

The white star apple (*Chrysophyllum albidum* G. Don), a revealed potential pan tropical forest food species in the context of climate and global changes

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Article

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Abstract

Chrysophyllum albidum is a forest food tree species of the Sapotaceae family bearing large berries of nutrition, sanitary, and commercial values in many African countries. It naturally grows in lowland rain forest and is widely distributed in West, Central, and East Africa. Because of its socio-economic importance, *C. albidum* is threatened at least by human pressure. However, we do neither know at which extent climate change can impact its distribution, nor whether it is possible to introduce the species in other tropical regions. In order to resolve our concerns we decided to model the spatial distribution of the species. We then used the SDM package for data modelling in R to compare predictive performances of algorithms among the most common used: three machine learning algorithms (MaxEnt, Boosted Regression Trees, and Random Forests) and three regression algorithms (Generalized Linear Model, Generalized Additive Models, and Multivariate Adaptive Regression Spline). We performed model transfers in tropical Asia and Latin America. At the scale of Africa, predictions with respect to Maxent, under Africlim (scenarios rcp 4.5 and rcp 8.5, horizon 2055) and MIROCES2L (scenarios SSP245 and SSP585, horizon 2060) showed that the favorable areas of *C. albidum* will extend mostly in West, East, Central, and Southern Africa as well as in East Madagascar. As opposed to Maxent, in Africa, the predictions of BRT and RF were unrealistic with respect to the known ecology of *C. albidum*. All the algorithms were consistent in predicting a successful introduction of *C. albidum* in Latin America, both at present and in the future. Predictions of spatial distribution of *C. albidum* at present and in future under MIROCES2L, scenarios SSP245 and SSP585, horizon 2060 were coherent and even complementary between BRT and RF and showed that the species can be successfully introduced in tropical Asia.

1- Introduction

Biodiversity and nature's contributions are of economic, social, and cultural importance to people. Indeed, they provide many goods and services indispensable to the survival of populations [1,2]. Despite its utmost importance, biodiversity is submitted to serious threats that are undermining human well-being and can impede the survival of humanity [1,2,3,4]. Biodiversity loss is mostly caused by human induced drivers among which, overexploitation, pollution, invasive alien species, habitat fragmentation, agricultural expansion, climate change, and poaching, as well as natural drivers such as diseases and pests outbreaks [1,3,4,5,6,7]. Across regions, human induced climate change is resulting in rise of temperature and sea-level, heat waves, changes in rainfall pattern like heavy precipitation, and droughts etc. [6]. All this affect the ecological niches of living organisms, and then exacerbate the other drivers of biodiversity loss [1]. Mitigating the impacts of climate change on biodiversity needs therefore to be tackled seriously. It's the reason why many studies are achieved worldwide to contribute to biodiversity conservation in the context of climate and global changes. Most of them used the species distribution models (SDMs). The SDMs (in geographic space), also known as ecological niche models (ENM) (in environmental space) explore the relationship between species occurrences and environmental variables to predict the distribution of species at present and in the future and therefore support policy decisions on biodiversity conservation and sustainable uses [8,9]. SDMs are widely used to answer many research

questions and provide guidance to biodiversity conservation in various fields of investigation. For examples, in field exploration to discover new populations and species [10]; identification of potential invasion hotspots of alien species, monitoring design and quarantine measures to prevent invasions [11]; predictions of range-shifting species [12]; prediction of pest risks to useful plants under climate change [13]; identification of suitable areas in the context of climate change of agroforestry, forestry and ornamental plant species [14,15,16,17]; identification of suitable areas in the context of climate change of birds and frogs to find out the effectiveness of protected areas in their conservation [18]; identification of suitable areas in the context of climate change of critically endangered parrot (*Amazona lilacina*) in order to contribute to its conservation [19]; tracking the pathways of suitable area of the disease fungus (*Batrachochytrium dendrobatidis*) in order to contribute to the conservation of amphibian [20]; identification of spatial pattern of species richness [21]; identification of regions with climate suitable for high diversity [22]; contribution to highlight crucial areas for biodiversity conservation [23]; model transfers to guide species relocations, introductions and reintroductions [24,25,26] etc.

Chrysophyllum albidum, our species of interest, is a forest food tree species of the Sapotaceae family. Its fruits are large berries of nutrition, sanitary, and commercial values in many African countries. The species is found in lowland rain forest and is widely distributed in West, Central and East Africa [27,28,29]. It grows in South Benin submitted to a sub equatorial climate on ferallitic soils [30].

In Africa, forest food trees are alternative sources of foods commonly used by people of various socio-economical categories as supplement for daily diets and therefore highly contribute to food diversity and security, and poverty alleviation [28,31,32]. Those authors reported that the fruits of forest food trees are rich in vitamins, minerals, sugars, proteins etc. and play therefore an important role in the nutritional balance of people. Many organs (barks, roots, leaves etc.) of the forest food trees are used in medicine and then contribute to health care delivery of people [28,31,32]. Among the forest food trees, *C. albidum* has a high socio-economic importance due to its multipurpose uses. Indeed, many use categories were recorded on the species among which food purpose was dominant, especially, the fleshy pulp of the fruits is largely eaten by local people [28,33,34]. Those authors pointed out that different parts of the species, especially the barks, the leaves, the seeds, and the fruits are used in folk medicine (treatments of malaria, sterility, sexual asthenia, asthma, intestinal worms, hemorrhoid, cough, icterus, yellow fever, avitaminosis, dental decay etc.).

Despite its socio-economic importance, *C. albidum* is threatened and neglected by people. Indeed, with respect to regeneration and improvement, *C. albidum* is considered as a neglected species [28]. In Nigeria the species is listed as endangered species, prone to extinction [35] while in Benin it is considered as vulnerable [33]. Due to the high socio-economic, health, nutrition, and commercial values of the species and its vulnerability to human pressure, we decided to investigate on it. The research questions that guided our investigation were as follows: 1) what are the favorable areas where to grow *C. albidum* in Africa in the context of human pressure and climate change? 2) Does a regional circulation model like Africlim best predict the spatial distribution of the species than a general circulation model like MIROCES2L? 3) Can the species successfully be introduced in tropical Asia and Latin America so as to

become a pan tropical forest food species of interest for the populations of America and Asia? Answering those questions will contribute to the conservation of the species, its dissemination and promotion worldwide in the context of climate and global changes.

2- Material And Methods

Species data

We explored many online repositories to download occurrence data. They are, databases of the Global Biodiversity Information Facility (GBIF, www.gbif.org), Atlas of living Australia (www.ala.org.au), iNaturalist (www.inaturalist.org), and speciesLink (www.splink.org.br). We cleaned the data, removing duplicates, data without coordinates, as well as managed, and introduced specimens. *Chrysophyllum albidum* is a terrestrial species and we therefore also removed data falling in Ocean. In order to address problems associated with spatial sampling biases of the occurrence records, we used the spThin R package version 0.2.0 [36] for spatial thinning of the records at a minimum distance of 5.0 km to comply with the spatial resolution of 2.5 arc minutes of the environmental data used in the models. The dataset used in the model calibration extended in Africa on terrestrial space located between -11.63 West to 13.37 degrees of East longitude and from 3.91 to 10.57 degrees of North latitude (**figure 1**).

Predictor data

Data resolution influences the quality of models, their predictions, and transferability [26,37]. Poorly resolved predictors are unlikely to match the ecology of the species [38]. Therefore, taking into account the spatial density of occurrence data available on *C. albidum*, we used predictor data at the resolution of 2.5 minutes arc. They are made of 17 bioclimatic variables of the present, downloaded at the spatial resolution of 2.5 minutes arc on Worldclim site [39]. We also used data on human population density as a proxy for human pressure, downloaded at the same resolution, on the Socio-Economic Data and Application Center (SEDAC) [40]. Future bioclimatic environmental data for projection purposes on Africa were downloaded at Africlim site [41]. The ensemble climatic models [41] were therefore used at the resolution of 2.5 minutes arc. We used Africlim data for future projection in Africa because, it is found advantageous over the general circulation models of Worldclim and available for Africa. Indeed, as regional models, they were downscaled to fit African realities (high density of population living in coastal areas, marked mountainous topography etc.) [41]. Future bioclimatic data for projections to tropical Asia, and tropical America were downloaded from Worldclim site. We therefore used the general circulation Model for Interdisciplinary Research on Climate, Earth System version 2 for Long-term simulations (MIROCES2L) [42] under the Shared Socioeconomic Pathways 2 (SSP2) and 5 (SSP5) which approximately correspond respectively to rcp 4.5 and 8.5 scenarios [43]. MIROCES2L is an improvement of the previous Earth System Models (ESM) (MIROC 5, MIROC 5.2, and MIROC6) [42]. Indeed, according to those authors, this new model includes a terrestrial biogeochemical component with explicit carbon-nitrogen interaction that enabled to account for the change in land carbon fluxes; the new model also

includes an updated ocean biogeochemical component to better describe the relationship between oceanic primary productivity and multiple nutrient limitations. We addressed the problem of collinearity between environmental variables. Indeed, collinearity can induce bias in parameter estimation by inflating variance of regression parameters and therefore misleads in the choice of the relevant predictors of models [44,45]. In order to account for this, we extracted the values of the predictors at occurrence points and run the variance inflation factor (VIF) function in SDM package [45]. We therefore retained in the models the less correlated variables. Furthermore, preliminary running of models helped us identify among the less correlated variables the most contributing ones to the models.

SDM package, model fitting, and evaluation

We used SDM package [45] for data modelling purposes in R [46]. It offered us the facilities needed to compare the predictive performances of several algorithms / modeling methods and to achieve the desired ensemble models. In order to compare algorithms and choose the best ones, among the most common, we used three machine learning algorithms: MaxEnt [47], Boosted Regression Trees (BRT) [48], Random Forests (RF) [49]; and three regression algorithms: Generalized Linear Model (GLM) [50], Generalized Additive Models (GAM) [51], and Multivariate Adaptive Regression Spline (MARS) [52]. In model calibration, the default settings [45] were used. However, when creating the SDM object data, we generated 10,000 random background points for both types of algorithms. The cross validation method with 2 replications, making a total of 10 replications was applied to run the models. The predictive performances of the models generated were measured through their discrimination capacities and reliabilities using different statistics, namely the area under the curve (AUC) of the receiver-operating characteristics plot [8,9], the True Skill Statistics (TSS) [53], the point biserial correlation (COR), and the proportion of explained deviance (Deviance) [8]. Ensemble models were generated using the threshold that maximized the TSS. This threshold was shown to produce the most accurate predictions [54]. That threshold was also used to achieve binary transformation of the outputs of the models in QGIS 3.18.1 [55].

3- Results

The results are presented here, first with predictions at present to appraise the performances of the different algorithms, and then the projections in the future are presented with outputs of the most efficient algorithms with respect to the known ecology of the species. The differences noted between the outputs based on environmental variables of MIROCES2L and those of Africlim are presented and commented as well. In order to account for the clarity of the text, some figures are presented as electronic supplementary materials online

3.1-Variables selected and model-validation

After running the variance inflation factor (VIF) function to account for collinearity between environmental variables, followed by preliminary runs of the models to identify the most contributing variables to the models, we finally retained 5 variables in the models. They are bio3 (isothermality), bio4 (temperature seasonality), bio5 (maximum temperature of the warmest Month), bio12 (annual precipitation), and pop (population density). Their relative importance is presented on **figure 2**. From that figure, bio3 (isothermality) is the most contributing variables followed by pop (population density) in the two types of methods (machine learning and regression). The least contributing variables is bio5 (maximum temperature of the warmest Month). The bioclimatic variables retained in the models are quite relevant to the known ecology of *C. albidum*, a forest food tree species growing in lowland rain forests of subequatorial Africa. The variable pop (population density) accounted for anthropogenic pressure in the context of global changes. From the results on model performance, the mean values of AUC ranged from 0.81 to 0.86 and the mean values of TSS ranged from 0.62 to 0.64 for all the models (**table 1**). We therefore deduced that the models performed better than random ones.

Table 1: Mean values of the statistics of model performance evaluation

Methods	AUC	COR	TSS	Deviance
	Mean value (standard deviation)			
Maxent	0.84 (0.05)	0.48 (0.06)	0.63 (0.11)	0.74 (0.05)
BRT	0.85 (0.04)	0.57 (0.10)	0.62 (0.10)	0.46 (0.04)
RF	0.86 (0.05)	0.6 (0.06)	0.64 (0.10)	0.42 (0.06)
GLM	0.81 (0.04)	0.19 (0.07)	0.64 (0.06)	0.18 (0.01)
GAM	0.83 (0.03)	0.39 (0.05)	0.62 (0.06)	0.17 (0.02)
MARS	0.85 (0.03)	0.39 (0.04)	0.64 (0.07)	0.15 (0.01)

3.2-Predictions at present at the scale of Africa

From **figures 3, 4, 5** the ability of Maxent, BRT, and RF to predict real presence is noted as the predictions covered most of the occurrence points of the species with additional predicted favorable areas across Africa (East and Central Africa, Center and North Madagascar). We point out however that the predictions of favorable areas of the species with BRT and RF are more extended than that of Maxent; however, under BRT and RF, the predictions of favorable areas spreading to southern and northern Africa are unrealistic with respect to the known ecology of *C. albidum*. As opposed to machine learning algorithms, the predictions of GLM, GAM, and MARS are mostly unrealistic with respect to the known ecology of *C. albidum*.

albidum, a forest food tree species found in lowland rain forests of subequatorial Africa (see Electronic Supplementary Material: **Appendices 1 and 2**).

NB: As lesson learnt on predictions at present in Africa, Maxent, BRT, and RF are the most efficient algorithms in predicting real presence of *C. albidum* across Africa. This is also attested by the mean values of the biserial correlation statistic (COR) which ranked Maxent, BRT, and RF higher than the other algorithms (**table 1**).

From the lesson learnt on the results on Africa, we only take into account the predictions of Maxent, BRT, and RF in our purposes of spatial and temporal model transfers.

Predictions at present at the scale of Latin America

According to **figures 6, 7, and 8**, *C. albidum* can be introduced and successfully grow in parts of Latin America, especially in Center and South Mexico, Honduras, Haiti, Venezuela, Colombia, Bolivia, and East Brazil.

Predictions at present at the scale of tropical Asia

According to **figures 9 and 10**, with respect to the outputs of BRT and RF, *C. albidum* can be introduced and successfully grow in parts of Asia, especially in East Pakistan, India, and Center-East China, Japan and southern parts of tropical Asia, especially Indonesia, Malaysia, Papua New Guinea. Those predictions are opposed to that of Maxent which predicted no favorable area of *C. albidum* in Asia (see Electronic Supplementary Material: **Appendix 3**).

Predictions for the future and impacts of climate change at the scale of Africa

We remind here that we used two sources of environmental data, the general circulation Model for Interdisciplinary Research on Climate, Earth System version 2 for Long-term simulations (MIROCES2L) and the regional circulation model downloaded from Africlim

Predictions with Africlim

According to the predictions of Maxent, under rcp 4.5 and rcp 8.5, horizon 2055, the favorable areas of *C. albidum* will extend mostly in West, East, Central, and Southern Africa as well as in East Madagascar (see Electronic Supplementary Material: **figures 11a and 11b, Appendix 4**). Compared to rcp 4.5, the predictions under rcp 8.5 showed sparsely more extensions of favorable areas in West African countries, East Africa, South DRC, and Madagascar (see Electronic Supplementary Material: **Appendix 5a**). Under

both scenarios, with respect to present, some limited losses of favorable areas will however sparsely be noted, mostly in Center-West Togo, in some East African countries, Center DRC, and Madagascar. As opposed to Maxent, the predictions of BRT and RF under both scenarios are unrealistic with respect to the known ecology of *C. albidum* (see Electronic Supplementary Material: **figure 12**)

Predictions with MIROCES2L

With respect to the predictions of Maxent, under scenarios SSP245 and SSP585, horizon 2060, the favorable areas of the species will be quite limited (see Electronic Supplementary Material: **figures 13a and 13b**) compared to the respective predictions under Africlim rcp 4.5 and rcp 8.5 horizon 2055 (see Electronic Supplementary Material: **figures 11 a and 11b**). The predictions of favorable areas of the three algorithms converged approximately and cover parts of West, East, and Central Africa as well as North of Madagascar (see Electronic Supplementary Material: **figures 13a, 13b, 14a, 14b, 15a, and 15b**). When compared to the present, the predictions of the algorithms also roughly converged and showed sparse extensions of favorable areas of the species in the same geographic sub regions.

From the predictions of Maxent under both scenarios, we also noted losses of favorable areas of the species with respect to the present, sparsely in West Africa (Benin), East and Central Africa as well as across Madagascar. Additional losses of favorable areas will also be noted in East Africa when the predictions of BRT and RF are considered.

The predictions of the three algorithms under SSP 585 also roughly converged when compared to the predictions under SSP245, and showed losses of favorable areas in West Africa (Benin and Togo), and across Central and East Africa as well as Madagascar.

Comparison of predictions under Africlim and MIROCES2L

The predictions of favorable areas with Maxent are more extended under Africlim than under MIROCES2L (see Electronic Supplementary Material: **figure 16**). Indeed, there is a significant extension of favorable areas of *C. albidum* in West, East, and Central Africa, as well as in Central Madagascar under Africlim rcp 4.5 and rcp 8.5 than under the scenarios of MIROCES2L. Some losses are however sparsely noted in East and Central Africa and North Madagascar under Africlim rcp 4.5 and rcp 8.5 compared to the scenarios of MIROCES2L.

Lessons learnt with respect to the predictions in Africa

At the scale of Africa, the predictions at present and in the future are consistent and coherent with Maxent either with Africlim, rcp 4.5 and 8.5 horizon 2055 or MIROCES2L SSP 245 and SSP 585 horizon 2060. The predictions with Africlim are however more extensive and realistic with respect to the known ecology of the species than with MIROCSE2L. As for BRT and RF, the predictions are coherent and realistic at present and in the future only with MIROCES2L. The predictions in the future with BRT and RF are incoherent and

unrealistic with Africlim as far as the known ecology of the species is concerned. Compatibility between climate models and algorithms is therefore suspected and need further investigation.

Predictions for the future and impacts of climate change at the scale of Latin America

The predictions of the three algorithms converged and showed that, under MIROCES2L, scenarios SSP245 and SSP585 horizon 2060, the favorable areas of *C. albidum* covers Central America (South Mexico, Guatemala, Honduras, and Haiti) and South America (Venezuela, Colombia, Ecuador, Peru, Bolivia, and Brazil) (see Electronic Supplementary Material: **figures 17a, 17b, 18a, 18b, 19a, 19b**).

Compared to the present, with Maxent and BRT, under both scenarios, extensions of favorable areas of the species will be noted in the same geographical area along with some losses. The favorable areas of the species will be more extended in parts of South America (Venezuela, Colombia, Peru, and Brazil) when RF is considered (see Electronic Supplementary Material: **figures 19a and 19b**) although along with some losses of favorable areas.

With respect to MIROCES2L, scenario SSP245, the predictions of the three algorithms under SSP585 converged and showed that extension of favorable areas will sparsely be noted in Central and South America while some losses will be deplored sparsely in the same geographical areas.

Lessons learnt with respect to the predictions in America

All the algorithms used are consistent in predicting a successful introduction of *C. albidum* in Latin America, mainly in Central America (Mexico, Guatemala, Honduras, Belize, Haiti) and North of South America (Venezuela, Colombia, Ecuador, Peru, Chile, Bolivia, and Brazil).

Predictions for the future and impacts of climate change at the scale of tropical Asia

The projection of the spatial distribution of *C. albidum* with BRT is quite complementary to that of RF. Indeed, with the predictions of BRT under both scenarios of MIROCES2L, the species can be introduced and successfully grow in South and East Asia (East Pakistan, India, and Center-East China) (see Electronic Supplementary Material: **figures 20a, 20b**); compared to the present, extension of favorable area will be sparsely noted across the same geographic areas along with limited losses of favorable areas in India. Complementary to BRT, the predictions of RF covers India, China, Taiwan, province of China, Japan and the Southern islands of the continent (Indonesia, Malaysia, PHL, North Papua New Guinea, and Malaysia (see Electronic Supplementary Material: **figures 21a, 21b**). With RF and compared to the present, extension of favorable areas will be sparsely noted across the same geographic areas. Limited losses of favorable areas will however be deplored across the same geographic areas.

Predictions of RF and BRT are opposed to those of Maxent which predicted no favorable area of the species in tropical Asia under the same scenarios.

Lessons learnt with respect to the predictions in tropical Asia

Predictions of spatial distribution of *C. albidum* at present and in future under MIROCES2L, scenarios SSP245 and SSP585, horizon 2060 were coherent and even complementary between BRT and RF and showed that the species can be successfully introduced to Center and southern countries of Asia, mainly India, China, Taiwan province of China, Japan, Indonesia, Malaysia, PHL, North Papua New Guinea. Predictions of BRT and RF are opposed to those of Maxent which predicted no favorable area of the species in tropical Asia under the same scenarios.

Discussion And Conclusion

Ecology of the species versus environmental factors governing its spatial distribution

According to [56] and [57] and as also reported by many authors, *Chrysophyllum albidum* is primarily a tropical rain forest food tree species widely distributed in West, Central, and East Africa [27,28,29].

Temperature and rainfall should therefore govern the spatial distribution of the species. In the models, the isothermality (bio3) measuring the rate of diurnal range of temperature with respect to the annual range [58] is the most contributing variable identified by almost all the algorithms. Furthermore and complementary to isothermality (bio3), temperature seasonality (bio4) that measures the variability of temperature or temperature change along the year [58] is also important in the models. Those variables are consistent with the known ecology of the species and clearly showed its sensitivity to the variability of temperature across its natural range. The annual precipitation (bio12) is the total water inputs along the year and helps ascertain the importance of water availability to the species distribution [58]; it also played a significant role in the models and this is obviously in line with the known ecological traits of *Chrysophyllum albidum*. The maximum temperature of the warmest month (bio5) is also retained in the model although with limited importance showing that *C. albidum* is not so affected by warm temperature anomalies throughout the year. In its natural range, the favorable areas of the species are submitted to human pressure causing its habitat degradation and fragmentation [34,59]. The variable population density (pop) accounts for human pressure and its importance is identified by all the models. Our results are supported by those of [60] who underlined the importance of temperature seasonality (bio4), and annual precipitation (bio12) among the environmental variables governing the distribution of the species in Benin. Apart from those two variables, [60] found out that precipitation of the driest quarter (bio17) was the most contributing variables to the distribution model of the species. Precipitation of driest quarter (bio17) also contributes to annual precipitation (bio12) and was eliminated from our models when performing the test of collinearity on environmental variables. Our results also align at least partially with those of [61]. Indeed, in their studies on the species in Nigeria, they listed the temperature seasonality (bio3) among the contributing variables to the distribution model of the species, although with limited

importance in comparison with the minimum temperature of the coldest month (bio6). The contribution of the variable “population density” as pointed out in the models highlighted that human pressure will impact the spatial distribution of the species. In respect to that, in favorable areas of the species, landscape management is required so as to avoid continuous land degradation that can impact the spatial distribution of the species.

Prediction performances of the modelling methods used in the study

From our results, machine learning methods (Maxent, BRT, and RF) performed better than regression methods (GLM, GAM, and MARS). Indeed at present in Africa, the predictions of favorable areas of *C. albidum* by the machine learning methods covered at least the occurrence points of the species while the predictions at present from the regression methods failed in that respect. This result is also attested by the values of the performance statistics AUC, TSS, and COR. AUC and TSS are correlated [54] and measure model performance in terms of their discrimination capacity or their ability in detecting real presence from absence [8,9,12,62]. In this study, the values of AUC ranged from 0.84 to 0.86 and from 0.81 to 0.85 respectively for machine learning methods and regression methods; the TSS values were however less discriminant with regards to the two types of methods and ranged from 0.62 to 0.64 for either of them. Deviance measures the deviation of the overall mean prediction values with respect to the overall presence and absence of the species [8]; it is a measurement of the goodness of fit of the models. When we observe the deviance mean values of the models, however, machine learning methods had the highest deviation mean values (0.42 - 0.74) whereas the lowest deviation values (0.15 – 0.18) were observed with regression methods. Reliability is another measure of model predictive performance and is related to the successfulness of a model in predicting real presence [8]. In this study, the point biserial correlation (COR) [62] is a measurement of the model’s reliability. Its values ranged from 0.48 to 0.6 for machine learning methods against 0.19 to 0.39 for regression methods. Our results are supported by those of [62] who compared the predictive performance of several methods including those used in this study on a large range of plant and animal species. On the basis of the statistics AUC and COR values, they found out that BRT and Maxent were among the methods that outperformed others like GLM, GAM, and MARS. [63] in their study on three cane species in China, pointed out the good predictive performance of RF. [25] in their study of model transferability applied to a range of species including birds, butterflies, and plants of Finland, found out among several modelling methods that Maxent and BRT was among the most performing ones as opposed to RF. In contrary to our results, they pointed out the good transferability of GLM and GAM. Our results are also in line with [26] when they pointed out that although GLM and GAM can prove good in model transfers, they can also generate unrealistic predictions outside the training data of the species. Our findings might however be relative or case dependent. Indeed, [64], modelling numerous amphibian and reptile species of Portugal, concluded that model performance strongly depends on the geographical and environmental distributions of the species being modelled. [65] in modelling potato species of South Africa used several modelling methods and found out variability

in their predictions mainly due to input type of data (presence / absence vs. presence only data) and extrapolation assumptions of the methods. They did not identify a best method for predictions. GLM, GAM, and MARS were initially conceived to use presence/absence data [65] and since we used only presence data in our study, background points' generation in modelling approaches like in SDM package [45] instead of real absence might be limiting for the ability of predictions of the regression methods.

***C. albidum*, a potential pan tropical forest food species, strategies for its conservation under climate and global changes**

Predictive models are vital to inform decisions on natural resource management in the context of climate and global changes [26]. In order to appraise the impacts of climate change on the management of the population of *C. albidum* in the tropics, we performed temporal and spatial transfers of the models achieved. Because regression models failed in predicting realistic presence of the species at present, we excluded them for spatial and temporal transfers.

Model transfers have many advantages and can guide decision making in resource management and biodiversity conservation [26]. The spatial model transfers at present across Africa with the outputs of Maxent, BRT, and RF were quite consistent with the known ecology of *Chrysophyllum albidum*. We can therefore take the prediction of the species at present in Madagascar as realistic and consider that the species can be successfully introduced in that country.

When we considered environmental data from Africlim [41], the predictions of the models developed with Maxent showed at future, a positive impact of climate change on the spatial distribution of the species across Africa under both scenarios rcp 4.5 and rcp 8.5 at horizon 2055. Indeed, the extension of the range of the species under both scenarios was noted in West, East, and Central Africa as well as in Madagascar. The species is therefore not at risk across Africa with respect to climate change. Our results are supported by those of [61] and [60] who respectively found out an extension of the favorable areas of the species in Nigeria and in Benin under climate change.

Globally, spatial and temporal model transfers with the outputs of Maxent are consistent and coherent with the known ecology of the species either with Africlim under rcp 4.5 and 8.5 horizon 2055 or MIROCES2L SSP245 and SSP585 horizon 2060. The predictions with Africlim were however more extensive and realistic than with MIROCSE2L.

As for BRT and RF, the predictions were coherent and realistic at present and in the future only with MIROCSE2L. Indeed, with respect to the known ecology of the species, the predictions in the future with BRT and RF are incoherent and unrealistic with Africlim. Environmental data from Africlim are derived from regional circulation models downscaled to fit the realities of Africa made of high density of populations in coastal areas and marked mountainous topography [41]. The outputs with Africlim should

therefore be more realistic than those from general circulation models like MIROCSE2L [42]. A problem of compatibility between algorithms and the source of environmental data can therefore be suspected and need further investigation.

Spatial transfers can contribute to species relocations or reintroductions like the case of Pale-headed Brush-Finch (*Atlapetes pallidiceps*) in the Andes of Ecuador [24]; field exploration to discover new populations and species [10]; identification of potential invasion hotspots of alien species, monitoring design and quarantine measures to prevent invasions [11]; predictions on range-shifting species [12]. Indeed, spatial transfers are quite exciting when it can help introduce new species in potential favorable areas. In this study, we transferred the models to Latin America and tropical Asia. All the algorithms used were consistent in predicting a successful introduction of *C. albidum* in Latin America both at present and in the future, mainly in Central America (Mexico, Guatemala, Honduras, Belize, and Haiti) and North of South America (Venezuela, Colombia, Ecuador, Peru, Chile, Bolivia, and Brazil). Predictions of spatial distribution of *C. albidum* at present and in future under SSP245 and SSP585 horizon 2060 were coherent and even complementary between BRT and RF and, showed that the species can be successfully introduced to Center and southern countries of Asia, mainly India, China, Taiwan province of China, Japan, Indonesia, Malaysia, PHL, North Papua New Guinea. In that respect, the predictions obtained with BRT and RF were opposed to those of Maxent which predicted no favorable area of the species in tropical Asia under the same scenarios.

Although extrapolation errors are inherent to model transfers [12], the successful introduction of *C. albidum* in tropical Asia is however credible from our experience and field observations. Indeed, the natural range of teak (*Tectona grandis* L. f.) is tropical Asia (Myanmar, India, Thailand, and Laos) [66, 67]. It was introduced in Benin, West Africa, in 1916 and has been intensively and successfully cultivated since then in the country [68]. *C. albidum* is growing just in adjacent lands to teak plantations and even inside teak plantations in Benin. We therefore deduce that some similarity traits exist between the ecology of the two species. The predictions of favorable areas of *C. albidum* in the natural range of teak in Asia must therefore be accredited. Furthermore, from the world distribution map of teak [69], teak is growing extensively in tropical America including Latin America and largely in tropical Asia. The favorable areas predicted in this work both at present and in future for *C. albidum* are comprised in the distribution range of teak predicted by [69] either in Latin America or in Tropical Asia. This further underlines the reliability of the projections obtained with our models. We can therefore infer that the predictions of favorable areas of *C. albidum* in Latin America and tropical Asia are credible.

The species is native to Africa and the favorable areas in the future under both scenarios of Africlim and MIROC2EL on the continent should be explored. In the predicted favorable area, we recommend to introduce the species where it is absent and increase its stocks where it is already present but at low densities. In Latin America and tropical Asia, it is worth to introduce the species in the predicted favorable areas and follow up with adequate care so as to enable its establishment. At the regional levels (Africa, Latin America, and tropical Asia), the variable soil was not considered in the modelling process. At local scale however, where the introduction of the species is envisioned, types of soil can become a limiting

factor for the successful establishments of the species [70]. Indeed, *C. albidum* is mostly found on ferrallitic well-drained soils in its natural range; its introduction elsewhere should therefore take into account the appropriate types of soils to enable success. In response to the important contribution of the variable "population density" to the models, human pressure will impact the spatial distribution of the species. Landscape management is therefore required so as to attribute clear vocations to land-use and then avoid continuous land degradation and conversion to agriculture or grazing. The species can therefore be introduced in agroforestry and forestry land-use vocations and then safeguarded with adequate cultural cares.

Declarations

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Conflict of interest

The author declares no conflict of interest

Data availability

All data generated or analyzed during this study are included in this published article [and its supplementary information files]

References

1. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). *Summary for policymakers of the regional assessment report on biodiversity and ecosystem services*

for Africa of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. (eds. Archer E. et al.) IPBES secretariat, Bonn, Germany (2018).

2. FAO. *Global Forest Resources Assessment 2020: Main report.* Rome.
<https://doi.org/10.4060/ca9825en> (2020)
3. Millennium Ecosystem Assessment (MA). *Ecosystems and Human Well-Being: Synthesis.* Island Press, Washington (2005)
4. CBD. Considerations for Implementing International Standards and Codes of Conduct in National Invasive Species. Strategies and Plans. CBD (2011).
5. Semper-Pascual, A. et al. Using occupancy models to assess the direct and indirect impacts of agricultural expansion on species' populations. *Biodiversity and Conservation.* **29**, 3669-3688 (2020).
6. Arias, P. et al. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; Technical Summary (2021).
7. Nunez, S. & Alkemade, R. Exploring interaction effects from mechanisms between climate and land-use changes and the projected consequences on biodiversity. *Biodiversity and Conservation,* **30**, 3685-3696 (2021).
8. Liu, C., White, M. & Newell, G. Measuring and comparing the accuracy of species distribution models with presence absence data. *Ecography* **34**, 232-243; 10.1111/j.1600-0587.2010.06354.x (2011).
9. Hao, T., Elith, J., Lahoz-Monfort, J. J. & Guillera-Arroita, G. Testing whether ensemble modelling is advantageous for maximising predictive performance of species distribution models. *Ecography* **43**, 549-558 ; 10.1111/ecog.04890 (2020).
10. Pearson, G. R., Raxworthy, J. C., Nakamura, M. & Peterson, A. T. Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *J. Biogeogr* **34**, 102-117 (2007).
11. Thuiller, W. et al. Niche-based modelling as a tool for predicting the risk of alien plant invasions at a global scale. *Glob. Chang. Biol.* **11**, 2234-2250 (2005).
12. Elith, J., Kearney, M. & Phillips, S. The art of modelling range-shifting species. *Methods in ecology and evolution.* **1**, 330-342 (2010).
13. Ashraf, U., Chaudhry, M. N. & Peterson, A. T. Ecological niche models of biotic interactions predict increasing pest risk to olive cultivars with changing climate. *Ecosphere* **12**, e03714. 10.1002/ecs2.3714 (2021).
14. Elith, J. et al. A statistical explanation of MaxEnt for ecologists. *Diversity and distributions.* **17**, 43-57 (2011).
15. Ganglo, J. C. et al. Ecological niche modeling and strategies for the conservation of *Dialium guineense* Willd.(Black velvet) in West Africa. *International Journal of Biodiversity and Conservation.* **9**, 373-388 (2017).

16. Djotan, A. K. G. *et al.* How far can climate changes help to conserve and restore *Garcinia kola* Heckel, an extinct species in the wild in Benin (West Africa). *International Journal of Biodiversity and Conservation*. **10**, 203-213 (2018).
17. Kakpo, S. B. *et al.* Spatial distribution and impacts of climate change on *Milicia excelsa* in Benin, West Africa. *Journal of Forestry Research*. **32**, 143-150 ; 10.1007/s11676-019-01069-7 (2021).
18. Campos-Cerqueira, M. *et al.* Climate change is creating a mismatch between protected areas and suitable habitats for frogs and birds in Puerto Rico. *Biodiversity and Conservation*. **30**, 3509-3528 (2021).
19. Biddle, R. *et al.* The value of local community knowledge in species distribution modelling for a threatened Neotropical parrot. *Biodiversity and Conservation*, **30**, 1803-1823 (2021).
20. Costa, A. *et al.* Modelling the amphibian chytrid fungus spread by connectivity analysis: towards a national monitoring network in Italy. *Biodiversity and Conservation*. **30**(10), 2807-2825 (2021).
21. Macdonald, D.W. *et al.* Predicting biodiversity richness in rapidly changing landscapes: climate, low human pressure or protection as salvation? *Biodiversity and Conservation*. **29**, 4035-4057 (2020).
22. Hoveka, L. N., van der Bank. M., Bezeng, B. S. & Davies, T. J. Identifying biodiversity knowledge gaps for conserving South Africa's endemic flora. *Biodiversity and Conservation*. **29**, 2803-2819 (2020).
23. Schüßler D, Mantilla-Contreras J, Stadtmann R., Ratsimbazafy, J. H., & Radespiel, U. Identification of crucial stepping stone habitats for biodiversity conservation in northeastern Madagascar using remote sensing and comparative predictive modeling. *Biodiversity and Conservation*. **29**, 2161-2184 (2020).
24. Oppel, S., Schaefer, H.M., Schmidt, V. & Schröder, B. How much suitable habitat is left for the last known population of the Pale-headed Brush-Finch? *The Condor* **106**, 429-434 (2004).
25. Heikkinen, R. K., Marmion, M. & Luoto, M. Does the interpolation accuracy of species distribution models come at the expense of transferability? *Ecography*. **35**, 276-288 (2012).
26. Yates, K. L. *et al.* Outstanding Challenges in the Transferability of Ecological Models. *Trends in Ecology & Evolution*. **33**, 790-802. 10.1016/j.tree.2018.08.001 (2018).
27. Orwa, C., Mutua, A., Kindt, R., Jamnadass, R., & Simons, A. Agroforestry Database: a tree reference and selection guide version 4.0. World Agroforestry Centre, Kenya. <http://www.worldagroforestry.org/af/treedb/> (2009).
28. Bolanle-Ojo, O. T. & Onyekwelu, J. C. Socio-economic importance of *Chrysophyllum albidum* g. Don. in Rainforest and derived savanna ecosystems of Ondo state, Nigeria. *European Journal of Agriculture and Forestry Research*. **2**, 43-51 (2014).
29. Ugwu, J. A. & Umeh, V. C. Assessment of African star apple (*Chrysophyllum albidum*) fruit damage due to insect pests in Ibadan, Southwest Nigeria. *Research Journal of Forestry* **9**, 87-92 (2015).
30. Akoegninou, A., Van der Burg, W. J. & Van der Maesen, L. J. G. *Flore Analytique du Bénin* (No. 06.2). Backhuys Publishers. (2006).

31. Fandohan, B. *et al.* Women's traditional knowledge, use value, and the contribution of tamarind (*Tamarindus indica* L.) to rural households' cash income in Benin. *Economic botany*. **64**, 248-259 (2010).
32. Gouwakinnou, G. N., Lykke, A. M., Assogbadjo, A. E. & Sinsin, B. Local knowledge, pattern and diversity of use of *Sclerocarya birrea*. *Journal of ethnobiology and ethnomedicine* **7**, 1-9 (2011).
33. Houessou, L. G., Lougbegnon, T. O., Gbesso, F. G., Anagonou, L. E., & Sinsin, B. Ethno-botanical study of the African star apple (*Chrysophyllum albidum* G. Don) in the Southern Benin (West Africa). *Journal of Ethnobiology and Ethnomedicine* **8**, 1-10 (2012)
34. Lougbégnon, O. T., Nassi, K. M., Gbesso, G. H. F. Ethnobotanique quantitative de l'usage de *Chrysophyllum albidum* G. Don par les populations locales au Bénin. *Journal of Applied Biosciences*. **95**, 9028 – 9038 (2015)
35. Olajide, O., Udo, E. S., & Out, D. O. Diversity and population of Timber Tree Species Producing Valuable Non-Timber Products in Two Tropical Rainforests in Cross River State, Nigeria. *Journal of Agriculture and Social Sciences* ISSN Print 1813-2235 (2008)
36. Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B., & Anderson, R. P. An R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*. **38**, 541–545 (2015)
37. Lannuzel, G., Balmot, J., Dubos, N., Thibault, M., & Fogliani, B. High-resolution topographic variables accurately predict the distribution of rare plant species for conservation area selection in a narrow-endemism hotspot in New Caledonia. *Biodiversity and Conservation*, **30**, 963-990 (2021).
38. Scales, K. L. *et al.* Scale of inference: on the sensitivity of habitat models for wide-ranging marine predators to the resolution of environmental data. *Ecography*. **40**, 210-220 (2017).
39. Fick, S. E. & Hijmans, R. J. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. *International Journal of Climatology* **37** (12): 4302-4315 (2017). Last accessed on 26th November, 2021
40. Center for International Earth Science Information Network - CIESIN - Columbia University. Gridded Population of the World, Version 4 (GPWv4): Administrative Unit Center Points with Population Estimates, Revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). doi.org/10.7927/H4BC3WMT (2018). Last accessed on 7th December, 2021
41. Platts, P. J., Omeny, P. & Marchant, R. AFRICLIM: high-resolution climate projections for ecological applications in Africa. *African Journal of Ecology*. **53**, 103-108 (2015).
<https://webfiles.york.ac.uk/KITE/AfriClim/> last accessed on 26th November, 2021
42. Hajima, T. *et al.* Development of the MIROC-ES2L Earth system model and the evaluation of biogeochemical processes and feedbacks. *Geoscientific Model Development*. **13**, 2197-2244 (2020)
43. Eyring, V. *et al.* Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geosci. Model Dev.* **9**, 1937-1958, 10.5194/gmd-9-1937-2016 (2016).

44. Dormann, C. F. et al. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography*. **36**, 27-46 (2013).
45. Naimi, B. & Araújo, M. B. sdm: a reproducible and extensible R platform for species distribution modelling. – *Ecography* 39: 368–375 (ver. 0). doi: 10.1111/ecog.01881 (2016).
46. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <https://www.R-project.org/> (2020)
47. Phillips, S. J., Anderson, R. P. & Schapire, R. E. Maximum entropy modeling of species geographic distributions. *Ecol. Model.* **190**, 231-259 (2006).
48. Elith, J., Leathwick, J. R. & Hastie, T. A working guide to boosted regression trees. *Journal of animal ecology*. **77**, 802-813 (2008).
49. Breiman, L. Random Forests. *Machine Learning* **45**, 5–32. <https://doi.org/10.1023/A:1010933404324> (2001).
50. Zheng, B. & Agresti, A. Summarizing the predictive power of a generalized linear model. *Statistic in medicine* **19**, 1771-1781 (2000).
51. Hastie, T. J. Generalized additive models. In *Statistical models in S* (pp. 249-307). Routledge. (2017)
52. Friedman, J. H. Multivariate adaptive regression splines. *The annals of statistics*. **19**, 1-67 (1991).
53. Allouche, O., Tsoar, A. & Kadmon, R. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J. Appl. Ecol.* **43**:1223-1232 (2006).
54. Barbet-Massin, M., Jiguet, F., Albert, C. H. & Thuiller, W. Selecting pseudo-absences for species distribution models: how, where and how many? *Methods in ecology and evolution*. **3**, 327-338 (2012)
55. QGIS Development Team. QGIS Geographic Information System. Open Source Geospatial Foundation Project. <http://qgis.osgeo.org> (2021)
56. Keay, R. W. J. *Trees of Nigeria*. (Clarendon Press, Oxford. 476 pp, 1989)
57. Bada, S. O. Preliminary information on the ecology of *chrysophyllum albidum* G. Don in West and central Africa in *Proceedings of National workshop on the potentials of the star Apple in Nigeria* (eds. Denton, D. A., Ladipo, D. O., Adetoro, M. A. & Serum, M. B.) 16-25 (1997).
58. O'Donnell, M. S. & Ignizio, D. A. Bioclimatic predictors for supporting ecological applications in the conterminous United States. *US geological survey data series* **691**, 4-9 (2012).
59. Anegbeh, P. O., Tchoundjeu, Z., Anuforom, B. C., Ukafor, V., & Usoro, C. Farmers' Participation In Ex-Situ Conservation Of Indigenous Fruit Trees In Southern Nigeria. *Journal of Agriculture and Social Research (JASR)*. **4**, 33-42 (2004).
60. Gbesso, F. H. G., Tente, B. H. A., Gouwakinnou, G. N., & Sinsin, B. A. Influence des changements climatiques sur la distribution géographique de *Chrysophyllum albidum* G. Don (Sapotaceae) au Benin. *International Journal of Biological and Chemical Sciences*. **7**, 2007-2018 (2013).
61. Lyam, P. T., Adeyemi, T. O. & Ogundipe, O. T. Distribution modelling of *Chrysophyllum albidum* G. Don. in South-West Nigeria. *Journal of Natural & Environmental Sciences*. **3**, 7-14 (2012).

62. Elith, J. *et al.* Novel methods improve prediction of species' distributions from occurrence data. *Ecography* **29**, 129-151 (2006).
63. Mi, C., Huettmann, F., Guo, Y., Han, X. & Wen, L. Why choose Random Forest to predict rare species distribution with few samples in large undersampled areas? Three Asian crane species models provide supporting evidence. *Peer J.* **5**, e2849 10.7717/peerj.2849 (2017).
64. Segurado, P. & Araujo, M. B. An evaluation of methods for modelling species distributions. *Journal of biogeography*. **31**, 1555-1568 (2004).
65. Pearson, R. G. *et al.* Model-based uncertainty in species range prediction. *Journal of biogeography*. **33**, 1704-1711 (2006).
66. Pandey, D. & Brown, C. Teak: a global view. *Unasylva* **51**, 3-11 (2000).
67. Midgley, S. *et al.* *Planted teak: global production and markets, with reference to Solomon Islands.* ACIAR Technical Reports No. 85. Australian Centre for International Agricultural Research, Canberra, 92 pp (2015)
68. Ganglo, C. J. Yield Table of Teak (*Tectona grandis* L. f.) Plantations in Benin (West-Africa). *Teaknet Bulletin* **13**, 1-9 (2020).
69. Centre for Agricultural Bioscience International (CABI). *Tectona grandis* in Invasive species Compendium. Wallingford, UK. <https://www.cabi.org/isc/datasheet/52899#toDistributionMaps> (2021).
70. Dambros, C. *et al.* The role of environmental filtering, geographic distance and dispersal barriers in shaping the turnover of plant and animal species in Amazonia. *Biodiversity and Conservation*. **29**, 3609-3634 (2020).

Figures

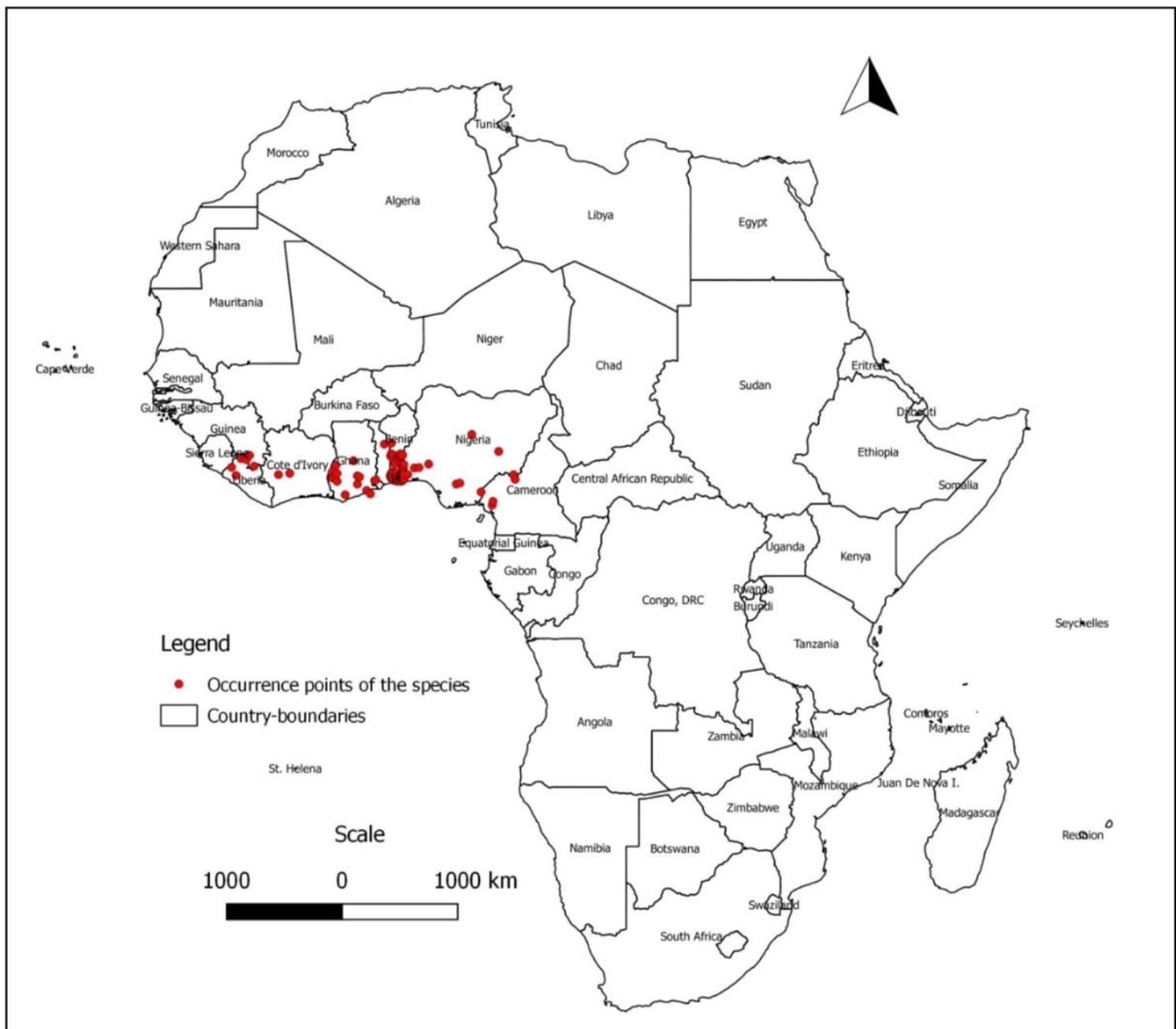


Figure 1

Spatial distribution of the occurrence points of *C. albidum* across Africa

Source of occurrence points: GBIF.org (1 March 2021) GBIF Occurrence

Download <https://doi.org/10.15468/dl.pg7stw>

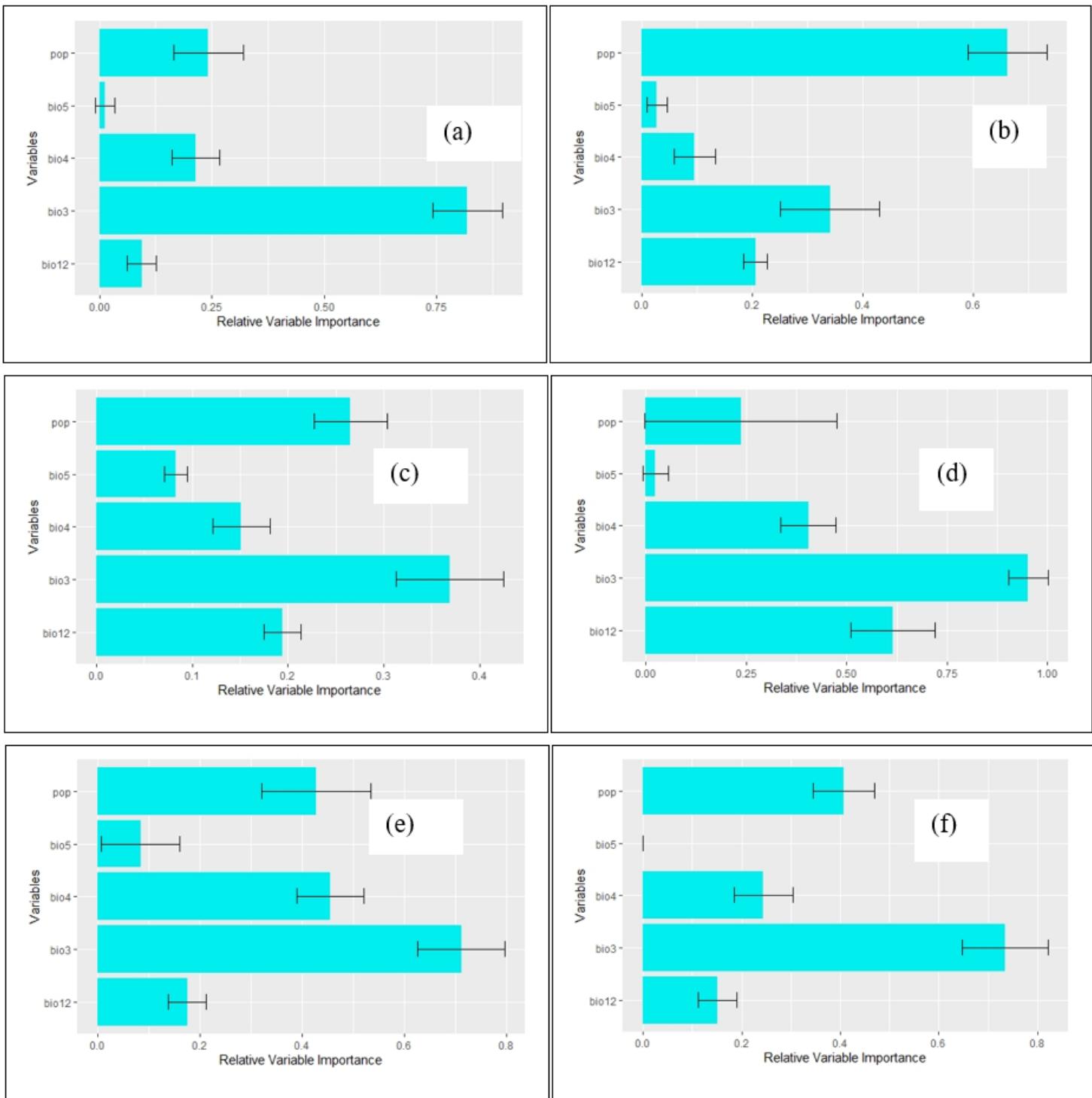


Figure 2

Relative importance of the environmental variables in the models: a) Maxent, b) BRT, c) RF, d) GLM, e) GAM, and f) MARS

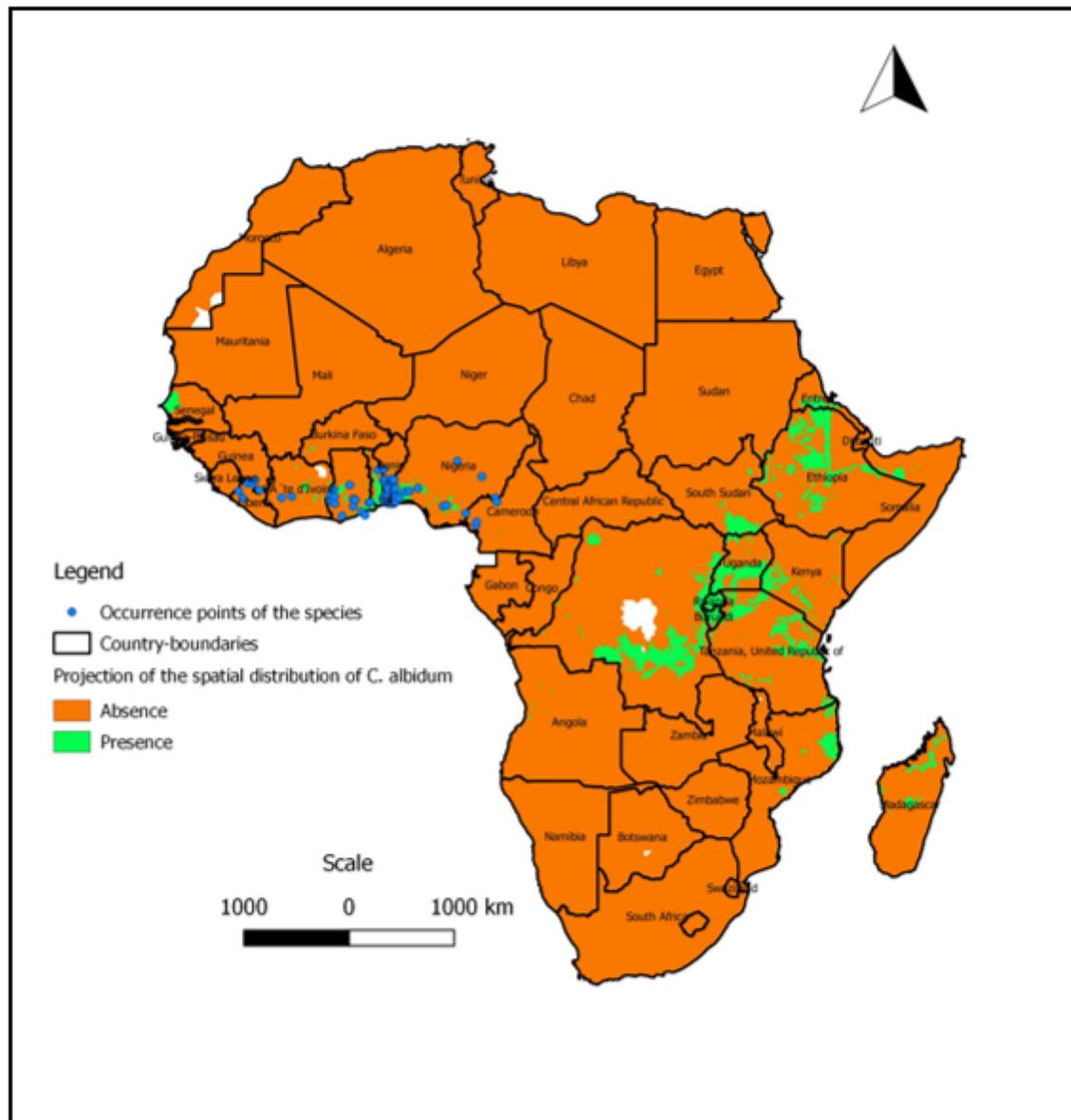


Figure 3

Projection at present of the spatial distribution of *C. albidum* according to Maxent across Africa with occurrence points

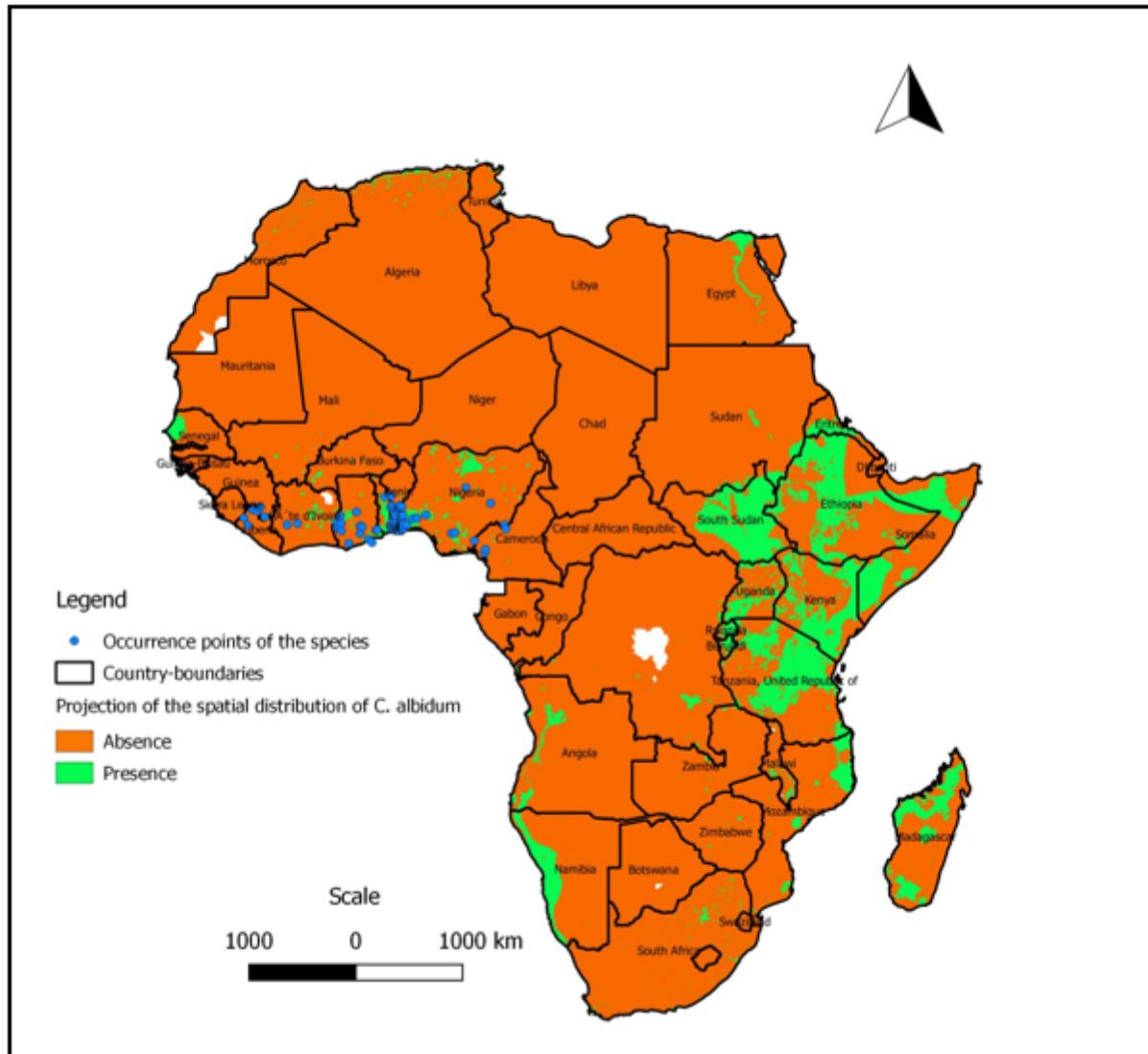


Figure 4

Projection at present of the spatial distribution of *C. albidum* according to BRT across Africa with occurrence points

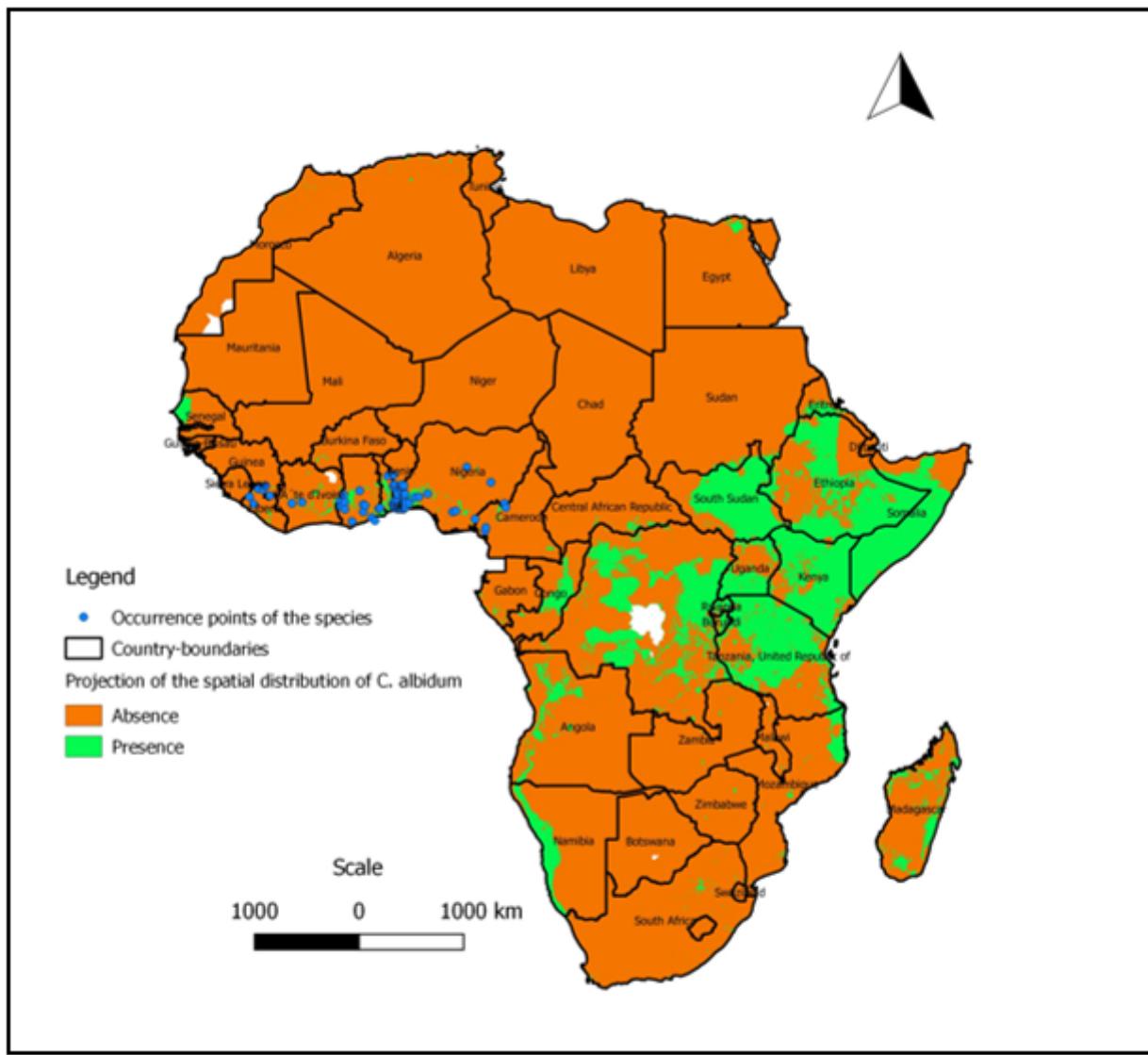


Figure 5

Projection at present of the spatial distribution of *C. albidum* according to RF across Africa with occurrence points

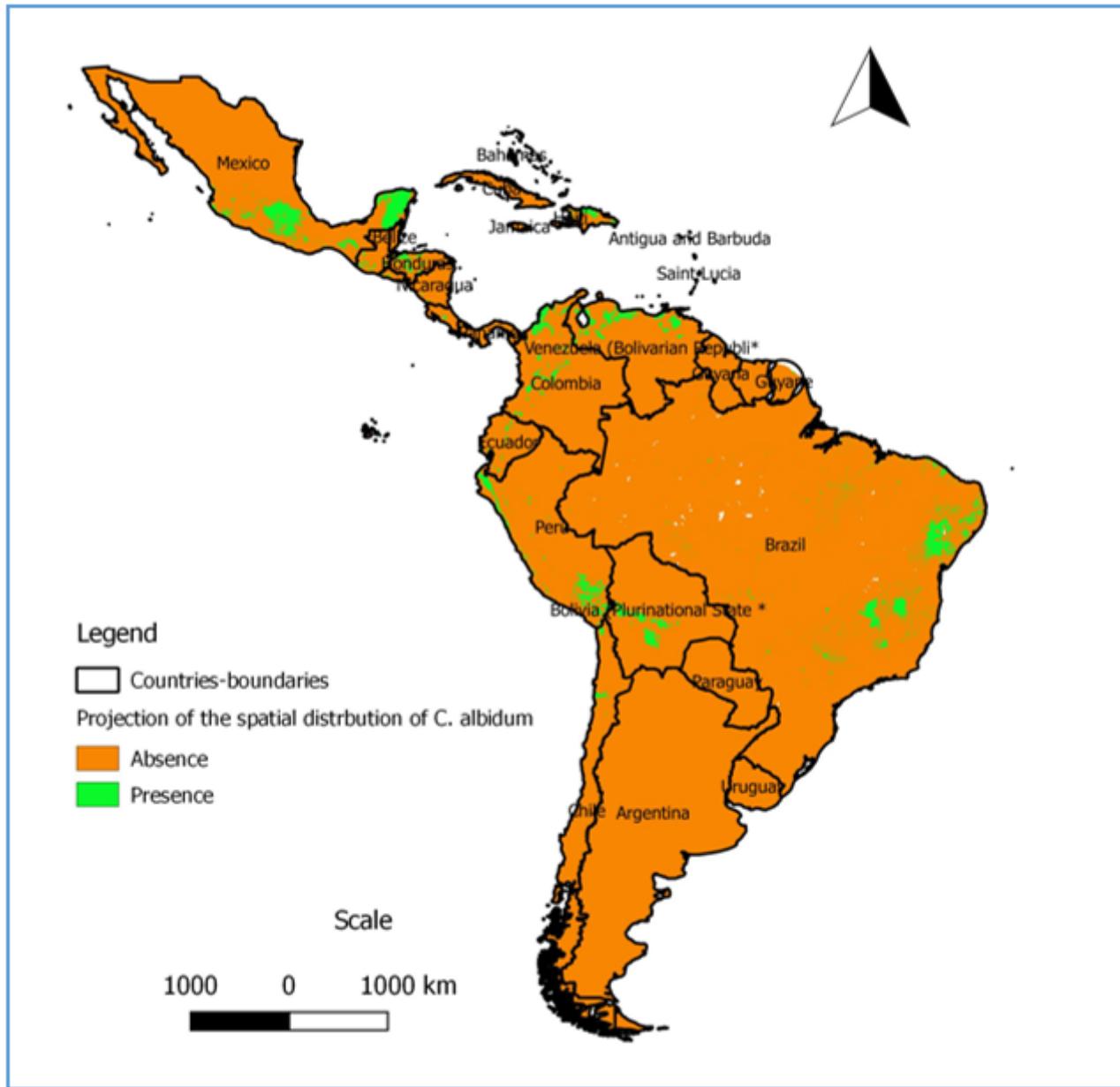


Figure 6

Projection at present of the spatial distribution of *C. albidum* across Latin America according to Maxent



Figure 7

Projection at present of the spatial distribution of *C. albidum* across Latin America according to BRT

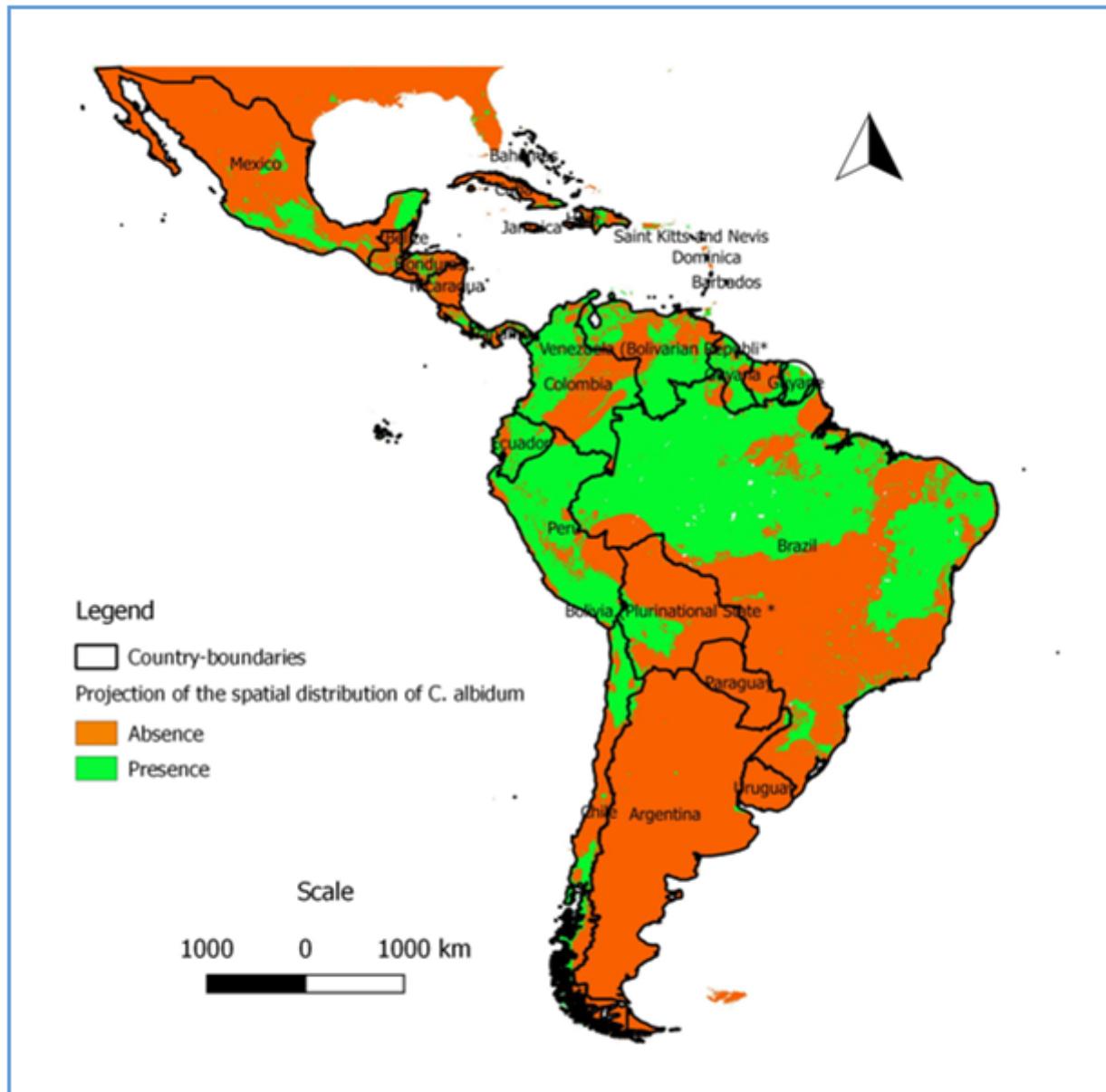


Figure 8

Projection at present of the spatial distribution of *C. albidum* across Latin America according to RF

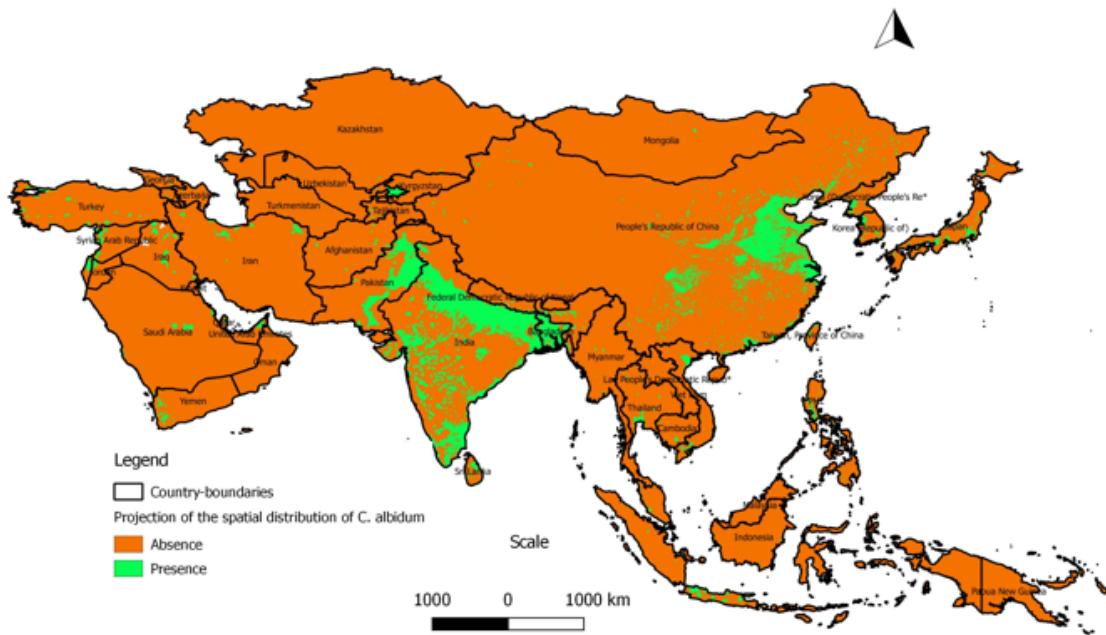


Figure 9

Projection at present of the spatial distribution of *C. albidum* across tropical Asia according to BRT

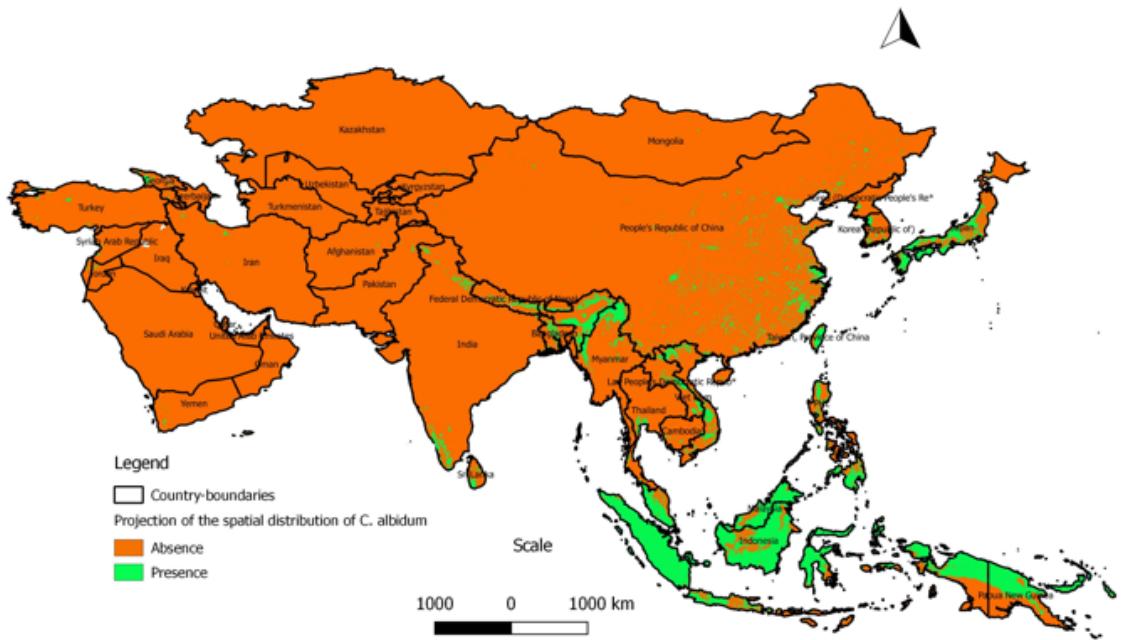


Figure 10

Projection at present of the spatial distribution of *C. albidum* across tropical Asia according to RF

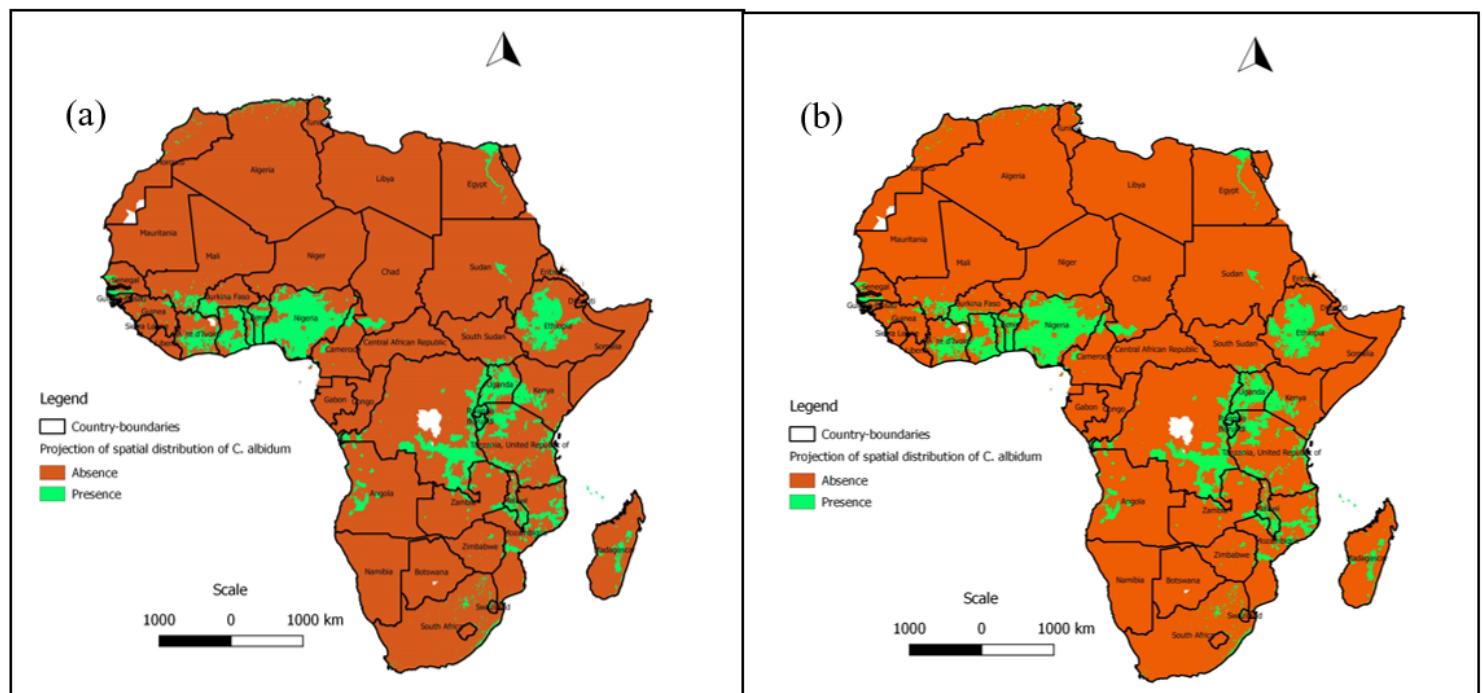


Figure 11

Spatial distribution of *C. albidum* across Africa according to Maxent: a) at horizon 2055 rcp 4.5; b) at horizon 2055 rcp 8.5.

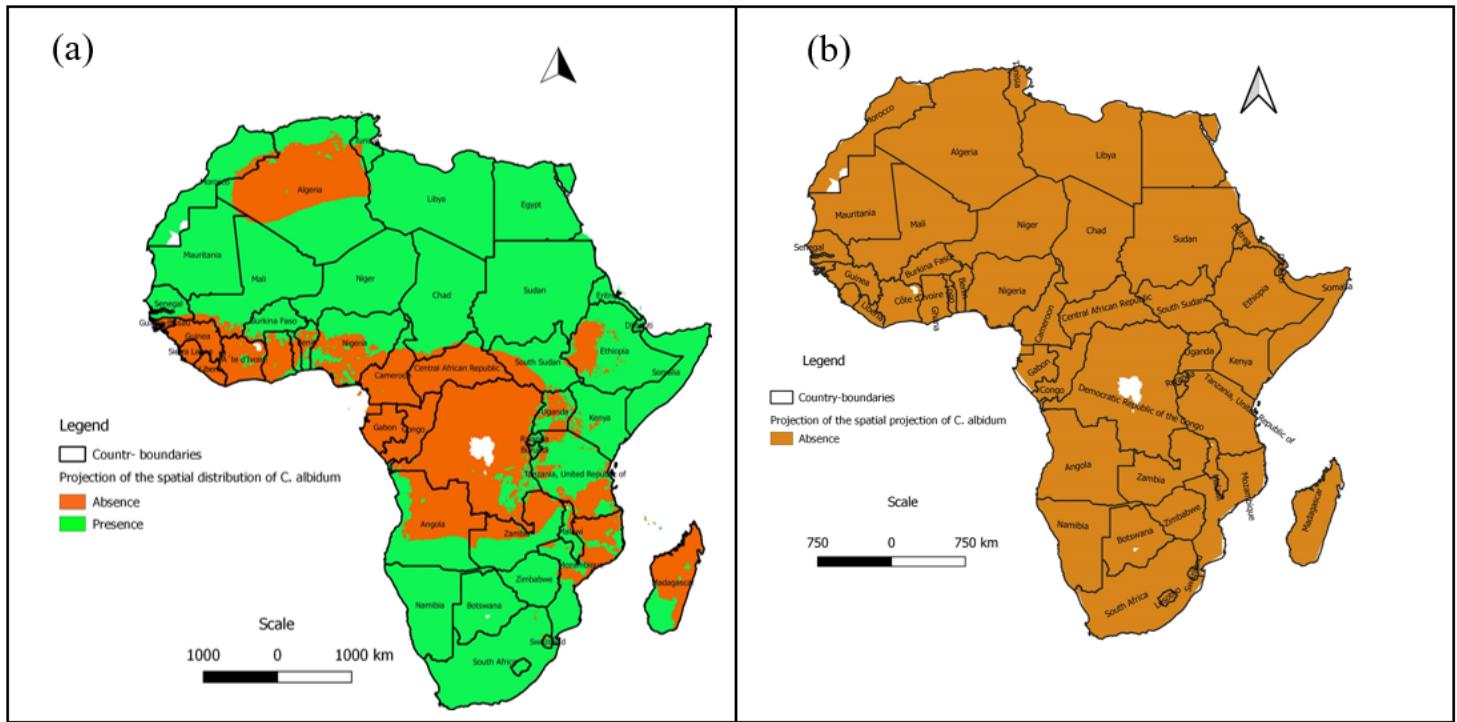


Figure 12

Spatial distribution of *C. albidum* across Africa: a) under rcp 4.5 / rcp 8.5, horizon 2055 according to BRT; b) under rcp 4.5 / rcp 8.5, horizon 2055 according to RF.

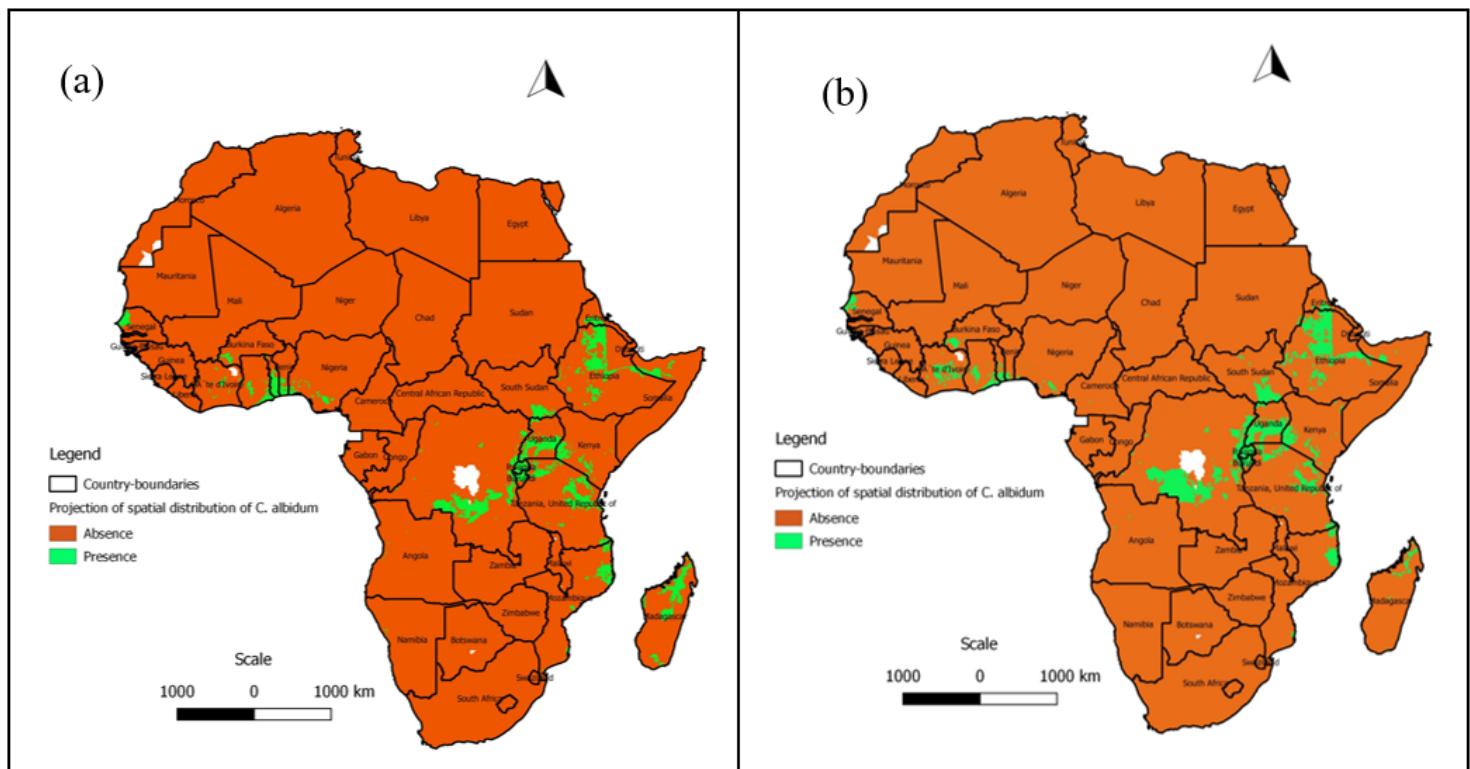


Figure 13

Spatial distribution of *C. albidum* across Africa according to Maxent: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585

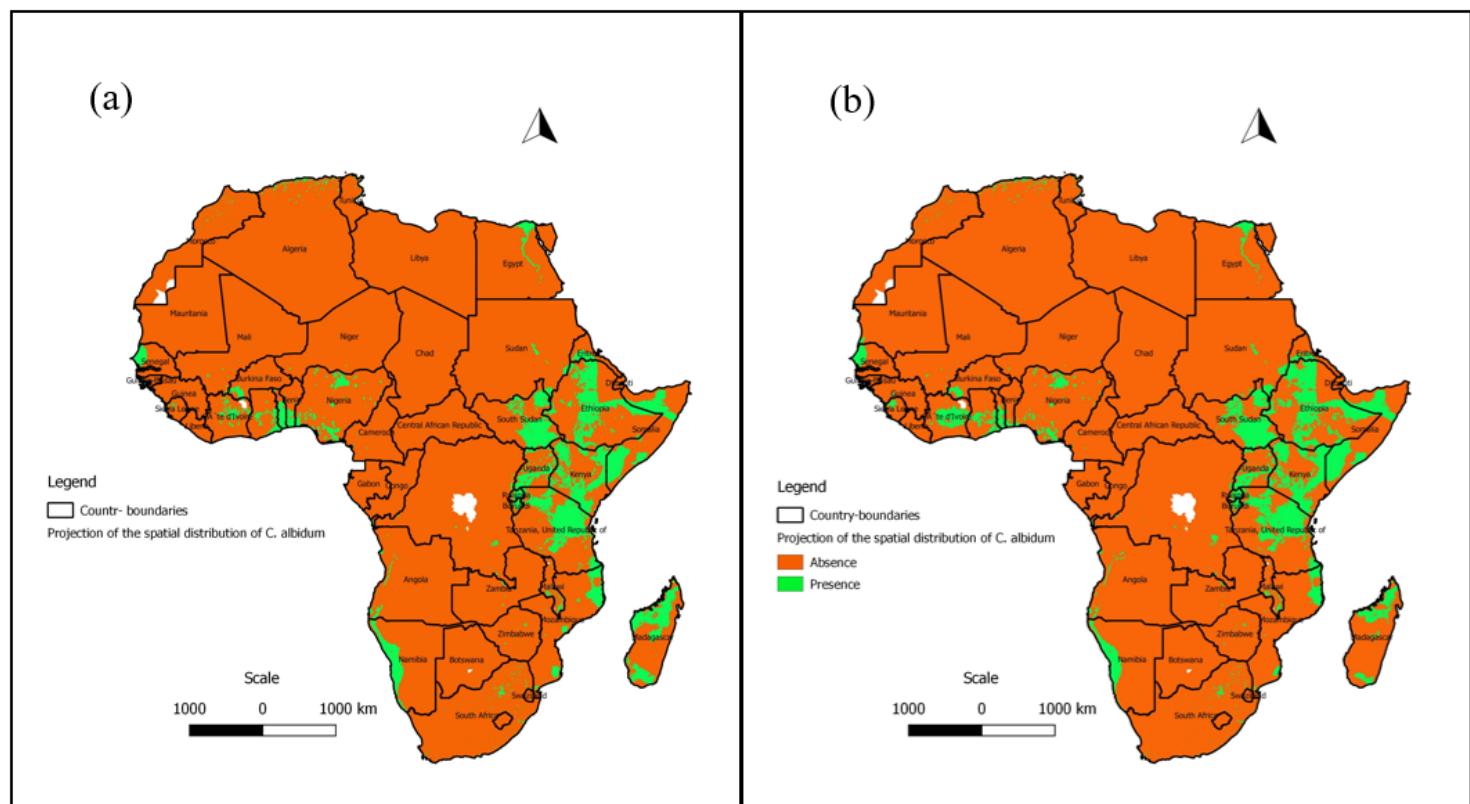


Figure 14

Spatial distribution of *C. albidum* across Africa according to BRT: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585.

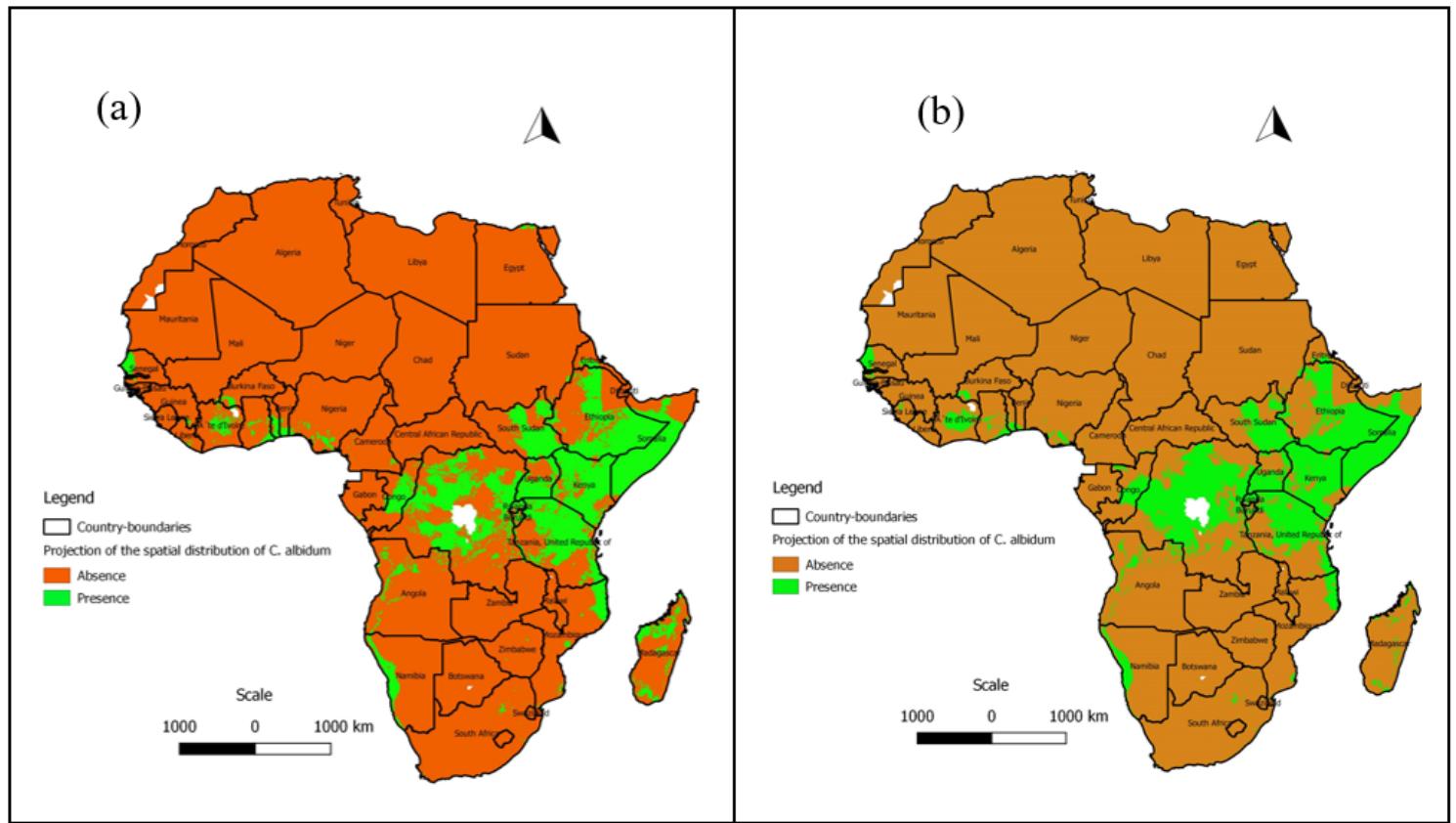


Figure 15

Spatial distribution of *C. albidum* across Africa according to RF: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585.

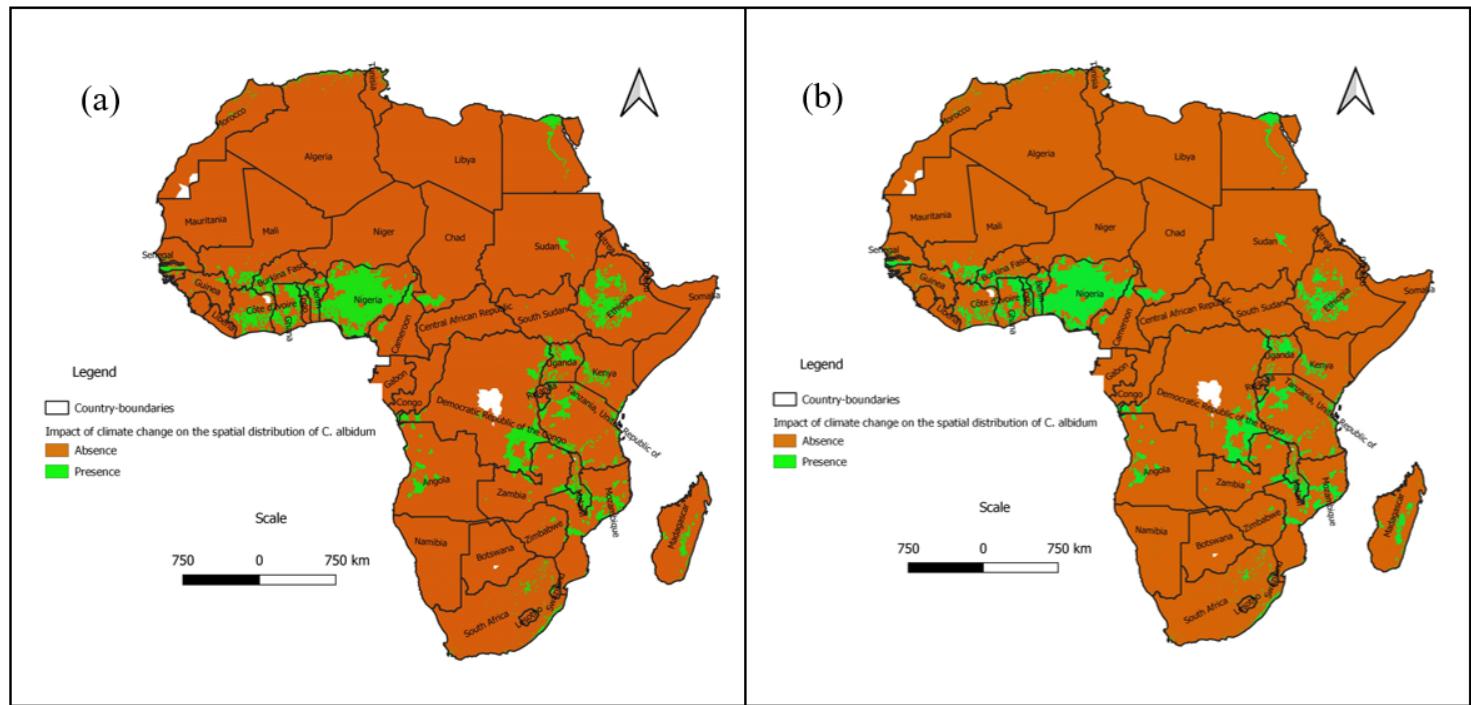


Figure 16

Comparison of predictions under Africlim and MIROCES2L according to Maxent: a) extension of favorable area of the species under Africlim rcp 4.5 horizon 2055 with respect to MIROCES2L SSP245 horizon 2060; b) extension of favorable area under Africlim rcp 8.5 horizon 2055 with respect to MIROCES2L SSP585 horizon 2060.

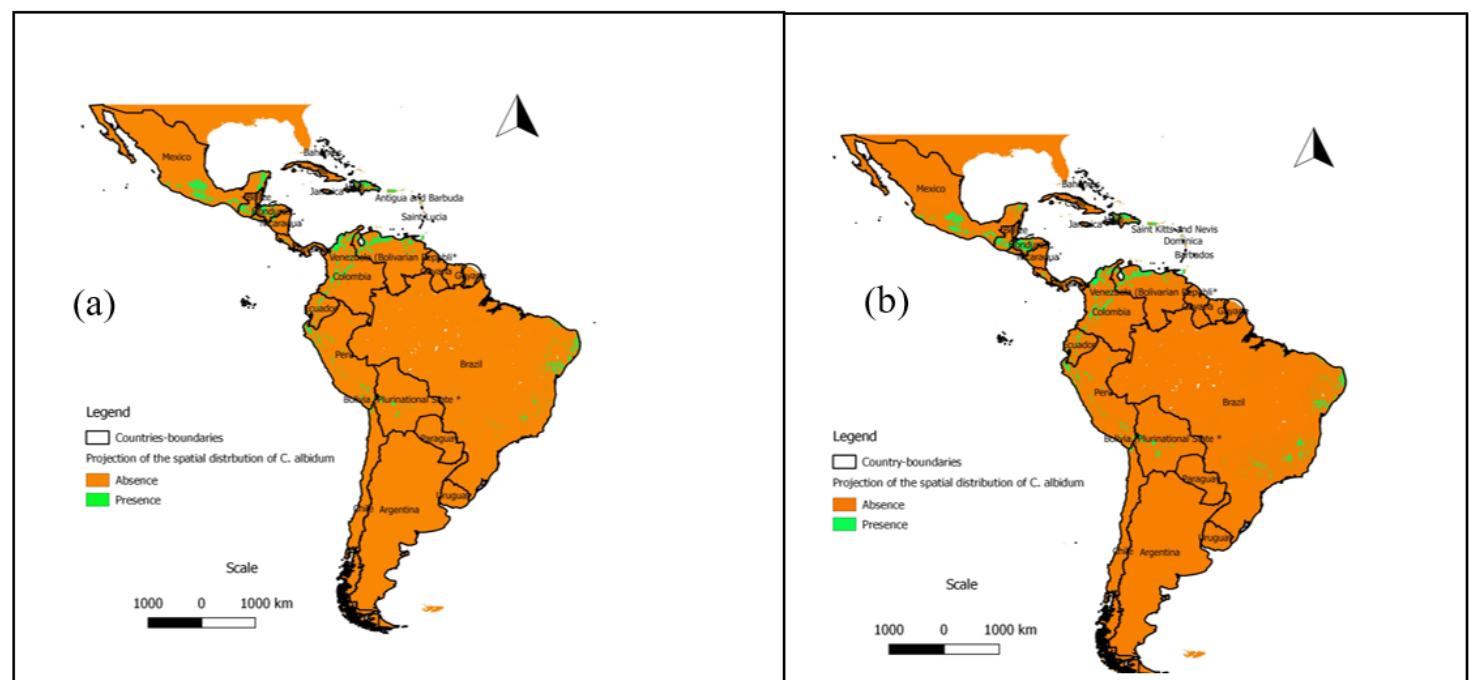


Figure 17

Spatial distribution of *C. albidum* across Latin America according to Maxent: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585

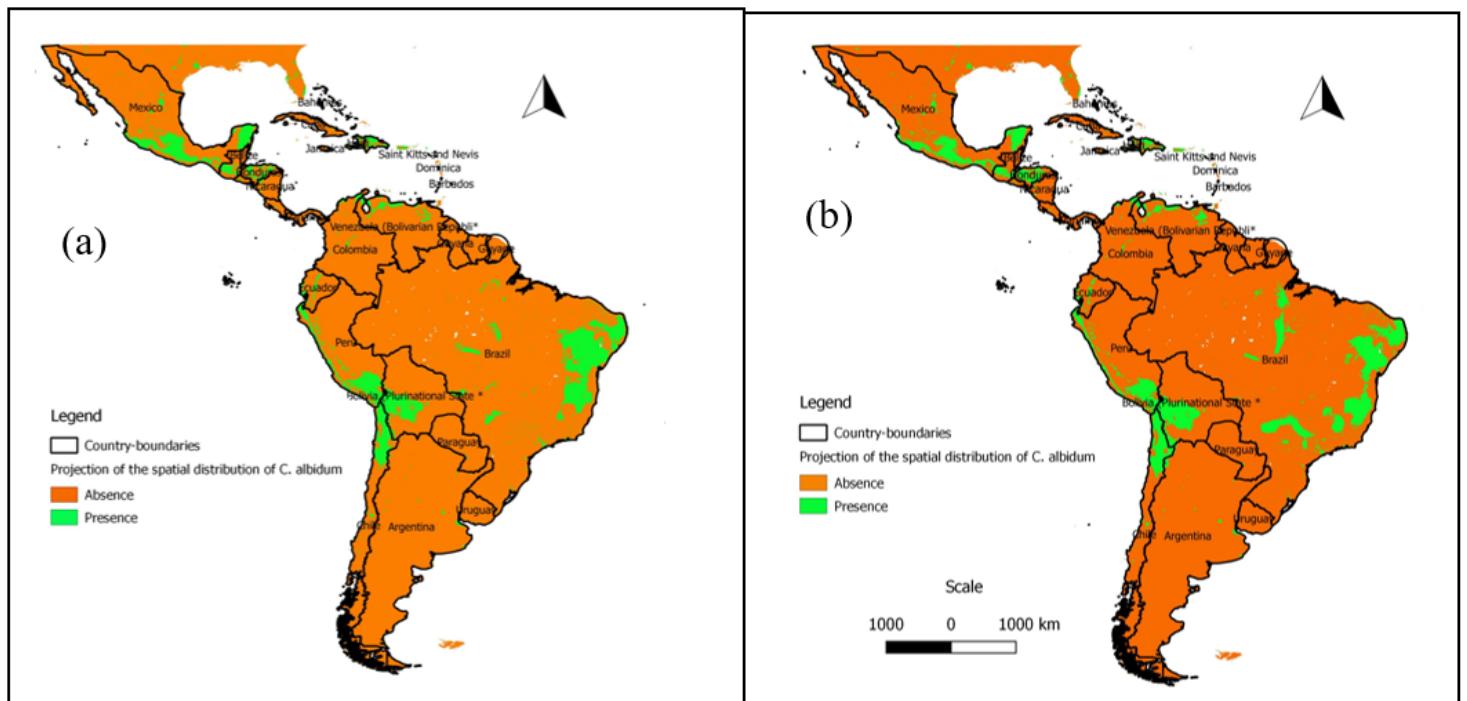


Figure 18

Spatial distribution of *C. albidum* across Latin America according to BRT: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585

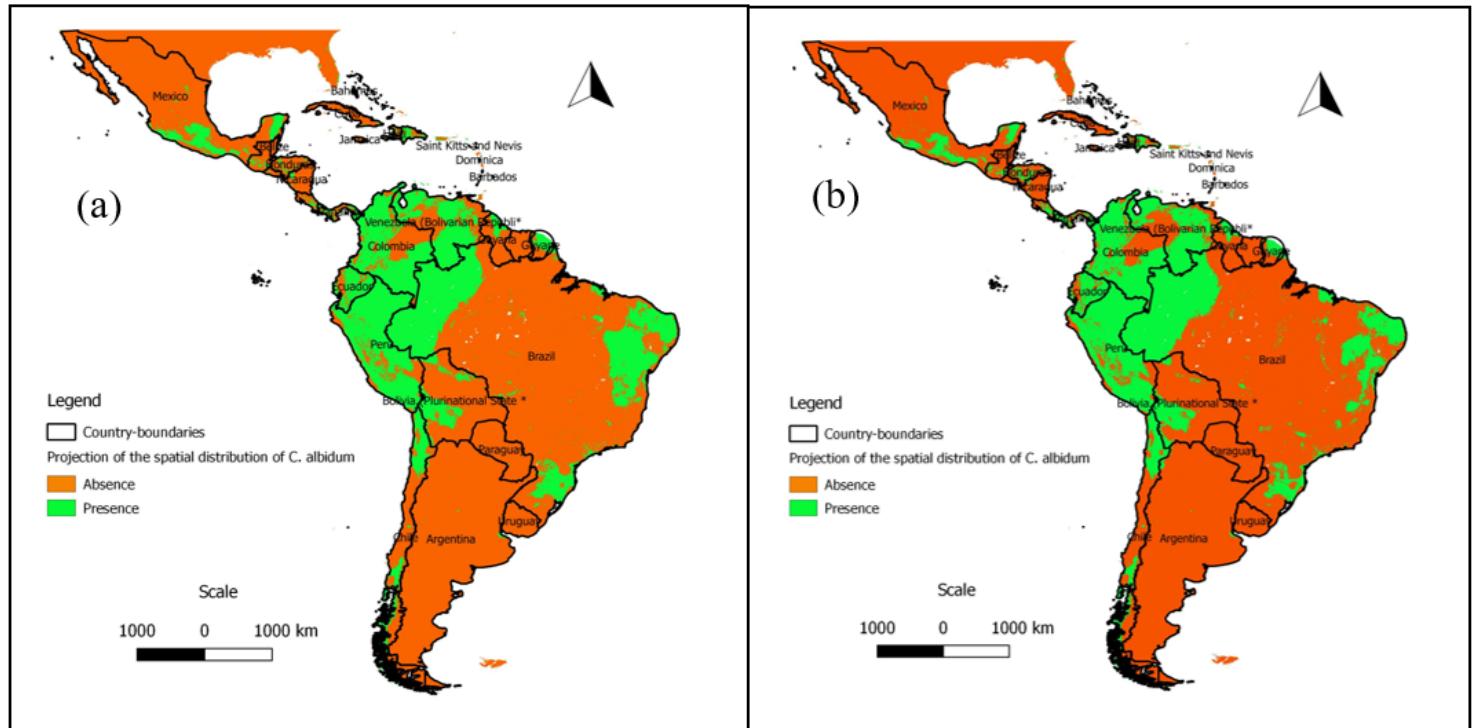


Figure 19

Spatial distribution of *C. albidum* across Latin America according to RF: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585

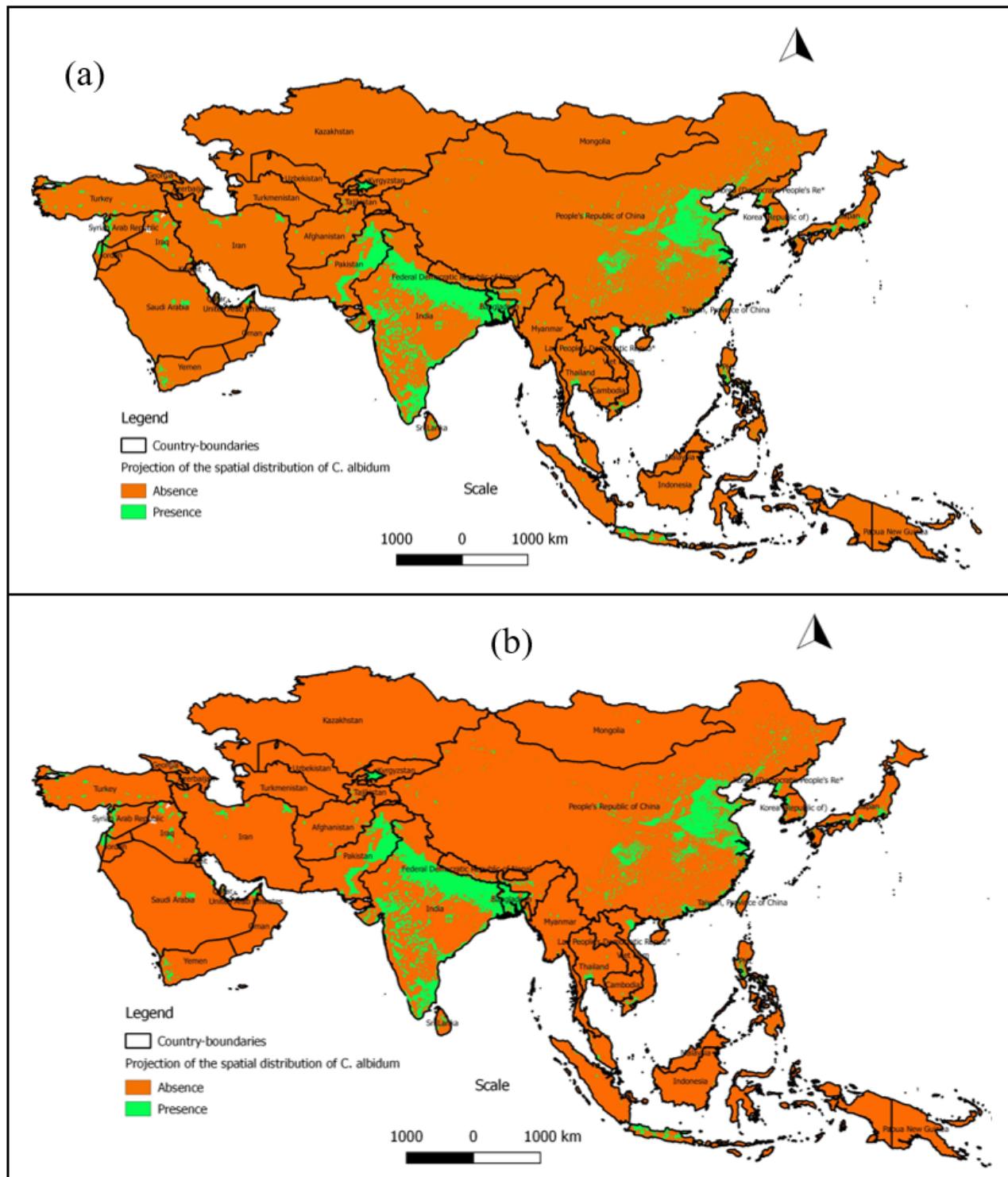


Figure 20

Spatial distribution of *C. albidum* across tropical Asia according to BRT: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585

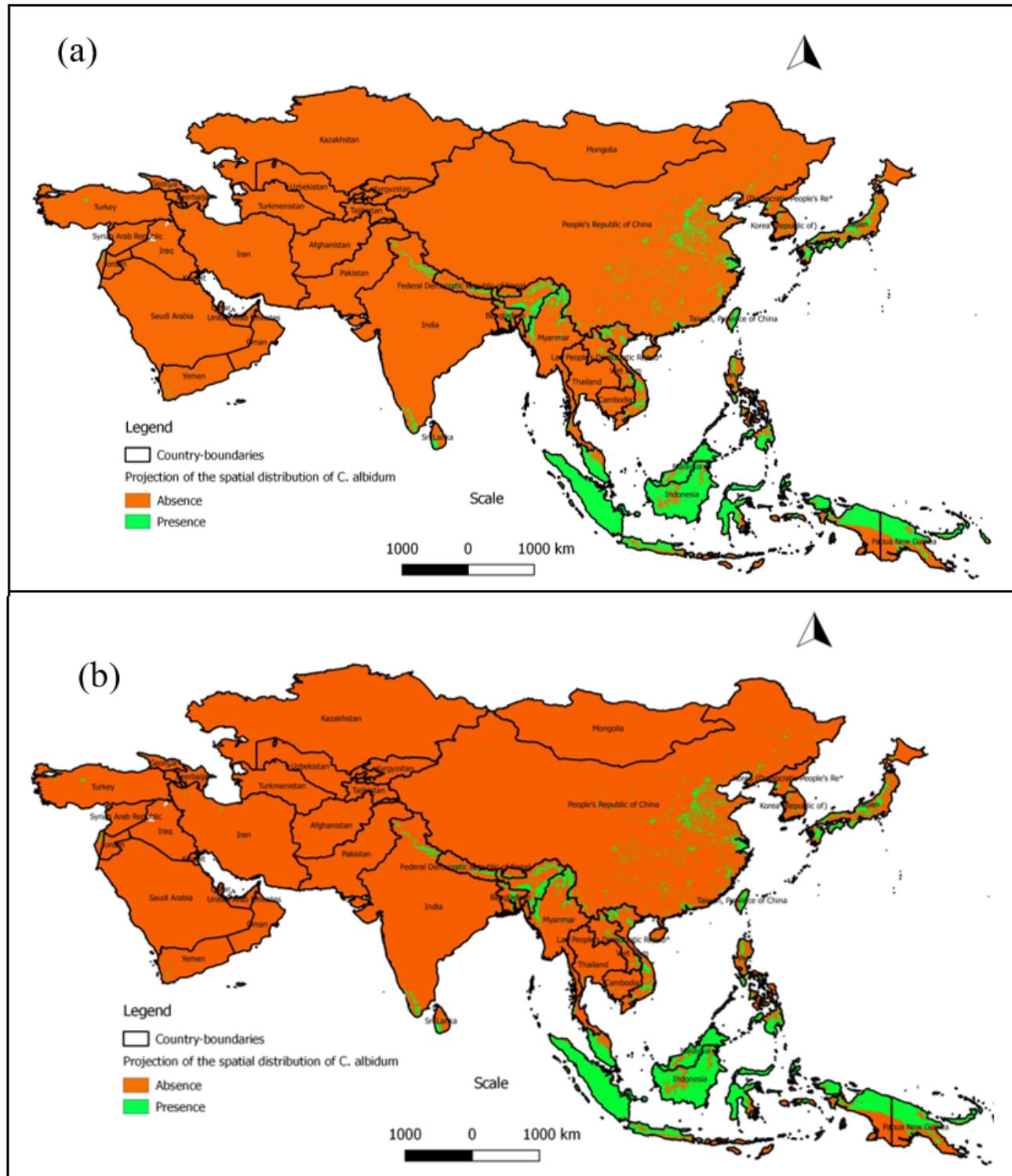


Figure 21

Spatial distribution of *C. albidum* across tropical Asia according to RF: a) at horizon 2060 SSP245; b) at horizon 2060 SSP585

Supplementary Files

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- [GangloAppendicesSR.docx](#)