

Climate change threatens the future use of native tree species in Brazilian agroforestry systems

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Abstract

Agroforestry systems help mitigate climate change by storing carbon, conserving biodiversity, and supporting rural livelihoods. In tropical regions, however, they are largely dominated by a few non-native tree species, while the potential use of native species remains poorly understood. Although recent conservation initiatives and public policies have promoted the incorporation of native trees into agroforestry systems, little is known about their long-term resilience to climate change. We assessed the impacts of climate change on 24 native tree species with high agroforestry potential in the Amazon and Atlantic Forest biomes of Brazil. Ecological niche models were used to estimate current climatic suitability and project future distributions under alternative climate scenarios and dispersal assumptions. We also evaluated the future suitability of these species for agroforestry on degraded lands under current Brazilian environmental legislation. Under the no-dispersal scenario, all species lost climatically suitable areas, with reductions ranging from 0.5% to 100% and average declines exceeding 50% in both biomes. Allowing dispersal produced species-specific responses, but climate change consistently reduced the area suitable for native agroforestry species on degraded lands. We identified climatically stable regions that could serve as priority areas for climate-resilient agroforestry and ecological restoration. Our findings suggest that climate change may substantially limit the future use of many native tree species, emphasizing the need to integrate climate adaptation into agroforestry planning and restoration strategies.

Introduction

Agroforestry systems are recognized as a key nature-based solution to address the intertwined challenges of food insecurity, biodiversity loss, and climate change (Cohen-Shacham et al. 2016). Compared with conventional agricultural systems, agroforests support higher levels of biodiversity, including greater species richness, abundance, and functional diversity (Boinet et al. 2019; Santos et al. 2019). Agroforests also enhance landscape connectivity and promote the persistence of ecologically important organisms such as pollinators and seed dispersers (Bentrup et al. 2019). In addition, agroforests provide a wide range of ecosystem services, including soil enrichment, erosion control, nutrient cycling, improved water and air quality, pest regulation, and carbon sequestration (Mortimer et al. 2018; Blanco-Canqui 2024). Beyond their environmental benefits, agroforestry systems contribute to rural development by increasing household income, strengthening livelihoods, enhancing economic resilience, and promoting social inclusion and gender equity (Mukhlis et al. 2022). By simultaneously supporting food production and biodiversity conservation, agroforests are particularly relevant in tropical regions (Raj et al. 2020; Melo et al. 2021).

Brazil stands to benefit substantially from the expansion of agroforestry systems. Agribusiness is the country's largest economic sector (Kureski et al. 2020), but it also represents a major driver of deforestation, particularly within the Amazonian deforestation arc (Pendrill et al. 2019). Consequently, agroforestry is a promising strategy to reconcile agricultural production with biodiversity conservation and forest restoration in Brazil. Although agroforests currently occupy only about 5% of Brazil's agricultural lands, their adoption has increased in recent years, generating documented economic benefits, such as higher farm incomes (Maia et al. 2021) and improvements in ecosystem service provision (Schuler et al. 2022). Within Brazil, the Amazon and Atlantic Forest biomes are among the most important regions for agroforestry implementation and research (Schuler et al. 2022). As an example, agroforestry offers a valuable opportunity to recover highly degraded Atlantic Forest landscapes while maintaining productive systems, especially through cacao cultivation (Lima et al. 2023; Mortimer et al. 2018; Shennan-Farpon et al. 2022).

Agroforestry is also an important strategy within the nexus linking food security, biodiversity conservation, climate change mitigation, and climate adaptation (Melo et al. 2021; Quandt et al. 2023; Sudomo et al. 2023). Agroforestry systems can store substantial amounts of carbon in both vegetation and soils, thereby contributing to reductions in atmospheric carbon dioxide concentrations (Cardinael et al. 2021; Ghale et al. 2022). Moreover, by diversifying production systems and modifying local microclimatic conditions, agroforests can increase resilience to climate-related disturbances, including droughts and extreme weather events (Abebaw et al. 2025; Yang et al. 2025). These benefits have stimulated growing interest in the concept of climate-smart agroforestry, which seeks to maintain ecosystem services and agricultural productivity under future climatic conditions (Ntawuruhunga et al. 2023).

A critical challenge for climate-smart agroforestry is the selection of tree species capable of persisting under future climates. Climate change is already driving shifts in species distributions, often resulting in range contractions, local extinctions, and geographic redistributions (Manes et al. 2021). These effects are expected to be particularly pronounced in Brazil (Manes and Vale 2022). For example, substantial distributional shifts are projected for thousands of tree species across both the Amazon and Atlantic Forest biomes (Zwiener et al. 2018; Gomes et al. 2019; Morais et al. 2024). In southern Brazil, the climatically suitable area for more than one hundred species of agroecological importance is expected to decline by 22–56%, potentially increasing their extinction risk (Lima et al. 2022). Such changes may compromise the future availability of native species currently considered suitable for agroforestry systems.

Despite the growing importance of agroforestry in Brazil, little is known about how climate change may affect the future suitability of native tree species used in these systems. Identifying species and areas likely to remain suitable under future climates is therefore essential for guiding long-term agroforestry planning and restoration efforts. Here, we used ecological niche models to (i) quantify projected changes in climatically suitable areas for 24 native tree species with agroforestry potential in the Amazon and Atlantic Forest biomes and (ii) identify priority areas projected to remain suitable under future climate scenarios. To increase the applicability of our results to restoration and land-use planning, we focused on degraded and deforested lands legally available for reforestation under the Brazilian Forest Code, which allows restoration activities in areas deforested before 2007. By integrating climate projections, species distributions, and legal land-use constraints, our study provides a framework for identifying priority areas for climate-resilient agroforestry expansion in Brazil.

Material and methods

Study area

The study encompassed the two largest tropical forest biomes in Brazil, the Amazon and the Atlantic Forest. Together, these biomes harbor high biodiversity and represent priority regions for agroforestry development and ecological restoration (Liévano-Latorre et al. 2025). The Amazon is predominantly covered by tropical ombrophilous forests and is characterized by a warm and humid climate, with annual precipitation generally exceeding 1,300 mm and mean temperatures around 26°C. The Atlantic Forest comprises a mosaic of forest types distributed across a broad climatic gradient, ranging from tropical to subtropical conditions, with annual precipitation varying from approximately 500 to 3,000 mm and mean annual temperatures between 10 and 25°C. Climate projections indicate substantial changes in temperature and precipitation patterns across both biomes during this century (Ballarin et al. 2023). In the Amazon, future scenarios generally predict increasing temperatures and declining precipitation, whereas in the Atlantic Forest temperatures are also expected to increase, accompanied by stable or increasing precipitation in many regions.

Species occurrence data and climatic predictors

We modeled 24 native tree species with high agroforestry potential in Brazil, including species from both the Amazon and Atlantic Forest biomes (Table S1). Occurrence records were obtained from the Global Biodiversity Information Facility (GBIF; <https://doi.org/10.15468/dl.fkkr5a>). Species names were standardized using the R package *flora* (Carvalho 2017), following the nomenclature adopted by the Brazilian Flora 2020 project. A total of 101,052 occurrence records from 839 datasets were initially compiled. Species represented by fewer than ten occurrence records after cleaning were excluded from modeling because small sample sizes reduce model reliability (van Proosdij et al. 2016).

Data cleaning followed the protocol proposed by Gomes et al. (2018). Records lacking geographic coordinates, records located outside the Neotropics, and records associated with geographic inconsistencies were removed using the *CoordinateCleaner* package (Zizka et al. 2019). Spatial outliers were subsequently identified and excluded using kernel density analyses. To reduce sampling bias and spatial autocorrelation, occurrence records were spatially filtered using a minimum distance of 20 km between records with the *spThin* package (Aiello-Lammens et al. 2015).

Current climatic conditions were represented using the 19 bioclimatic variables available from WorldClim version 2.1 at a spatial resolution of 5 arc-minutes (~ 10 km at the equator) (Fick and Hijmans 2017). To reduce multicollinearity among predictors, we calculated variance inflation factors (VIF) using the *vifstep* function in the *usdm* package (Naimi et al. 2015). Variables with VIF values greater than five were excluded (Fremout et al. 2020). The final predictor set included isothermality (BIO3), maximum temperature of the warmest month (BIO5), precipitation seasonality (BIO15), precipitation of the wettest quarter (BIO16), and precipitation of the driest quarter (BIO17). The same predictors were used for all species.

Ecological niche modeling

Current and future climatically suitable areas (CSAs) were estimated using an ensemble forecasting approach implemented in the *biomod2* package (Thuiller et al. 2009). We used three modeling algorithms that consistently perform well in comparative evaluations: generalized linear models (GLM), random forests (RF), and maximum entropy (MAXENT) (Elith et al. 2006; Aguirre-Gutiérrez et al. 2013). For presence-only modeling approaches, 10,000 pseudo-absences were randomly generated and repeated across five independent runs following Barbet-Massin et al. (2012). Species prevalence was fixed at 0.5 to give equal weight to presences and pseudo-absences during model calibration.

To evaluate model performance while accounting for spatial autocorrelation, we adopted a spatial block cross-validation approach using the *blockCV* package (Valavi et al. 2019). The distribution of each species was partitioned into five spatial folds, with models calibrated using four folds and evaluated on the remaining fold. Model performance was assessed using the Area Under the Receiver Operating Characteristic Curve (AUC). Only models with AUC values greater than 0.8 were retained for ensemble forecasting. Final ensemble predictions were generated using weighted ensemble means. To ensure ecological realism, species response curves were visually inspected following the evaluation-strip approach proposed by Elith et al. (2005).

Future climate projections

Future projections were based on two Shared Socioeconomic Pathways (SSPs) from the IPCC Sixth Assessment Report (AR6): SSP2-4.5 (intermediate stabilization scenario) and SSP5-8.5 (high-emissions scenario). Projections were generated for two future periods: 2041–2060 and 2061–2080. To account for uncertainty among climate models, future climatic suitability was projected using the ensemble average of eight General Circulation Models (GCMs): BCC-CSM2-MR, CNRM-CM6-1, CNRM-ESM2-1, CanESM5, IPSL-CM6A-LR, MIROC-ES2L, MIROC6, and MRI-ESM2-0. Continuous suitability outputs were converted to binary maps using the maximum training sensitivity plus specificity threshold, which has been shown to perform well in identifying suitable areas (Jiménez-Valverde and Lobo 2007; Bean et al. 2012).

Dispersal Scenarios and Priority Areas for Agroforestry

Changes in climatically suitable areas were quantified by comparing the number of occupied pixels under current and future climatic conditions. We evaluated two dispersal assumptions: (i) no dispersal, in which species were unable to colonize newly suitable areas, and (ii) unlimited dispersal, in which species were assumed to occupy all newly suitable areas within their respective biome.

To identify priority areas for agroforestry implementation under climate change, we restricted our analyses to lands legally available for restoration under the Brazilian Forest Code. Specifically, we considered areas deforested before 2008, corresponding to the period preceding major policy changes aimed at reducing deforestation rates in Brazil. Binary suitability maps were then intersected with maps of accumulated deforestation in the Amazon and Atlantic Forest to identify climatically suitable areas available for agroforestry implementation under current and future scenarios. Deforestation data were obtained

from the National Institute for Space Research (INPE; <http://terrabrasilis.dpi.inpe.br>). Finally, we assessed climatic stability by identifying areas predicted to remain suitable under both current and future climatic conditions. These analyses allowed the identification of regions with high potential for long-term agroforestry implementation under climate change. All analyses were performed in R version 4.6.1 (R Core Team 2026).

Results

Model performance

All ecological niche models showed high predictive performance. Using spatial block cross-validation, ensemble models achieved AUC values ranging from 0.943 ± 0.08 to 0.996 ± 0.16 , indicating a strong ability to discriminate between climatically suitable and unsuitable areas. Consequently, all models met the predefined performance threshold and were retained for subsequent analyses.

Changes in climatically suitable areas

Climate change substantially altered the climatically suitable areas (CSAs) of the studied agroforestry species. Under the no-dispersal scenario, all 24 species were projected to experience reductions in CSA under both climate scenarios and future periods evaluated (Tables 1 and 2). The magnitude of decline varied considerably among species, ranging from 0.5% for *Cordia goeldiana* to complete loss of suitable area for *Schizolobium parahyba* var. *amazonicum* under some scenarios (Table 1). Overall, 18 species experienced CSA reductions greater than 50%, whereas seven species showed declines exceeding 70% in at least one future scenario.

Table 1

Changes in climatic suitability (%) for agroforestry tree species from the Amazon in different climate change scenarios (SSP24.5 and SSP5-8.5) and dispersal their entire range, deforested lands up to 2007 and deforested lands between 2008 and 2021. Positive values indicate increases while negative values indicate climatically suitable areas.

	No dispersal				Dispersal within Amazon				Dispersal within deforested lands up to 2007 in the Amazon				Dispersal within deforested lands between 2008 and 2021 in the Amazon	
	SSP2-4.5		SSP5-8.5		SSP2-4.5		SSP5-8.5		SSP2-4.5		SSP5-8.5		SSP2-4.5	
	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080
<i>Bagassa guianensis</i>	-33.8	-17.3	-13.1	-16.3	46.0	94.5	143.7	145.8	-9.0	25.8	54.8	77.0	-41.5	-12.3
<i>Bertholletia excelsa</i>	-55.9	-69.4	-66.0	-94.3	144	131	115	-3.1	22.7	-17.3	-17.6	-90.3	16.4	-24.6
<i>Carapa guianensis</i>	-87.9	-89.1	-90.9	-97.0	-41.1	-44.2	-50.7	-76.9	-91.1	-85.9	-90.4	-94.1	-91.8	-78.6
<i>Copaifera multijuga</i>	-64.9	-27.4	-28.3	-20.0	323	454	559	872	336	405	532	667	223	280
<i>Cordia goeldiana</i>	-12.3	-6.9	-2.4	-0.5	166	343	404	650	130	209	222	261	121	220
<i>Dinizia excelsa</i>	-99.1	-99.2	-98.7	-99.7	-64.9	-62.3	-78.2	-82.1	-86.3	-94.2	-93.9	-92.7	-88.7	-94.4
<i>Dipteryx odorata</i>	-35.7	-45.0	-25.1	-29.4	233	307	310	369	136	121	141	86.4	180	169
<i>Euterpe oleracea</i>	-64.7	-53.1	-51.8	-48.0	12.4	64.3	70.4	107	-63.9	-23.3	55.2	143	-66.6	-27.7
<i>Handroanthus serratifolius</i>	-57.5	-57.7	-60.0	-38.0	320	495	487	852	700	887	982	1312	786	1040
<i>Jacaranda copaia</i>	-63.6	-60.9	-65.1	-56.7	189	339	343	510	218	459	562	757	182	285
<i>Ochroma pyramidale</i>	-44.3	-61.7	-60.2	-49.1	114	166	189	341	1868	2777	3469	4389	2824	4275
<i>Schefflera morototoni</i>	-60.0	-68.2	-67.6	-52.3	355	491	583	951	572	926	1347	1600	929	1429
<i>Schizolobium parahyba</i> var. <i>amazonicum</i>	-100	-98.8	-93.4	-100	-89.0	-88.7	-88.7	-96.4	-93.9	-98.9	-98.7	-100	-97.1	-99
<i>Simarouba amara</i>	-56.3	-52.1	-53.1	-40.5	489	654	711	1077	674	863	937	1204	710	983
<i>Swietenia macrophylla</i>	-32.5	-62.8	-58.2	-28.9	517	755	786	1361	1809	2405	2641	3561	5733	8100
<i>Theobroma cacao</i>	-62.1	-73.1	-64.7	-60.0	157	181	244	177	368	465	791	52.6	1012	687
<i>Virola surinamensis</i>	-65.2	-65.1	-66.6	-50.0	143	303	373	745	254	517	732	1300	311	319
<i>Vochysia maxima</i>	-83.5	-89.3	-84.7	-67.0	-28.1	-73.9	-34.4	-39.0	-20.7	-59.8	-53.3	-50	37.7	-44.9

Table 2

Changes in climatic suitability (%) for agroforestry tree species from the Atlantic Forest in different climate change scenarios (SSP24.5 and SSP5-8.5) and within their entire range, deforested lands up to 2007 and deforested lands between 2008 and 2021. Positive values indicate increases while negative values indicate decreases in climatically suitable areas.

	No dispersal		Dispersal within Atlantic Forest				Dispersal within deforested lands up to 2007 in the Atlantic Forest				Dispersal within deforested lands between 2008 and 2021 in the Atlantic Forest			
	SSP2-4.5		SSP5-8.5		SSP2-4.5		SSP5-8.5		SSP2-4.5		SSP5-8.5		SSP2-4.5	
	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080	2041–2060	2061–2080
<i>Calophyllum brasiliense</i>	-29.0	-30.0	-25.2	-34.0	328	250	277	384	470	376	410	585	207	139
<i>Cariniana legalis</i>	-57.8	-64.4	-67.8	-59.0	84.7	26.6	44.7	64.5	78.8	14.1	26.7	64.2	-46.4	-54.5
<i>Cordia alliodora</i>	-73.9	-73.9	-73.9	-91.3	613	630	1034	234	496	482	773	181	182	87.2
<i>Cordia trichotoma</i>	-71.0	-74.3	-84.4	-71.7	-27.1	-30.0	-24.3	-19.2	-39.2	-52.3	-53.3	-21.3	-41.6	-24.2
<i>Tectona grandis</i>	-1.7	-1.7	-6.3	-11.0	147	181	114	115	195	265	184	171	99	79
<i>Theobroma cacao</i>	-96.1	-89.6	-96.1	-96.7	-81.1	-68.8	-57.8	-84.4	-83.7	-72.6	-76.7	-86	-82.3	-77.1
<i>Zeyheria tuberculosa</i>	-30.6	-34.3	-47.7	-24.0	55.5	60.2	35.6	88.1	82.6	67.4	46.5	104	105	131

The species most negatively affected by climate change included *Carapa guianensis*, *Dinizia excelsa*, *Schizolobium parahyba* var. *amazonicum*, and *Vochysia maxima* in the Amazon (Table 1), and *Cordia trichotoma* and *Theobroma cacao* in the Atlantic Forest (Table 2). For example, *S. parahyba* var. *amazonicum* exhibited reductions ranging from 88.7% to 100% of its current CSA, while *T. cacao* in the Atlantic Forest lost between 57.8% and 84.4% of its suitable area depending on the climate scenario and projection period.

Under the unlimited-dispersal scenario, species responses were more variable. Several species expanded their potential distributions by colonizing newly suitable areas, whereas others continued to exhibit substantial reductions in CSA (Tables 1 and 2). Despite these differences, climate change consistently produced marked shifts in species distributions across both biomes.

Climatic suitability in areas available for agroforestry

When analyses were restricted to deforested lands legally available for restoration, climate change substantially altered the availability of climatically suitable areas for agroforestry implementation. Considering areas deforested before 2008 and between 2008 and 2021, nine and ten species, respectively, were projected to experience reductions in suitable area under at least one future climate scenario (Tables 1 and 2). These results indicate that climate change may reduce the future availability of native tree species suitable for agroforestry establishment in both the Amazon and Atlantic Forest.

Spatial patterns of climatic stability and species richness

Spatial projections revealed pronounced shifts in the distribution of climatically suitable areas across both biomes. As an illustrative example, we used *Theobroma cacao* because it is among the most economically important native species used in Brazilian agroforestry systems and showed contrasting responses between biomes. *T. cacao* currently exhibits high climatic suitability in western Amazonia and southern Bahia. Under future climate scenarios (SSP2-4.5 and SSP5-8.5), suitable areas are projected to shift toward central Amazonia and remain concentrated along portions of the southern coast of Bahia (Fig. 1). The overlap between current and future projections identified regions of high climatic stability for *T. cacao*, particularly within the state of Amazonas, southern Bahia, and coastal areas of São Paulo (Fig. 2).

Species richness maps derived from ensemble models also showed marked geographic shifts under climate change (Fig. 3). Under current climatic conditions, areas with the highest richness of agroforestry species are concentrated in northeastern and southwestern Amazonia and along large portions of the Atlantic Forest coast. Future projections indicate a redistribution of species richness toward central Amazonia and coastal regions of Bahia, Espírito Santo, Rio de Janeiro, São Paulo, and Santa Catarina. Although the exact spatial patterns varied among climate scenarios, these regions consistently emerged as areas retaining relatively high concentrations of climatically suitable species.

Discussion

Our study demonstrates that climate change should substantially reduce the climatically suitable areas (CSAs) of native tree species currently considered promising for agroforestry systems in the Amazon and Atlantic Forest. Under the no-dispersal scenario, all 24 species experienced contractions in suitable area, many of them exceeding 50% of their current distributions. These reductions resulted into a decline in the availability of native species suitable for agroforestry establishment in degraded lands and were accompanied by decreases in projected species richness across large portions of both biomes. At

the same time, our analyses identified climatically stable regions that may function as long-term refugia and priority areas for agroforestry implementation under future climate conditions.

The projected contraction of suitable areas is consistent with a growing body of literature demonstrating that climate change is reshaping the distribution of tropical tree species. Previous studies have predicted substantial reductions in climatically suitable habitats for Amazonian and Atlantic Forest tree species under future climate scenarios (Zwiener et al. 2018; Gomes et al. 2019; Lima et al. 2022; Lima et al. 2023; Morais et al. 2024). In the Amazon, increasing temperatures and altered rainfall regimes may destabilize forest-climate feedbacks, potentially triggering large-scale vegetation changes and reducing the extent of humid forest environments (Nobre et al. 2016). Such climatic shifts are expected to disproportionately affect species adapted to warm and humid conditions, helping explain the widespread declines observed in our projections. Similar patterns have been reported elsewhere in the tropics. For example, more than half of the tree species in Thailand could lose all climatically suitable habitat by 2050 (Trisurat et al. 2023), suggesting that climate-driven contractions may become a common feature of tropical forest floras worldwide.

Despite the predominance of negative responses, species did not respond uniformly to climate change. While species such as *Dinizia excelsa*, *Schizolobium parahyba* var. *amazonicum*, and *Cordia trichotoma* experienced severe reductions in suitable habitat, others retained climatically suitable areas or even expanded their distributions when dispersal was allowed. These contrasting responses likely reflect differences in climatic tolerances, environmental requirements, and adaptive capacity among species, highlighting the need for species-specific assessments when planning restoration and production systems under future climatic conditions.

The strong influence of dispersal assumptions on model projections emphasizes the importance of landscape connectivity for species persistence under climate change. Allowing dispersal greatly reduced projected habitat losses for several species and, in some cases, resulted in net expansions of suitable areas, which is consistent with previous studies (e.g., Thomas et al., 2004; Roques et al., 2008). From an ecological perspective, this suggests that some species may be capable of tracking suitable climates through migration and colonization of newly favorable regions. However, from the perspective of agroforestry planning, dispersal does not fully offset the challenges imposed by climate change. Agroforestry systems are long-term investments, with many tree species requiring years or decades to reach productive maturity. Consequently, species selected based solely on current climatic suitability may experience different environmental conditions during their productive lifespan, creating a temporal mismatch between species selection and future environmental suitability. This mismatch may reduce productivity, compromise restoration outcomes, and increase economic risks for landowners and restoration practitioners. Therefore, we highlight the importance of incorporating future climate projections into species selection and planting decisions as a central component of climate-smart agroforestry planning.

We showed that climate change may reduce the area available for the establishment of native-species agroforestry systems in lands already deforested and legally available for restoration. Although Brazil contains extensive areas suitable for restoration and productive reforestation, only a fraction of these lands is projected to remain suitable for many native species under future climate scenarios. This pattern is particularly evident in ecotonal regions, which historically have experienced intense land-use change and agricultural expansion. Agricultural frontiers in Brazil have advanced from more open ecosystems and coastal regions toward more densely forested landscapes, contributing to habitat conversion in transitional zones between major biomes (Richards 2015). We indicate that these regions are also among the most vulnerable to future climatic shifts. Because ecotones are characterized by strong environmental gradients and high ecological sensitivity (Marques et al. 2020), they should experience disproportionate losses in climatic suitability for species of agroforestry interest. Consequently, although these areas remain important targets for restoration (Liévano-Latorre et al. 2025), they may also represent zones of elevated climatic uncertainty.

In contrast, our analyses identified regions that retained high climatic suitability across future scenarios and therefore may function as climate refugia for agroforestry species. In the Amazon, these areas were concentrated primarily within the Brazilian Legal Amazon, whereas in the Atlantic Forest they occurred mainly along the coastal corridor extending from the States of Bahia to Santa Catarina. These regions maintained high species richness under future climates and therefore represent strategic locations for long-term investments in restoration and agroforestry expansion. Prioritizing such areas may increase the likelihood of restoration success while maximizing the ecological and socioeconomic benefits associated with agroforestry systems.

The contrasting responses observed for *Theobroma cacao* illustrate the complexity of species-specific responses to climate change. Cacao is one of the most economically important species used in Brazilian agroforestry systems and forms the basis of traditional systems such as cabruca in the Atlantic Forest. Our projections indicated potential gains in climatically suitable areas within portions of the Amazon under some dispersal scenarios, whereas suitable conditions in the Atlantic Forest become increasingly restricted to a limited number of climatically stable regions. These findings are consistent with previous studies reporting high sensitivity of cacao cultivation to changes in temperature and water availability (Läderach et al. 2013; Igawa et al. 2022). More broadly, the results demonstrate that even species widely considered suitable for agroforestry may require substantial adjustments in cultivation regions and management strategies under future climates.

Our projections are subject to uncertainty as with all ecological niche modeling studies. Future suitability estimates depend on assumptions regarding species–climate relationships, dispersal capacity, climate scenarios, and model structure (Thuiller et al. 2019; Zurell et al. 2020). Furthermore, physiological information remains scarce for many tropical tree species used in agroforestry systems. Most available studies focus on temperature responses, whereas the effects of water availability, drought tolerance, and physiological plasticity remain poorly understood (Valladares et al. 2014). Even for economically important species such as cacao, important gaps persist regarding physiological responses to heat and water stress (Lahive et al. 2019). Improving knowledge of species ecophysiology will therefore be essential for refining future projections and strengthening climate adaptation strategies for agroforestry systems.

Although our study focuses on Brazil, its implications extend to other tropical regions where agroforestry plays an important role in balancing agricultural production, biodiversity conservation, and ecosystem restoration. Similar climate-driven reductions in suitable areas for perennial crops and agroforestry

species have been reported in Central Africa and Southeast Asia (Läderach et al. 2013; Trisurat et al. 2023). The convergence of these findings across tropical regions suggests that climate change may become a major constraint on the future expansion of agroforestry unless adaptation measures are incorporated into planning and policy frameworks.

Agroforestry systems are increasingly recognized as a powerful strategy for simultaneously addressing biodiversity loss, ecosystem degradation, climate mitigation, and rural development. However, our results indicate that their long-term success will depend on anticipating climate-driven shifts in species suitability. Integrating climate projections into species selection, restoration planning, and land-use policies will be essential to ensure that agroforestry remains a viable strategy throughout the twenty-first century. By identifying species most vulnerable to climate change and regions likely to remain climatically suitable, our study provides a framework for designing climate-resilient agroforestry systems capable of supporting both ecological sustainability and human well-being in a rapidly changing world.

Declarations

Author Contribution

VPL, VGO and VFF contributed to the study conception and design. Material preparation, data collection and analysis were performed by VPL. The first draft of the manuscript was written by VPL, SM, HSS and GA, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data Availability

The datasets generated in this study are publicly available through GBIF (<https://doi.org/10.15468/dl.fkkr5a>) and Zenodo (<https://doi.org/10.5281/zenodo.21312760>).

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Figures

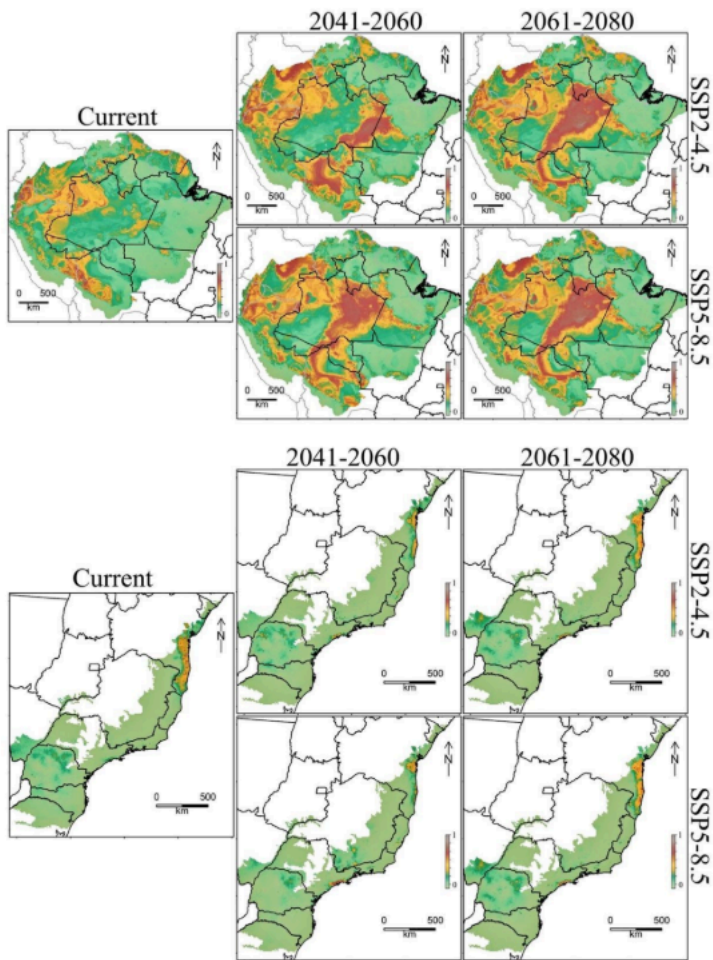


Figure 1

Climatic suitability for *Theobroma cacao* in the Amazon and Atlantic Forest under different climate scenarios and projected years. Orange, red, and gray tones indicate areas of high climatic suitability, whereas green and lighter tones represent areas of low climatic suitability. Maps created with custom R script version 4.6.1 (<https://www.R-project.org/>). Brazilian states shapefile obtained from the Brazilian Institute of Geography and Statistics (<https://www.ibge.gov.br/>).

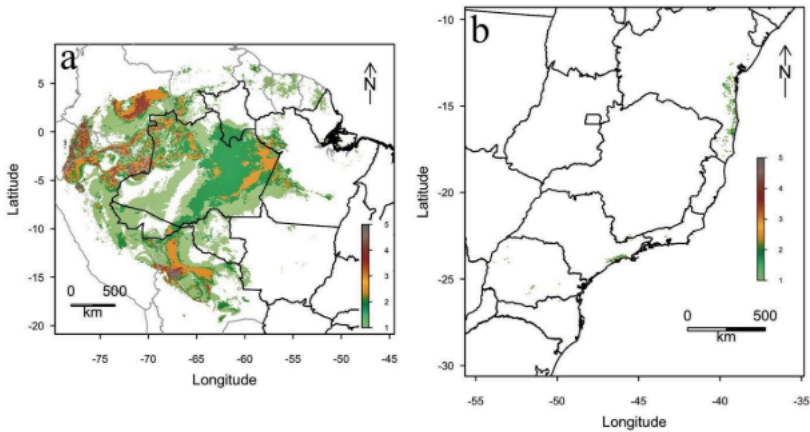


Figure 2

Areas of high climate stability for *Theobroma cacao*(cacau) in the (a) Amazon and the (b) Atlantic Forest based on current and future climate scenarios. Legend indicates agreement between different climate models (current + 4 future climate scenarios). Brazilian states are highlighted in black lines. Maps created with custom R script version 4.6.1 (<https://www.R-project.org/>). Brazilian states shapefile obtained from the Brazilian Institute of Geography and Statistics ([https:// www.ibge.gov.br/](https://www.ibge.gov.br/)).

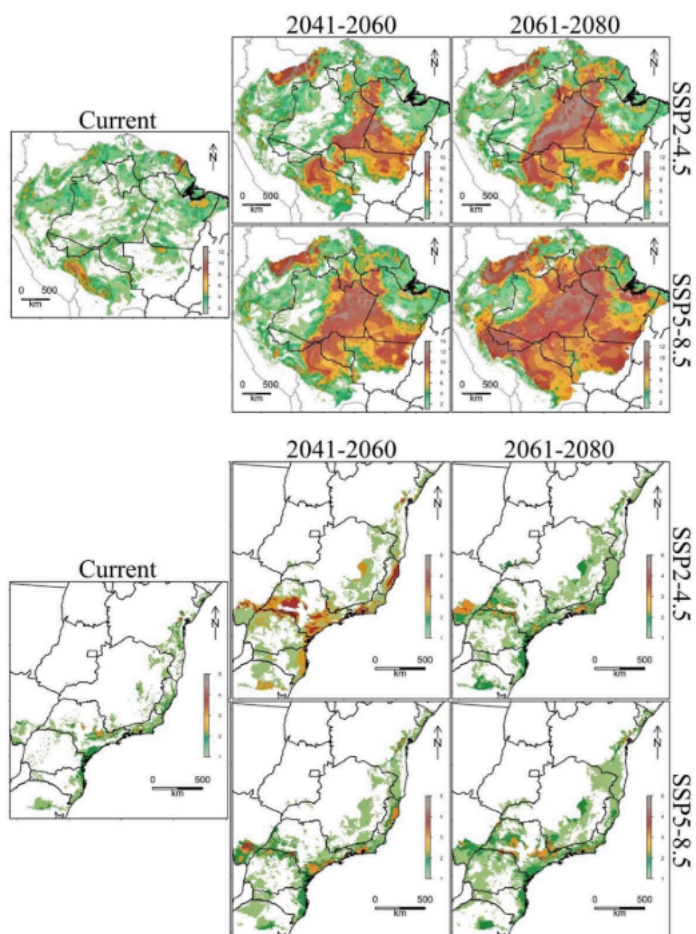


Figure 3

Species richness (green to gray) derived from ENMs based on bioclimatic layers. Legend indicates the number of species. Maps created with custom R script version 4.6.1 (<https://www.R-project.org/>). Brazilian states shapefile obtained from the Brazilian Institute of Geography and Statistics (<https://www.ibge.gov.br/>).

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