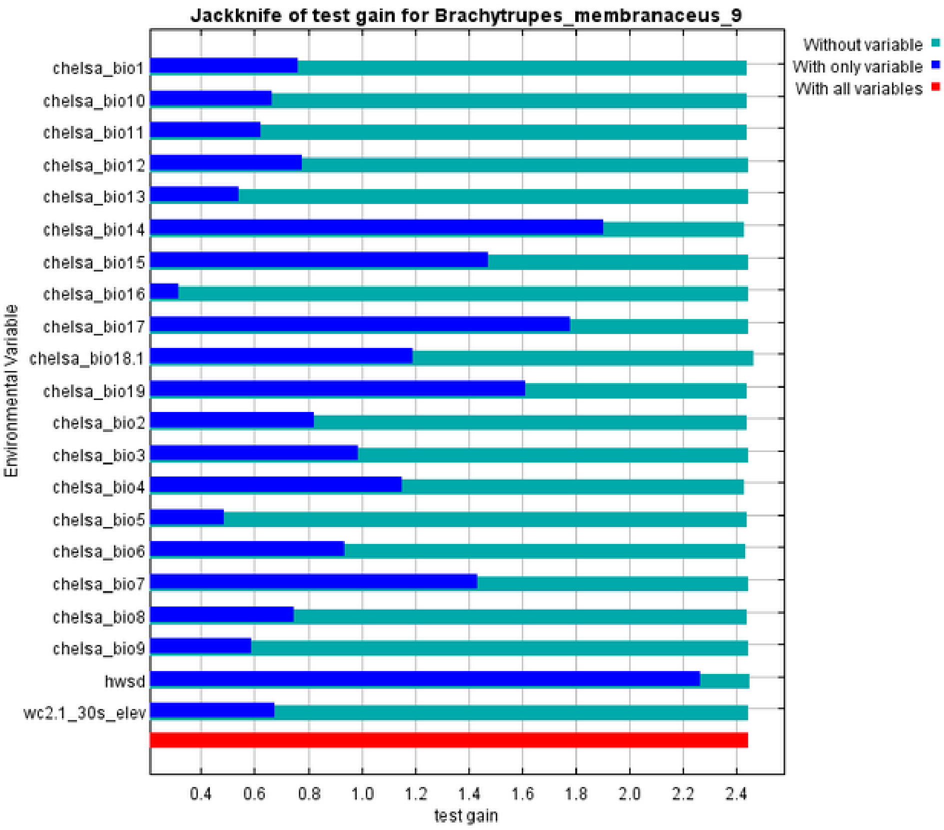

Figure 3. Contribution of variables to modeling.

Table 3. Values of bioclimatic and environmental variables

Variable	Percent contribution	Permutation importance

chelsa_bio14	38.4	42.6
hwsd	28.9	14
chelsa_bio19	13.9	2.4
chelsa_bio17	10.2	12.7
chelsa_bio4	3.2	7.2
chelsa_bio8	1.2	6.5
chelsa_bio6	1	4.6
wc2.1_30s_elev	1	0.1
chelsa_bio5	0.9	0.1
chelsa_bio15	0.8	0.1
chelsa_bio18.1	0.3	6
chelsa_bio7	0.1	0.5
chelsa_bio1	0.1	2.4
chelsa_bio3	0	0
chelsa_bio2	0	0.6
chelsa_bio11	0	0.1
chelsa_bio16	0	0.1
chelsa_bio12	0	0
chelsa_bio13	0	0
chelsa_bio10	0	0
chelsa_bio9	0	0

The mean AUC value of the area under the ROC curve is 0.969 (Figure 4). This AUC value reveals the model's excellent ability to predict the distribution of habitats favourable to the conservation and development of *B. membranaceus*.

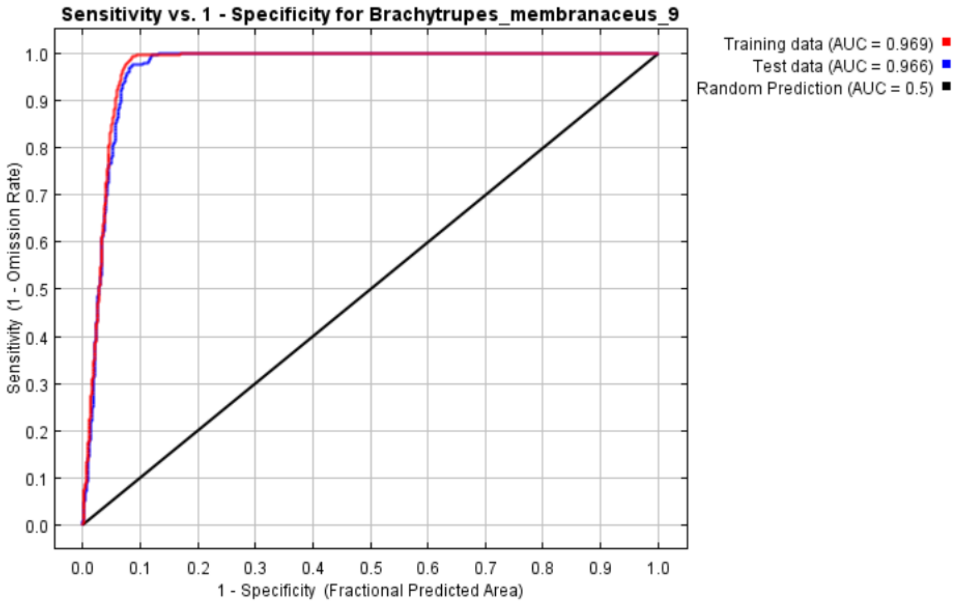

Figure 4. Mean AUC curve.

Potential current and future habitats (Horizons 2055 and 2100) in Kinshasa

Figure 5 shows the current and future distribution for 2055 and 2100 (SSP126 and SSP585) of potential habitats for *B. membranaceus*, based on localities and ecological zones in Kinshasa. For the current distribution, around 89.3% of Kinshasa's territory is predicted to be highly favourable to the development and conservation of the species studied. Moderately favourable and lowly favourable habitats occupy around 7.6% and 1.1% respectively. The urban (far east) and peri-urban (far east) areas are predicted to be unfavourable (2.0%). Highly favourable habitats are mainly found in the urban zone (North: commune of Mont Ngafula).

For the optimistic scenario (SSP126-H2055), around 69.5% of Kinois territory is predicted to be highly favourable to the development and conservation of *B. membranaceus*; moderately favourable and lowly favourable habitats occupy around 29.1% and 1,3% respectively; and the urban (extreme east) and peri-urban (extreme east) zones are predicted to be unfavourable (0.1%). Highly favourable habitats are mainly found in the urban zone (North: commune of Mont Ngafula). For the pessimistic scenario (SSP585-H2055), around 47.5% of the Kinois territory is predicted to be highly favourable to the development and conservation of *B. membranaceus*; moderately favourable and lowly favourable habitats occupy around 42.3% and 9.2%

respectively; and the urban (extreme east) and peri-urban (extreme east) zones are predicted to be unfavourable (1.0%). Highly favourable habitats are mainly found in the urban zone (North: commune of Mont Ngafula).

For the optimistic scenario (SSP126-H2100), around 61.5% of Kinois territory is predicted to be highly favourable to the development and conservation of *B. membranaceus*; moderately favourable and lowly favourable habitats occupy around 27.1% and 6.9% respectively; and the urban zone (extreme east) and peri-urban zone (extreme east) are predicted to be unfavourable (4.5%). Highly favourable habitats are mainly found in the urban zone (commune of Mont Ngafula, Kasavubu and Limete). For the pessimistic scenario (SSP585-H2100), around 39.2% of Kinois territory is predicted to be highly favourable to the development and conservation of *B. membranaceus*; moderately favourable and lowly favourable habitats occupy around 30.1% and 12.0% respectively; and the urban (extreme east) and peri-urban (extreme east) zones are predicted to be unfavourable (18.7%). Highly favourable habitats are mainly found in urban areas (Mont Ngafula, Kasa Vubu and Limete communes).

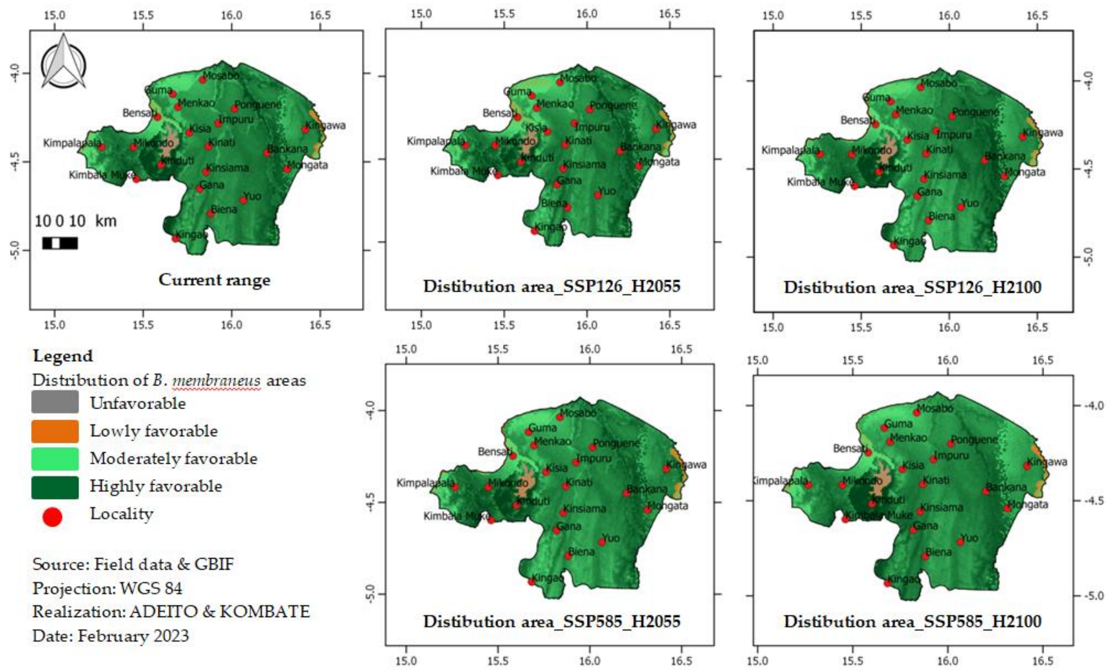

Figure 5. Area of distribution and development of *B. membranaceus* in Kinshasa.

Dynamics of current and future potential habitats for *B. membranaceus* in Kinshasa

By 2055, the two (2) scenarios predict a decline in highly favorable habitats and an increase in moderately and low favorable habitats (Fig. 6). The decline in highly favorable habitats is 19.8% and 41.8% respectively for SSP126 and SSP585. The rate of increase in moderately favorable habitat is 21.4%, compared with 34.8% for SSP585 and SSP125 respectively, while the predicted increase in low favorable habitat is 0.2% for SSP125 and 8.1% for SSP585. Current unsuitable habitat will decrease according to SSP125 (1.8%) and SSP585 (1.1%). By 2100, the two (2) scenarios predict a decline in highly favorable habitats and an increase in moderately and low favorable habitats (Figure 6). The decline in highly favorable habitats is 27.8% and 50.1% respectively for SSP126 and SSP585. The rate of increase in moderately favorable habitat was 19.5%, compared with 22.5% for SSP125 and SSP585 respectively. As for low favorable habitat, the predicted increase is 5.8% for SSP125 and 10.9% for SSP585. Current unsuitable habitat will increase by 2.5% for SSP125 and 16.7% for SSP585.

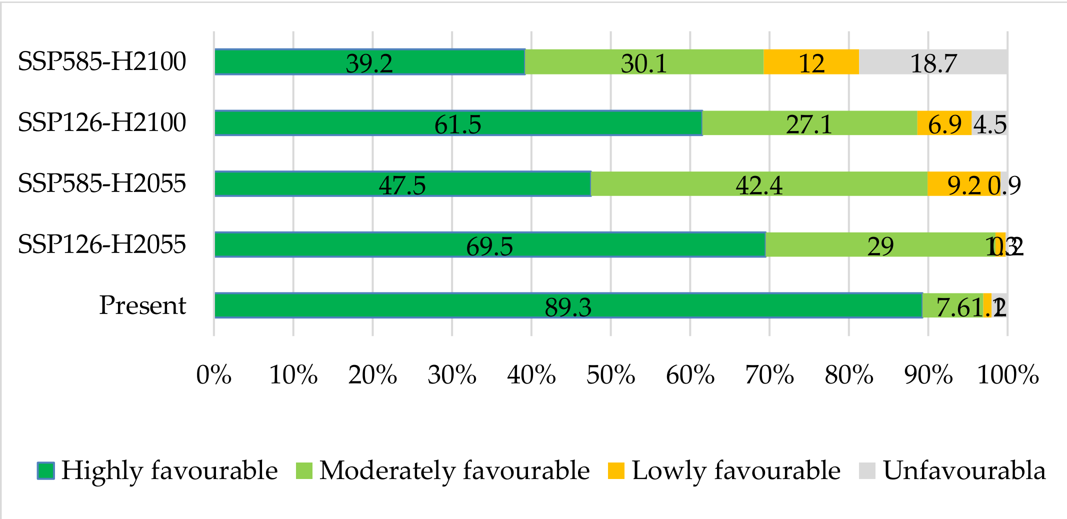

Figure 6. Quality of current and future potential habitat for *B. membranaceus* in Kinshasa for 2055 and 2100.

4. Discussion

Potential habitats and contribution of variables

The quality of the ecological niche models for *B. membranaceus* in Kinshasa was assessed using the AUC statistic, as done by several authors (Assang et al., 2023;

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Kiebooms, 2022; Wouyo et al., 2022). For this study, the AUC values are greater than 0.9. To ensure model reliability, (Petitpierre et al., 2017) suggests AUC values > 0.90. The result of the present study indicates a good ability of the model to predict favourable habitats (Petitpierre et al., 2017) for the development of *B. membranaceus* in Kinshasa under different climatic scenarios (optimistic and pessimistic).

The fact that the modelling of the potential distribution of *B. membranaceus* took into account the most important limiting factors in the species' distribution (soil and rainfall) means that credit can be given to the quality of the results obtained. This AUC value (> 0.90) is comparable to that obtained by (Dicko, 2011) (0.9) for the prediction of tsetse fly distribution using remote sensing in the Niayes area of Senegal. The contribution of edaphic variables to the distribution of this species is highly significant. Rainfall in the driest month and rainfall in the driest quarter are relegated to second place. The position occupied by these latter variables in modelling the ecological niches of the species under study would be due to the low variability of these variables over time in the study area. Pour ce qui est du sol, la profondeur du sol et le substrat basaltique stimule positivement l'accroissement du cèdre de l'Atlas mieux que le calcaire (Said & Bakhyi, 2016).

Ecological niche modelling has often been cited as a powerful tool for mapping the current and future distribution of species and predicting the impact of climate change on their distribution (Saliou et al., 2015; Synes & Osborne, 2011). However, these models have also been widely criticised for their weaknesses in predicting (van Zonneveld et al., 2009). However, these models have also been widely criticised for their weaknesses in predicting the impact of climate change on the geographic distribution of species. These weaknesses include the uncertainties associated with the models used, difficulties in parameterising ecological interactions, the idiosyncratic individual responses of species to climate change, species-specific dissemination limitations, the plasticity of physiological limits and the adaptive responses of disseminating agents (Schwartz, 2012). Various sources of error can impair the performance of modelling methods based solely on presence data. Five of the most common in species distribution models (SDMs) have been described by (Syfert et al., 2013): absence, sampling and imperfect detection biases (Dorazio, 2014); survey-related biases, particularly those linked to the accessibility of sites where the species is observed; spatial autocorrelation bias; effects of imperfect detection during repeated surveys (Guélat & Kéry, 2018); georeferencing errors of species presence points and inaccuracies of GPS coordinates in collection data (Bloom et al., 2018; Chapman & Wieczorek, 2020).

Furthermore, the basic assumption that the current climate in which a species is found (its current realised niche) is its original niche is also questionable. It is indeed possible that when the species was established in its current areas of occurrence, the climate was very different (wetter or drier), and that its current presence implies several millennia of adaptation to different climatic changes. It would therefore be risky to predict the disappearance of species from their current areas by 2055 and 2100, as the results of the present study show a centripetal niche evolution by 2055 and 2100. This evolutionary trend leaves something to be desired, as the evolution of anarchic urbanisation in the study area would be responsible for the destruction of this niche, and therefore the probable extinction of the species. Despite its weaknesses, this model provides very important bioclimatic information for decision-making, in particular for identifying new areas potentially favourable to the conservation of a given species (Schwartz, 2012). This result from (Schwartz, 2012) corroborates perfectly with that of the present study.

Implications for conservation and potential risks

The results of the predictions indicate that the surface area of habitats currently favourable for the development and conservation of *B. membranaceus* will not remain stable in the future according to the scenarios considered (SSP126 and SSP585) for the 2055 and 2100 horizons. The SSP126-H2055 and SSP585-H2055 scenarios show a decline in the area of highly favourable habitat in favour of moderately favourable habitat, and an increase in highly favourable habitat at the expense of moderately favourable habitat.

Scenarios SSP126-H2100 and SSP585-H2100 show an increase in the area of highly favourable habitat at the expense of moderately favourable habitat. This contrast in results between the 2055 and 2100 scenarios is due to a probable condition of climatic variables (temperature and precipitation) and a probable modification of soil physicochemical parameters (pH, temperature and precipitation) favourable to the development and conservation of *B. membranaceus* in the area, in the days to come. This scientific reality comes close to the prediction of (Maltrud & McClean, 2005), which states that the species favourable areas vary continuously and that a large part of these variations are due to climatic changes. Compared with the result of (Kiebooms, 2022), according to the optimistic scenario SSP1-2.6 (RCP2.6) and the most pessimistic scenario, SSP5-8.5 (RCP8.5), the average migration speed of Alpine species between the LGM (Last Glacial Maximum) and today (0.005 km/year for most species) is 20 times slower than the velocity of current climate change in mountainous regions (0.11 km/year) (Loarie et al., 2009). This result does not corroborate the findings of the present study, as altitude and temperature are the most influential variables in species habitat dynamics. Nevertheless, it supports the hypothesis of the present study that the long-term niche distribution of *B. membranaceus* is due to certain environmental variables (mainly soil and precipitation). This result confirms the fact that climatic parameters such as temperature and precipitation have the greatest effect on species distribution (Aussenac & Finkelstein, 1983).

According to International Union for Conservation of Nature (IUCN) status, *Brachytrupes membranaceus* is one of the Not Evaluated (NE) species, despite its high demand for human food and the degradation of its habitat as a result of its overlaying with urbanised areas. The present study visualises the present and future (horizon 2050 and 2100) realities of the different potential distribution areas of *B. membranaceus* in order to mitigate the probable threats (present and future) due to anarchic urbanisation.

The feasibility of this approach is unquestionable, and allows us to model distribution potential in conjunction with other parameters such as pedology and geomorphology.

Study limits

This study has not explored and predicted the change that might occur within the environmental variables that play a determining role in predicting favourable habitats for *B. membranaceus*. Their change is likely to modify the future distribution of *B. membranaceus*. Other environmental variables (eg: vegetation indices, slope or additional measures of human activities) and aspects of the species' ecology should also be taken into account in the future (Andriamasimanana & Cameron, 2013; Loarie et al., 2009; Tsetagho et al., 2023). In this study, the interaction between the variables considered was not taken into account, which could also influence the species' distribution and favourable habitat. The study was unable to calculate the migratory speed of habitats in order to reserve decision-making power for the future distribution of the species. This posture gives discretionary power to the present results and conservative power to predict potential present and future habitats.

5. Conclusions

The results of this study suggest that the probability of occurrence can be used to study the biogeography of species and participate in the assessment of the biodiversity of natural environments and ecosystem restoration. In the case of peri-urban ecosystem management, species distribution modeling remains a relevant means of defining the geographical extent of favorable areas for this species, identifying the environmental variables that affect its distribution and guiding urban development planning.

This study of the ecological niche of *B. membranaceus* in Kinshasa highlighted the link between climate variables and its ecological niche distribution. The methodological approach adopted in this work led to a globally satisfactory approach to the distribution of *B. membranaceus* as a function of ecological factors.

The result of this study identifies two environmental variables (soil and rainfall) as the most influential in modelling the ecological niche distribution of the species studied in Kinshasa. Four different habitat types (highly favourable, moderately favourable, lowly favourable and unfavourable) are defined, with the highly favourable habitat predominating in terms of surface area for all scenarios (SSP126 and SSP585) and at all times (2055 and 2100).

Modelling of the evolution of environmental parameters reveals that *B. membranaceus* should in future move from the peripheral zone to the urban zone in Kinshasa, mainly under the influence of edaphic factors and rainfall but also anthropogenic factors (uncontrolled urbanization and slash and burn agriculture). Such studies could serve as a basis for decision-making in the implementation of an urban development plan suitable for the sustainable management of entomological resources (in the case of *B. membranaceus*) and the improvement of food security in Kinshasa.

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Authors' contributions

C.A.M. and M.D.: Conceptualization; C.A.M. and F.F.: methodology; M.K. and D.M.-e.B.: software; C.A.M. and B.K.: formal analysis; C.A.M.: investigation, data curation and writing original draft preparation; C.A.M., D.M.-e.B., H.E: software, J.Y: methodology, F.B.B: methodology, J.K.M: formal analysis and K.A: writing review and editing. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abbreviations

AUC: Area Under Curve

CERViDA-DOUNEDON: Regional Center of Excellence on Sustainable Cities in Africa

DRC/DR. Congo: Democratic Republic of Congo

IDA: International Development Association

IUCN: International Union for Conservation of Nature

LGM: Last Glacial Maximum

RCP: Representative Concentration Pathways

ROC: Receiver Operating Characteristic

TIFF: Tagged Image File Format

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