Combining pedological information with bioclimatic scenarios for evaluating the effect of climate change on the modelled distribution of forest species: case of study Apuleia leiocarpa

Diêgo Faustolo Alves Bispo
Universidade Estadual do Norte Fluminense - Darcy Ribeiro
Adnane Beniaich (adnane.beniaich@um6p.ma)
Mohammed VI Polytechnic University
Juliana Müller Freire
Embrapa Agrobiologia
Ricardo Siqueira Silva
Universidade Federal dos Vales do Jequitinhonha e Mucuri - Campus J.K
Deborah Guerra Barroso
Universidade Estadual do Norte Fluminense - Darcy Ribeiro

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Abstract

Sustainable wood production is one of the current challenges due to the increasing demand for wood worldwide. Despite, forest planting has proved to be a good solution; the high wood productivity can be achieved only under favorable bioclimatic conditions, which makes this study of great value for government policies. This study aimed to assess the impact of climate on the distribution of *Apuleia leiocarpa* in Rio de Janeiro and Minas Gerais, Brazil. The Species Distribution Models (SDMs) were performed using the MaxEnt model-based on-field survey of *A. leiocarpa* (n = 54). Pedological and bioclimatic data were used to identify suitable areas and climate change effects on the distribution of this species. Ours results have shown that the MaxEnt presented a good performance in modelling the distribution of the *A. leiocarpa*. The temperature was the main controlling variable of the distribution of this species. The pedological models overestimated of the suitable area. Despite that, the results provide useful information to be considered in the future in order to refine the selection of variables for a better characterization of the ecological niche. Regarding the projection of the future *A. leiocarpa* distribution, there was found an alarming scenario, which it must be taken into the consideration for the local authorities in order to establish a successful species-replanting program.

1. Introduction

Sustainable wood production management has become a significant concern worldwide, particularly in the tropics, where bioclimatic conditions reach high potential productivity. Planted forests play a central role in different elements cycles (for example, in carbon) and the water cycle, cooling the earth's surface temperature, regularizing earth energy, and biodiversity preservation (Ellison et al. 2017).

Brazil is a leader in wood-based products from planted forests worldwide. Planted forests for industrial purposes reached 7.84 million hectares of the national area in 2016 (Martins et al. 2020), compared to 485 million hectares of natural forest (Oliveira et al. 2020). In 2019, the total area of planted forests was 9.0 million hectares, a 2.4% increase over 2018 (8.79 million hectares) (Oliveira et al. 2020). The majority of the planted forests (77%) represented by introduced species in Brazilian ecosystems : eucalyptus plantation, with 6.97 million hectares and 18% pine forests, with 1.64 million hectares. Besides these planted forests, there are an additional 0.39 million hectares planted with other species, including rubber, acacia, teak, and paricá (IBA 2020). Thus, the planted forest is a good option for the increasing demand for wood in Brazil (Martins et al. 2020) and can reach 90% of the wood produced by the Brazilian industrie (Oliveira et al., 2020).

On the other hand, several studies present alarming data on climate change on dynamic and forest structure, like biodiversity loss, impact on providing ecosystem services increasing fire risk, drought, and non-native plant invasion (Foster 2001; Rodrigues et al. 2015; Scarano and Ceotto 2015; Martins et al. 2020; Cui et al. 2021). However, climate change presents a significant challenge for the current economic model with a high population growth rate and intense natural resources pressing (Medeiros et al., 2020).This challenge becomes more involved in economic activities dependent on climate conditions like planted forests, and the role that planted forests can play in the future the mitigate the effect of climate change (Choi et al. 2021).

Species distribution modeling (SDM) is a useful technique that can overcome the difficulties related to complexity of studying the interaction between plant species behavior and climate changes. Furthermore, this modeling allows predicting species geographical distribution from the occurrences data and bioclimatic variables (Lobo et al. 2010). It can help the governments plan policies for mitigation of the climate change impact thought a plantation of forest species adapted to a specific region.

SDM is a predictive species distribution based on applying mathematical and geostatistical methods to environmental variables to fit predictive habitat distribution modeling and map the species distribution in the space and in the time. SDM has achieved different ecology and conservation sciences applications related to the planted forest (Cayuela et al. 2009).

These applications include predicting potential planting areas (Martins et al. 2020), identifying the extent and direction of range shift of forest species (Shabani and Kumar 2017), assessing the impact of climate change, and supporting conservation planning and reserve selection.

Throughout its large extension, Atlantic Forest has marked by high rate of degradation, which has increased the demand for adapted forest species mainly that can generate income-associating conservation with economic return, to adopt the rural properties that are located there legally.

Apuleia leiocarpa (Vogel) J. F. Macbr. is a native monoic species of the Brazilian Atlantic Forest domain (Lauterjung et al. 2019), and it is widely recognized due to the high quality of the wood, beekeeping, medicinal, landscape, and forestry potential of this species. The *A. leiocarpa* has a significant environmental and industrial role because it is used in wood products and the reforestation of degraded areas. Its distribution extends to different South American countries: Brazil, Argentina, Uruguay, Bolivia, and Paraguay (Zimmerman et al. 2013). Currently, the occurrence of *A. leiocarpa* in Brazilian territory is discontinuous because of the high rate of deforestation and the lack of replanting and being classified, as to the risk of extinction, as a vulnerable species (Salemi et al. 2013). In this sense, correlations between attributes of soils and *A. leiocarpa* matrices can be useful tools in checking restrictions on their natural distribution, as well as in the management of species in commercial plantations or seed orchards.

In view of the growing importance of the supply of wood from native forests, the identification of potential habitats for planting trees can provide great opportunities for the conservation and management of natural forests. This justifies the creation of specific governmental policies to encourage legal production of native forest species in order to mitigate the impacts of natural forest exploitation (Martins et al. 2020).

In this context, this study aims to estimate the potential distribution and the impact of climate change on the future distribution of *A. leiocarpa* in Rio de Janeiro and Minas Gerais, Brazil. Here, we addressed the following questions: (a) how is the *A. leiocarpa* distribution pattern in Rio de Janeiro and Minas Gerais states ? (b) Do climate conditions and soil variables congruent predict the patterns of species distribution? Finally, we discuss conservation issues based on the obtained results.

2. Material And Method

2.1. Species occurrence dataset

We developed a spatial distribution model based on-field survey occurrence of *A. leiocarpa* (n = 54) in the States of Rio de Janeiro and Minas Gerais, Southeastern Brazil (Fig. 1). Different field trips were organized to cover all possible locations of *A. leiocarpa* occurrences in the studied region, according to local stakeholders and the experience of our team. The dataset was recorded during different periods in 2020 using the Garmin Etrex 10 GPS for the geolocalisation. To avoid spatial autocorrelation between points and eliminate the redundant presences in 1 x 1 km, we used SDMtoolbox in ArcGIS 10.4, using average nearest neighbor analyses. After this step, 32 occurrences were used to generate the final species distribution model.

2.2. Environmental and soil dataset

Different species distribution models (SDMs) of *A. leiocarpa* were tested in order to identify suitable areas and climate change effects on the distribution of this tree species. The occurrences of the species *A. leiocarpa* (32 occurrences) were combined with the two groups of the variable bioclimatic and soil variables and then tested. The bioclimatic variables were performed in **Method 1**; nineteen bioclimatic variables were obtained from the WorldClim database (http://www.worldclim.org), and one topographic variable (elevation) was obtained from de Shuttle Radar Topography

Mission (SRTM) elevation data (https://earthexplorer.usgs.gov/), all variables at a spatial resolution of 30 arc-second (~ 1 km) (Table 1). All variables were examined for any cross-correlation to avoid multicollinearity (Dormann et al. 2013). This procedure was undertaken using the SDMtoolbox in ArcGIS 10.4, and the variables are compared pair by pair, and only one variable has highly correlated predictors (Pearson correlation coefficient, r≥|0.75|) was included in the model. The correlation matrix can be found in supplementary materials (Table S.1).

Table 1
The environmental variables considered in the *Apuleia leiocarpa* niche models and the parameters used in the MaxEnt. The general statistics were calculated using all recorded occurrences (n = 54).

Variable		PC	PI	Min	Max	Mean	SD
Bio3	**Isothermality (%)**	**79.4**	**85.5**	**57.0**	**67.2**	**59.8**	**2.2**
Bio2	**Mean diurnal range in temperature (ºC)**	**6.6**	**1.5**	**9.3**	**13.3**	**10.6**	**0.9**
Bio1	**Annual Mean Temperature (ºC)**	**5.8**	**2.0**	**18.2**	**23.6**	**21.0**	**1.4**
Bio12	**Annual Precipitation (mm)**	**5.3**	**3.4**	**1,144.0**	**1,484.0**	**1,309.4**	**95.3**
Bio15	**Precipitation Seasonality (%)**	**2.5**	**7.6**	**49.0**	**87.3**	**66.0**	**9.9**
Bio14	**Precipitation of Driest Month (mm)**	**0.4**	**0.0**	**10.0**	**45.0**	**25.9**	**8.2**
Bio18	Precipitation of Warmest Quarter (mm)	-	-	447.0	610.0	520.5	57.2
Elevation	Elevation (m)	-	-	23.0	938.0	440.5	261.5
Bio4	Temperature Seasonality (%)	-	-	212.7	242.7	231.1	8.2
Bio7	Temperature Annual Range (ºC)	-	-	16.0	19.8	17.7	0.9
Bio8	Mean Temperature of Wettest Quarter (ºC)	-	-	20.1	26.1	23.2	1.5
Bio6	Min Temperature of Coldest Month (ºC)	-	-	8.6	14.8	11.5	1.8
Bio13	Precipitation of Wettest Month (mm)	-	-	168.0	333.0	230.3	39.3
Bio10	Mean Temperature of Warmest Quarter (ºC)	-	-	21.0	26.3	23.7	1.4
Bio19	Precipitation of Coldest Quarter (mm)	-	-	34.0	142.0	89.1	26.6
Bio5	Max Temperature of Warmest Month (ºC)	-	-	26.2	32.3	29.3	1.4
Bio17	Precipitation of Driest Quarter (mm)	-	-	34.0	142.0	89.0	26.6
Bio11	Mean Temperature of Coldest Quarter (ºC)	-	-	15.1	21.1	18.0	1.5
Bio9	Mean Temperature of Driest Quarter (ºC)	-	-	15.1	21.1	18.0	1.5
Bio16	Precipitation of Wettest Quarter (mm)	-	-	487.0	804.0	614.1	83.9

Percent contribution (PC); permutation importance (PI); minimum (Min); maximum (Max); standard deviation (SD). Bold font indicates the variables in the final model.

Soil variables were tested to verify the impact of pedolological information on the potential spatial distribution of *A. leiocarpa* (**Method2**). We obtained soil organic carbon content, soil bulk density, clay content, and field capacity water content at 10 cm depth from Soil Grids (https://soilgrids.org/) data at 250 m resolution. The choose of theses properties is based on its effects on the chemical and physical soil proprieties. Besides, in **Method3**, we evaluated the relationship between the potential distribution of *A. leiocarpa* and the mean of Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) for the period 2014–2019 (https://land.copernicus.eu/global/products/fapar), FAPAR constituted an essential climate variable for forest monitoring (Brown et al., 2020). Soil variables were aggregated to have the same resolution as bioclimatic variables. Other models were performed by one variable from soil variables and all variables of **Method 1**.

2.3 MaxEnt model processing

The correlative maximum entropy-based model - MaxEnt model (Phillips et al. 2006), was chosen to evaluate the suitable areas and climate change impacts on the

A. leiocarpa distribution. MaxEnt model calculated the probabilities of geographic species distribution by estimating the relationship between species records at sites and those sites environmental and spatial characteristics (Elith et al. 2011). The studied areas were classified using the probability of the habitat suitability from 0 to 1: 0 represents areas unsuitable for the species development; 1 represents highly suitable areas. Thus, the following suitability classes were used: Unsuitable: <0.1; low suitability: 0.1–0.4; medium suitability:0.4–0.6; and high suitability: 0.6-1.0.

Different settings were adjusted in MaxEnt to select the best model. Thus, different combinations of the regularization multiplier (RM) and feature types were set to generate different models. RM should be higher than 1 and affects the out distribution (focused or closely-fitted) (Radosavljevic and Anderson 2014). The performance model was evaluated using the AUC (area under the receiver operating characteristic curve) values. The model is considered to have a good fit where the AUC ranged from 0.7 to 1.0.

The contribution of each variable in the construction of the model is estimated by a jack-knife test, in which a higher percent contribution and the permutation value indicates a better fit of the variable in the model (Xu et al. 2020).

2.4. Future projections

Future projections of *A. leiocarpa* distribution were made for 2050 and 2070 by using the global climate models (GCMs) MIROC5 and HadGEM2-AO under the representative concentration pathways (RCP) RCP4.5 and RCP8.5, this data obtained from the WorldClim database (http://www.worldclim.org) at a spatial resolution of 30 arc-second (~ 1 km). These GCMs have been used widely to assess the spatial distributions of many species based on climate change, ecosystems, and other long-timescale components of the earth, including the simulations of the currently available RCPs (Shabani and Kumar 2017; Ramos et al. 2018). These models consider greenhouse gas emissions, aerosols, solar irradiance, ozone, and others (Andrews et al. 2012). Thus, RCPs are used to make projections of the effects of climate change.

The RCPs are divided into RCP2.6, which predicts a severe mitigation scenario; RCP4.5, and RCP6.0, which predicts intermediate scenarios; and RCP8.5, which predicts very high GHG emissions. In this study, we selected the RCP4.5 and RCP8.5 scenarios to project climate change effects on *A. leiocarpa*. RCP4.5 projects an increase in the global surface temperature from 1.1 to 2.6°C by the end of the 21st century, while RCP8.5 projects an increase from 2.6 to 4.8°C by the end of the same period. Changes in precipitation patterns are also predicted to occur.

3. Results

3.1. Prediction bioclimatic variables

From 20 environmental variables analyzed, only six were sufficiently biologically relevant to be included in the models: annual mean temperature (Bio1); mean diurnal range in temperature (Bio2); Isothermality (Bio3); annual precipitation (Bio12); precipitation of driest month (Bio14); and precipitation seasonality (Bio15) (Table 1). Based on the current distribution of the *A. leiocarpa* in the States of Rio de Janeiro and Minas Gerais, this forest species occurs mainly in areas with a mean annual temperature of 21.0 ± 1.4°C and high annual precipitation (1,309.4 ± 95.3 mm). These results confirm the high hydric demand of this species.

The Isothermality (79.4%) was the predictor variable that individually contributed to the *A. leiocarpa* model projections (percent contributions in parentheses). This result highlights the role of smaller temperature fluctuations within a month relative to the year in limiting the *A. leiocarpa* distribution. Therefore, this tree species favors areas where there is a low diurnal range in temperatures (10.6 ± 0.9°C), mean precipitation seasonality equal to 66.0 ± 9.9%, and precipitation of driest month equal to 25.9 ± 8.2 mm.

3.2. Assessment of current potential distribution - bioclimatic variables

The current distribution of *A. leiocarpa* and the MaxEnt projections were very well matched (Figs. 1 and 2). Most of the projected areas as highly suitable for this forest species include sites in Rio de Janeiro, where there are remnants of the Atlantic Forest. By contrast, most areas in Minas Gerais were considered to be currently unsuitable for the *A. leiocarpa*.

3.3. Comparisons between different distribution models

A comparison between different models used in the study using AUC values (area under the receiver operating characteristic curve) is presented in Table 2. Lower values of RM presented a good fit. However, it is recommended to use RM values greater than or equal to one. **Method 1** (only bioclimatic variable) showed an excellent performance to predict *A. leiocarpa* distribution. **Method 2** (only soil variables) presented a good fit. However, this model tends to overestimate the suitable area of *A. leiocarpa*. The addition of soil variable to **Method 1** caused a reduction in performance and a low contribution to variable importance (Table 3). The variables mean diurnal temperature (Bio3) and Isothermality (Bio2) were the most important predictive variables. Variable Bio3 presented the highest contribution in all models, which confirms the importance of the temperature constancy for distributing the studied species.

Table 2
AUC (area under the receiver operating characteristic curve) values of the different distribution models based on current climatic conditions using soil and bioclimatic variables.

Variable		**Regularization multiplier (RM)**			
		0.5	**1.0**	**1.5**	**2.0**
Model1	Bioclimatic variables	0.983	0.973	0.963	0.951
Model2	Soil variables	0.883	0.863	0.856	0.849
Model3	Soil variables + vegetation index (FAPAR)	0.903	0.885	0.876	0.864
Model4	Bioclimatic variables + Clay content	0.983	0.969	0.961	0.950
Model5	Bioclimatic variables + Field capacity water content	0.982	0.969	0.961	0.949
Model6	Bioclimatic variables + FAPAR	0.983	0.971	0.962	0.950
Model7	Bioclimatic variables + soil pH	0.981	0.970	0.961	0.950
Model8	Bioclimatic variables + Soil organic carbon	0.982	0.969	0.961	0.95

Table 3
Analysis of variable contributions of different models using bioclimatic and soil variables.

Variables	**PC**	**PI**	**Variables**	**PC**	**PI**	**Variables**	**PC**	**PI**	**Variables**	**PC**	**PI**
	Model1		Model2			Model3			Model4		
Bio3	**79.4**	**85.5**	**Soil WC**	**66**	**55.4**	FAPAR	**48**	**42**	**Bio3**	79	85
Bio2	**6.6**	**1.5**	**Soil Clay**	**28**	**39**	Soil WC	**26.5**	**28.9**	**Bio12**	6.7	6.8
Bio1	5.8	2	Soil pH	3.3	2.6	Soil Clay	24.3	28.9	Bio2	5.9	2.2
Bio12	5.3	3.4	SOC	2.9	3.1	SOC	1.3	0.2	Bio1	3.5	1.4
Bio15	2.5	7.6				Soil pH	0	0	Bio15	2.7	5
Bio14	0.4	0							Soil Clay	2.1	0
									Bio14	0	0
	Model5		Model6			Model7			Model8		
Bio3	78.8	82.8	**Bio3**	77	79.7	**Bio3**	80	83.2	**Bio3**	80	83
Bio2	6.3	2.2	**Bio12**	8.3	8.8	**Bio12**	6.5	6.8	**Bio12**	6.6	6.8
Bio12	5.6	7.1	Bio2	5.2	1.5	Bio2	6.3	2.2	Bio2	6.3	2.2
Bio1	3.7	1.8	Bio1	3.9	2.3	Bio1	4	1.9	Bio1	4	2
Bio15	3.5	6	Bio15	2.7	7.8	Bio15	3.2	5.9	Bio15	3.2	5.8
Soil WC	2.1	0.1	FAPAR	2	0	Bio14	0	0	SOC	0	0.1
Bio14	0	0	bio14	0.8	0	Soil pH	0	0	Bio14	0	0

Bio3: Isothermality; Bio2: mean diurnal range in temperature; Bio1: annual mean temperature; Bio12: annual precipitation; Bio15: precipitation seasonality; Bio14: precipitation of driest month; Soil WC: field capacity water content; SOC: soil organic carbon; FAPAR: fraction of absorbed photosynthetically active radiation; PC: percent contribution; PI: permutation importance.

Figure 3 displays the results of distribution models based on current conditions using only bioclimatic variables (**Method 1**), only soil variables (**Method 2**), and soil variables + vegetation index FAPAR (Method 3). By combining the soil variables + vegetation index FAPAR for the current scenario, we hoped it would be possible to improve **Method 1**. However, there was no good agreement between the occurrences observed in the field and areas identified by Method 2 and Method 3 as highly suitable for the *A. leiocarpa*.

3.4. Future projections and model combinations

In general, all two models (MIROC5 and HadGEM2-AO) under both the RCP4.5 and RCP8.5 scenarios will increase the suitability for *A. leiocarpa* (Figs. 4 and 5). A linear increase in an area suitable for *A. leiocarpa* from current to 2070 projection in RCP8.5 scenario (Fig. 6). However, under the RCP4.5 scenario, the area suitable for *A. leiocarpa* will be slightly highest for the 2050 projection and slightly lowest for the 2070 projection, compared with the current scenario.

4. Discussion

4.1 Predicted distribution of *Apuleia leiocarpa*

In the present paper, we studied the *A. leiocarpa* distribution using bioclimatic and soil variables. Our models presented goods performance compared with other models for forest tree species in the Brazilian Atlantic Forest, presented in various studies (Carnaval and Moritz 2008; Giovanelli et al. 2010; Rodrigues et al. 2015; Scarante et al. 2017; Wrege et al. 2017). *Apuleia leiocarpa* is an appreciated forest tree for its wood quality and medicinal uses. Its distribution in Brazil, is principally concentrated in the State of Rio de Janeiro, with a slight presence in the state of Minas Gerais, according the current records and also as was mentioned in various studies (Zimmerman et al. 2013; Lauterjung et al. 2019; Martins et al. 2020). The results of our study brought a novelty in relation to areas favored for planting *Apuleia leiocarpa*, especially in the south-eastern region of the state of Minas Gerais.

Climate, soil variables, topography, and photosynthesis activity are important variables. These variables determine environmental conditions in an ecological niche, potential variables that control species distribution and regulate interactions with the environment biotic and abiotic factors (Stephan et al. 2020). Evaluating soil variables and suitable distribution for a native forest species is important for environmental and industrial aspects. In this study, the models based on soil variables presented a low AUC compared to variables constituted by bioclimatic variables. Nevertheless, when we integrated the soil variables one by one into the bioclimatic models, the soil variables contribution remains very low (Table 3). Similar results were presented by Selvalakshmi et al. (2020) when they studied soil variables impact on rubber plantations suitable habitat distributions. The low contribution of soil variables in the distributions of *A. leiocarpa* can explain the high variability of soil, and soil variables in Southeastern Brazil, which resulted in an overestimation of *A. leiocarpa* as we can observe in the maps generated (Fig. 3).

Regarding the model of distributions of *A. leiocarpa* based on bioclimatic variables, the models presented good performance (AUC = 0.973). In this model, the Isothermality and the variables related to temperature presented the models with highest contribution. This result confirmed the study lead by Martins et al. (2020) when they found that the potential distribution of different plantation forest species in the State of Minas Gerais was strongly related to temperature. This research highlights the importance of niche modeling in determining a suitable area that can present a high potential for the plantation of *A. leiocarpa.* Besides, water availability can be an additional factor that can control the A. leiocarpa distribution, since the suitable areas of this species is characterized by high rainfall and the annual precipitation (Table 1).

4.2 Impact of projected climate changes on *A. leiocarpa* distribution

The results showed the impact of climate change in the distribution of *A. leiocarpa*. Both models used MICRO5 and HadGEM2-AO to present the same trend but with different magnitude. We tested two models, which present two contradictory approaches (RCP 4.5 and RCP 8.5). In the RCP 4.5 that presents the optimist projection, with a Global Mean Surface Temperature Change of 1.4°C and CO_2 emissions increase only slightly before the decline begins around 2040 (Collins et al. 2013). The RCP 8.5 model presented the pessimist projection, with a very high concentration of the rate of CO_2 emitted into the atmosphere in 2100 and high-energy intensity, and without the implementation of climate policies (Collins et al. 2013). A suitable area of *A. leiocarpa* will increase in the future. However, the results showed that in Minas Gerais, the suitable area for *A. leiocarpa* would increase in 2050 and 2070; nevertheless, this novel area will present suitable conditions for the plantation of *A. leiocarpa* presented a severe problem of water scarcity. The state of Rio de Janeiro that presents the region of *A. leiocarpa* will that showed a reduction in suitable areas, which can be explained by the high future temperature variation range, with an average between 2°C to 5°C (Dereczynski et al. 2013). This result presents a warning sign for the local authorities to adopt the necessary measures to reduce forest degradation and launch reforestation programs.

4.3 Limitation of the models of *A. leiocarpa* distribution

The models of A. leiocarpa distribution present some limitation related to the variables used in the prediction, because this study is based on bioclimatic and soil variables, but not take in consideration other variable like geographical variables (exposition, slope..) or ecological variables (allometry, and interaction with other species).

5. Conclusion

The use of MaxEnt presents a good performance to model the current distribution of *A. leiocarpa*. The obtained model showed the importance of temperature in the distribution of the specific tree species. The pedological information for modeling the distribution of *A. leiocarpa* showed an overestimation of the suitable area. This result provides useful information, and it will consider in the future, refining the selection of soil variables for a better characterization of the ecological niche in terms of the soil variable.

Regarding the future projection of the distribution of *A. leiocarpa*, the data presented an alarming result, which it must be taken into consideration for the local authorities to establish a conservation program for the species.

Declarations

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Figures

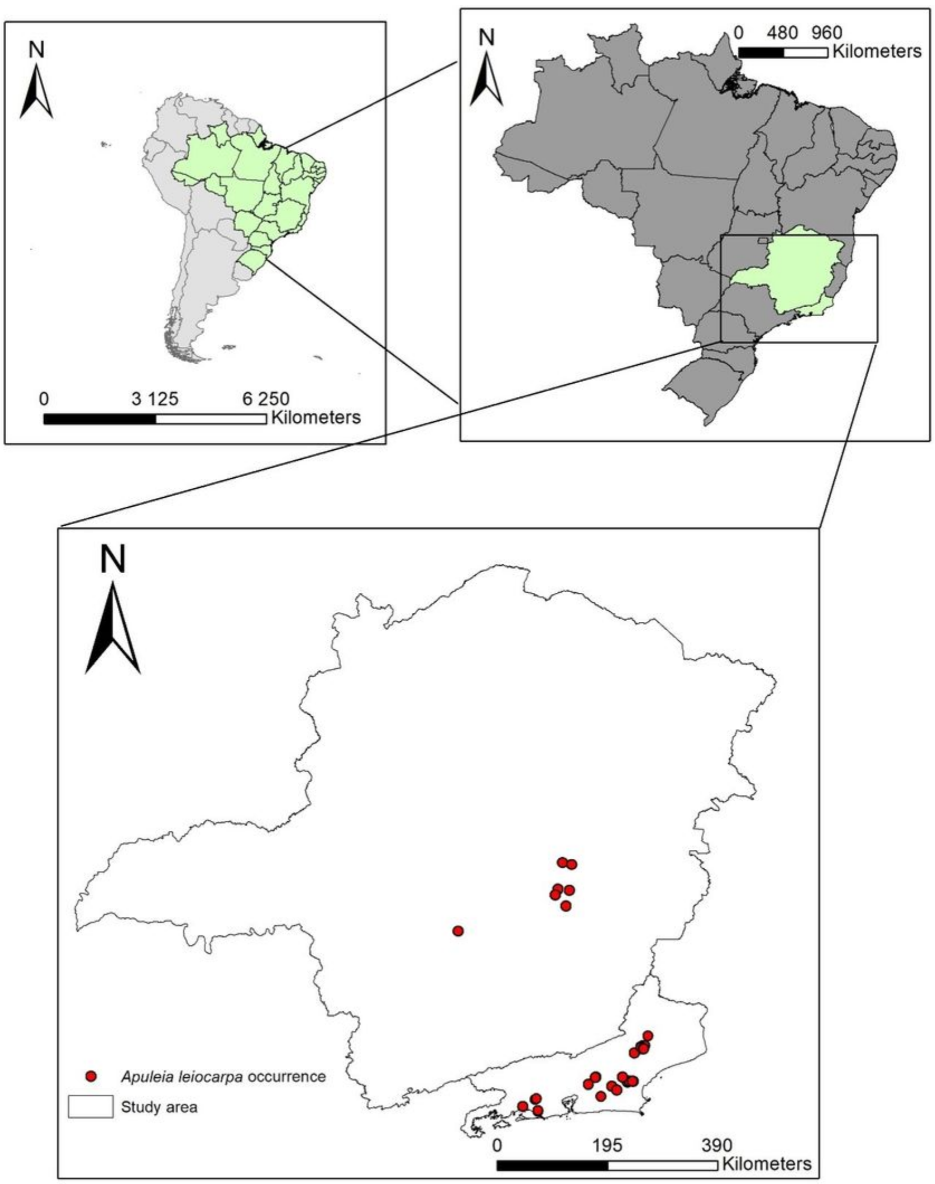

Figure 1

Current occurrence of *Apuleia leiocarpa* in the states of Rio de Janeiro and Minas Gerais (Brazil). Data recorded in 2020.

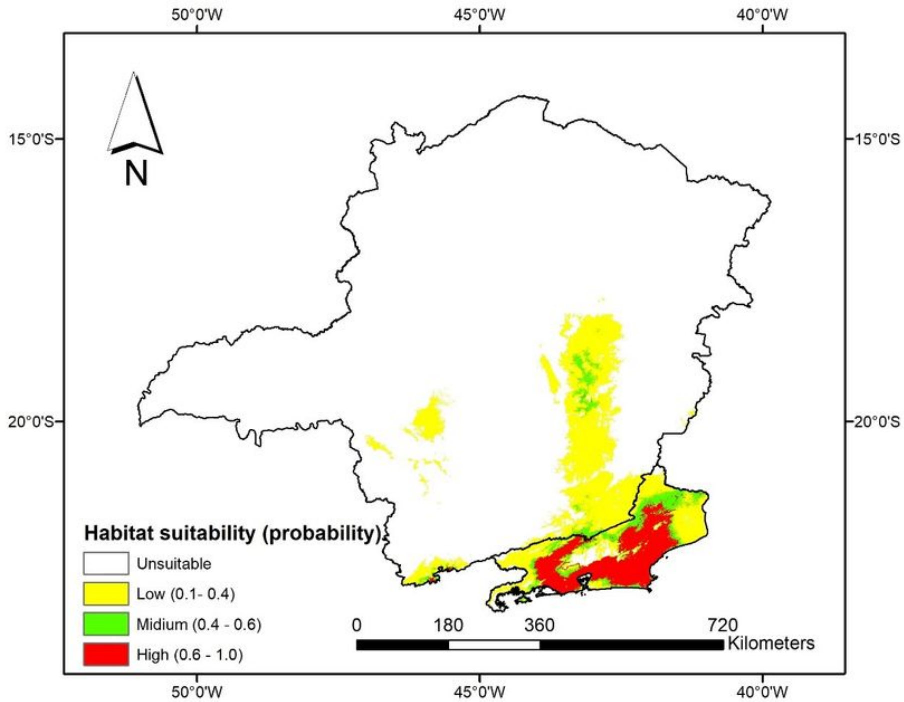

Figure 2

Current potential suitable areas for *Apuleia leiocarpa* in the State of Rio de Janeiro and Minas Gerais (Brazil) using the MaxEnt model.

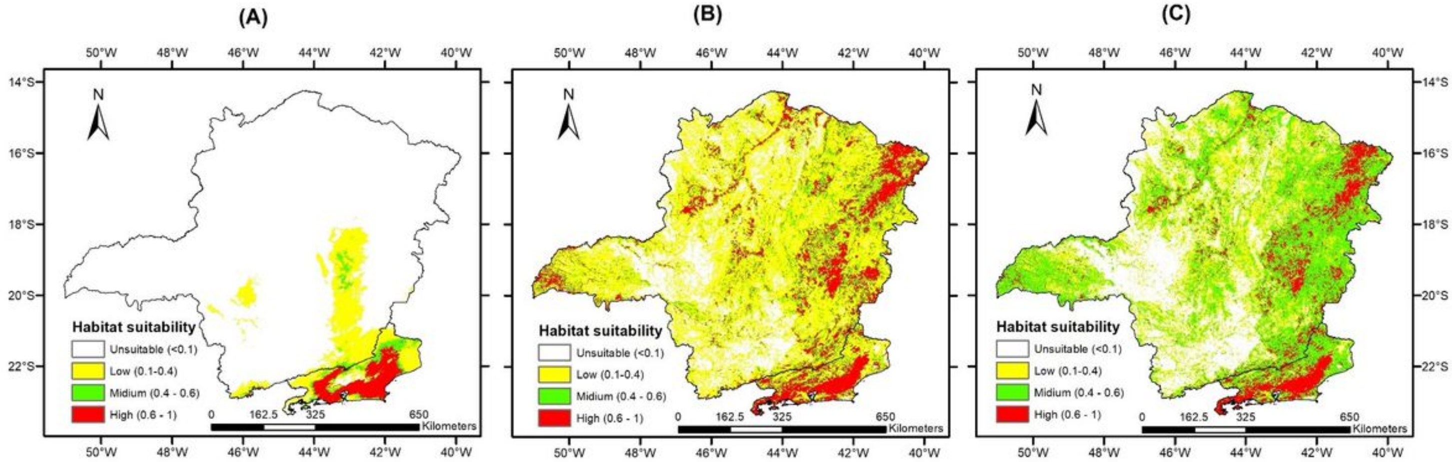

Figure 3

Predicted potential suitable habitat for *Apuleia leiocarpa* in the State of Rio de Janeiro and Minas Gerais (Brazil), using the MaxEnt model. A) Model 1: using the bioclimatic variable, B) Model 2: using soil variables, C) Model 3: using soil variables + vegetation index FAPAR.

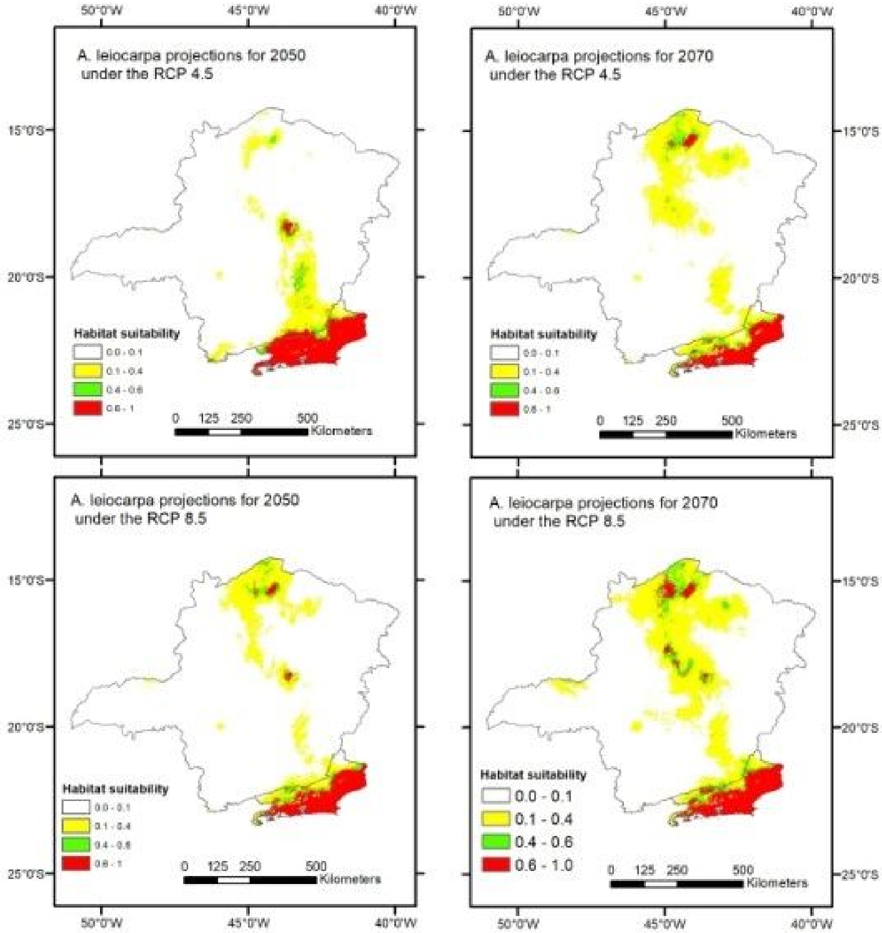

Figure 4

Future projections for 2050 and 2070 for *Apuleia leiocarpa* using the MaxEnt model running the MIROC5 (GCM) under the RCP 4.5 and RCP 8.5scenarios.

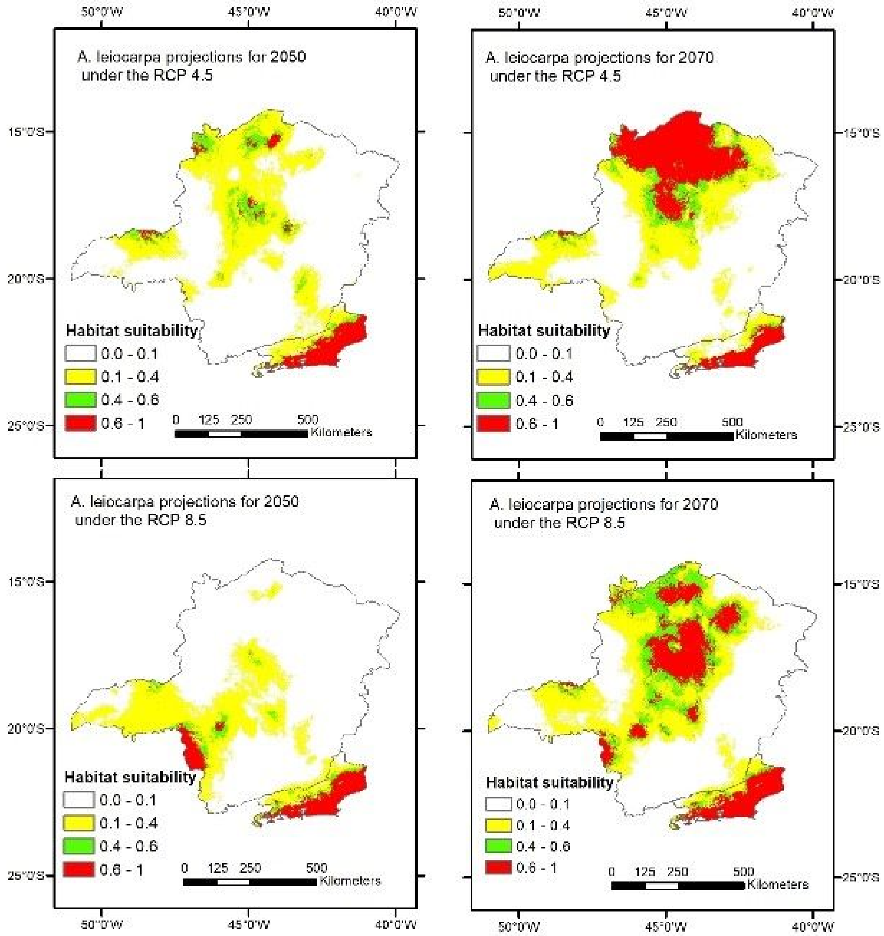

Figure 5

Future projections for 2050 and 2070 for *Apuleia leiocarp*a using the MaxEnt model running the HadGEM2-AO (GCM) under the RCP 4.5 and RCP 8.5scenarios.

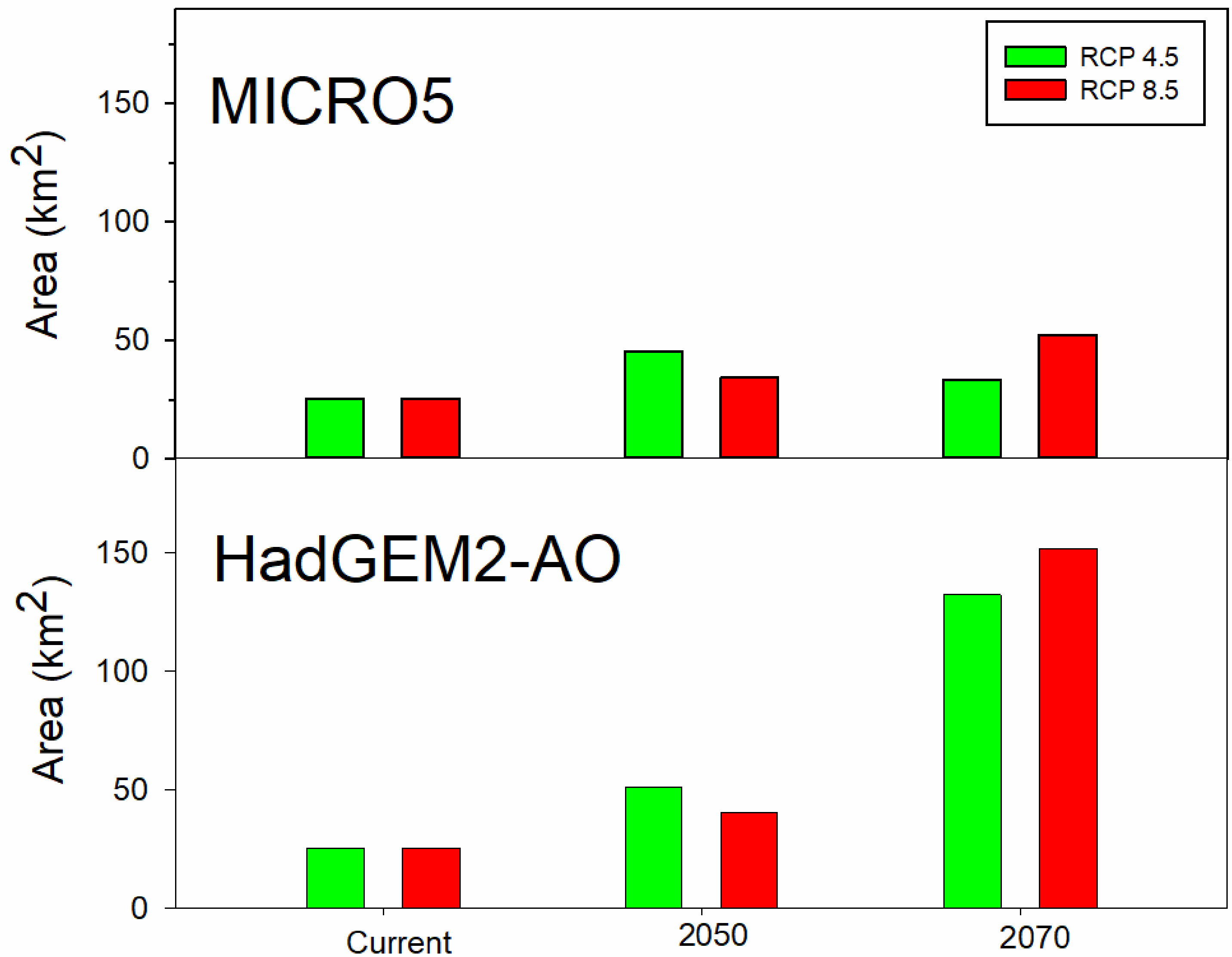

Figure 6

Evolution of the area of habitat suitability for *Apuleia leiocarpa*under the RCP 4.5 and RCP 8.5 scenarios using the MICRO5 and HadGEM2-AO models.

Supplementary Files

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- TableS1.docx