Predicting the current and future potential distributions and biotic interactions between an herbivorous insect and its host plants in southern Africa

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ABSTRACT

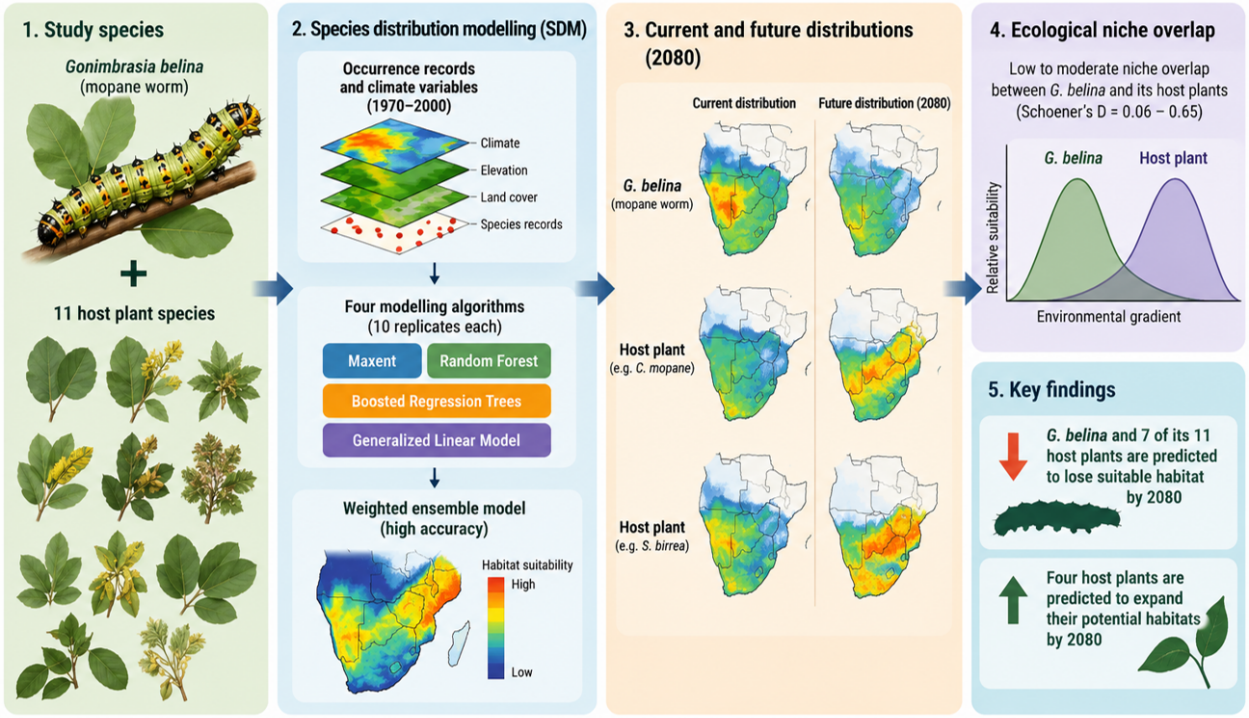
Climate change will have profound impacts on species distributions and persistence in the near future, however, biotic interactions may mitigate climate effects among interacting species. In this study, we fitted species distribution models (SDMs) to predict the current and future habitat suitability of *Gonimbrasia belina*, a culturally and economically significant insect in southern Africa, and 11 of its host plants. SDMs were fitted with four algorithms using publicly accessible species occurrence records and bioclimatic variables (1970-2000) at 1 km resolution, while predicted habitat suitability were generated using weighted model ensembles. Future predictions were generated using four shared socioeconomic pathways of the EC-Earth3-Veg general circulation model (2061-2080). We also quantified ecological niche overlap (Schoener's *D*) between the insect and the host plants with equivalency tests (1,000 randomizations) to evaluate statistical significance. Results show strong contributions and constraints of predictors representing water availability and water-energy balance to the distributions of the 12 species. *G. belina* and seven host plants were predicted to lose portions of their future suitable habitats, while the remaining four hosts may experience range expansions under climate change. Niche overlap was significantly lower between *G. belina* and most of its host plants (D=0.06–0.65) indicating a generalist herbivorous relationship. Range losses may disrupt biotic interactions between *G. belina* and some of its host plants, but herbivorous relationships may be sustained in predicted climatic refugia and with climate-adapted host plants. Nonetheless, long-term persistence of *G. belina* will depend on sustainable harvesting and protection of host plant diversity.

Keywords: *Gonimbrasia belina*, biotic interactions, climate change, species distribution modeling, niche overlap, mopane moth.

Highlights

1. Low to moderate niche overlap between Mopane moth and the 11 host plants
2. Significantly lower niche overlap indicates the moth is a generalist herbivore
3. Mopane moth and seven host plants are predicted to lose portions of their ranges
4. Future habitat loss will disrupt plant-moth relationship in parts of its range

Graphical Abstract



The graphical abstract was generated using OpenAI's ChatGPT image-generation tool. The authors provided the information and key findings from the study, which were used to generate the graphical abstract. The AI tool generated the visual layout, illustrations, diagrams, maps, and other graphical elements.

1. Introduction

Biotic interactions are fundamental drivers of biodiversity patterns, community assemblages, species distributions, and ecosystem functioning (Keddy, 1992; Peterson and Soberón, 2012). These interactions are particularly strong in tropical and subtropical regions, contributing to higher species richness and the macroecological pattern of higher species richness for most taxonomic groups toward the equator (that is, latitudinal diversity gradient; Willig et al., 2003; Hillebrand and Thomas, 2004). In tropical ecosystems, negative density-dependent biotic interactions are predicted to reduce the dominance by a species (Janzen-Connell hypothesis; Janzen, 1970; Connell, 1971; Comita et al., 2014), while herbivory pressures, predation, and parasitism drive co-evolutionary arms race (theory of co-evolution; Thompson, 2005; de Vries and Feussner, 2024). Like other biomes, higher biodiversity in Africa is not only shaped by historical climatic stability, primary productivity, and higher net diversification (Hawkins et al., 2003; Dowle et al., 2013), but also reinforced by strong biotic interactions such as herbivory, pollination, parasitism, and mutualism (Coley and Barone, 1996; Schemske et al., 2009). Plant-insect interactions are especially influential, with herbivorous insects playing key roles in community structure, nutrient cycling, and energy transfer across trophic levels (Hunter, 2001; Schowalter, 2016). For example, specialized pollination systems such as those involving fig trees (*Ficus sycomorus*) and their obligate pollinators, *fig wasps* (Agaonidae), represent tightly co-evolved mutualisms that contribute to the maintenance of plant diversity in tropical ecosystems (Janzen, 1979; Herre et al., 2008). In savanna ecosystems, interactions between *Acacia* species such as *Vachellia drepanolobium* and symbiotic ants exemplify defensive mutualisms, where ants protect host plants from herbivores in exchange for food resources and nesting sites (Palmer et al., 2008; Stanton and Palmer, 2011). Additionally, extensive defoliation by insects such as the

mopane moth (*Gonimbrasia belina*) on *Colophospermum mopane* and other plants play a key role in influencing the community structure, ecological productivity, and regeneration dynamics of mopane woodlands in southern Africa (Ghazoul, 2006; Makhado et al., 2014; Schowalter, 2016). Therefore, diverse and sometimes specialized plant-insect interactions are central to maintaining ecological complexity and high biodiversity across African ecosystems.

It is well established in literature that temperature and other abiotic factors drive species distributions and community assemblages (Keddy, 1992; Woodward et al., 2004; Peterson and Soberón, 2012), therefore climate change will have profound effects on community dynamics and potential range shifts (Thuiller et al., 2005; Parmesan, 2006). For example, precipitation variability is expected to widen in the future and increase the vulnerability of tropical and subtropical ecosystems to climate-driven changes (DeLucia et al., 2012; Jamieson et al., 2017). In African savanna ecosystems, precipitation seasonality plays a central role in regulating plant phenology, leaf production, and forage quality, which subsequently regulate herbivore life cycles and population dynamics (Ogutu et al., 2015; Kharouba et al., 2018). However, the effects of climate change on biotic interactions have produced mixed results. In many cases, climate variability is shown to disrupt the synchrony between interacting species that have evolved under relatively predictable seasonal regimes, leading to phenological mismatches, which can destabilize plant-insect interactions and cascade through higher trophic levels (Vanbergen and Initiative, 2013; Forrest, 2016). On the other hand, empirical evidence has also demonstrated that deviations from the widely accepted expectations of species moving to higher altitudes and latitudes (Lenoir et al., 2008) may be due to stress-mitigating and positive below and above-ground biotic interactions (Lau and Lennon, 2012; Rubenstein et al., 2023; Osmolovsky et al., 2025). Therefore, reliable predictions of climate change effects on biodiversity must consider

biotic interactions (Maestre et al., 2009). This is particularly important in African flora and fauna that maintained their ancestral niches during diversification due to historical climatic stability (that is, tropical niche conservatism hypothesis; Wiens and Donoghue, 2004), and thus are more vulnerable to slight climatic changes (Newbold et al., 2020; Linck et al., 2021).

The mopane moth *(Gonimbrasia belina*), belonging to the Saturniidae family, is a keystone insect widely distributed across southern and central Africa and is closely associated with mopane woodlands dominated by *Colophospermum mopane*. The female moth lays hundreds of eggs on *C. mopane* (known as the mopane tree) leaves which hatch to produce mopane worm, the larvae, that depends mainly on mopane leaves for food before burrowing on the ground for pupal development and emergence of adult moths (Mpuchane et al., 2000; Ghazoul, 2006; Akpalu et al., 2009; Sekonya et al., 2020). The adult moth has a short life span during which they only mate and lay eggs to start a new life cycle (Dube and Chitakira, 2024). While mopane worms are most strongly associated with *C. mopane*, they exhibit broader host plant interactions and have been recorded on several other woody species, including *Sclerocarya birrea, Senegalia nigrescens*, *Vachellia karroo*, *Terminalia sericea*, and *Ficus sycomorus*, among others (Fakazi et al., 2021). These interactions are generally considered commensal or herbivorous associations, where larvae depend on host plants for nutrition without necessarily providing reciprocal benefits. Beyond its ecological role, the mopane worm has substantial cultural and economic importance, serving as a major source of protein and income for rural communities in southern Africa (Makhado et al., 2009; Nemadodzi et al., 2023; Sinthumule, 2025). The worms are usually harvested between December and April, processed, dried, and consumed in local meals or packaged for sale in urban centers (Sekonya et al., 2020; Nemadodzi et al., 2023). In recent times, increasing demand and regional markets for mopane worms have

resulted in commercialized and unsustainable harvesting from wild stocks (Baiyegunhi and Oppong, 2016; Sekonya et al., 2020; Fakazi et al., 2021), raising the concerns about the impacts of harvesting pressure on mopane population declines (Sekonya et al., 2020). This resulted in the call for regulated harvesting (Dube and Chitakira, 2024) and prompted the South African and Namibian governments to impose regulatory measures to promote sustainable utilization. However, climate change further exacerbates the risk through direct impacts on the moth's life cycle, as extreme weather events such as drought and wildfires destroy food sources for worms, and indirectly through increased dependence on mopane worms as protein source following climate-induced crop failure (Kapuka and Hlásny, 2021; Dlamini et al., 2026). Therefore, effective conservation of mopane worms requires adequate understanding of its ecological niche, and the resilience of its floristic habitats to climate change.

Species distribution models (SDMs) are widely used to describe the ecological niche and predict the geographic distributions of species based on their correlative relationships with environmental conditions (Phillips et al., 2006a; Elith and Leathwick, 2009; Safdar et al., 2025). Grounded in the ecological niche theory, these correlative models are based on the principle that species occupy distinct realized niches shaped by biotic interactions, abiotic factors, and the ability of the species to reach suitable locations (Austin et al., 1990; Guisan and Zimmermann, 2000; Soberón, 2007). By integrating species occurrence records with ecological predictors, SDMs can map potential spatial distributions, identify key drivers of species' ecological niches, describe species-environment relationships (Morin and Thuiller, 2009; Jiménez-Valverde et al., 2011), and detect previously undocumented populations (Sousa-Silva et al., 2014; Burns et al., 2020; Borokini et al., 2023). They are also commonly used to extrapolate species distributions in new geographical space (Gallien et al., 2012; Petitpierre et al., 2017), model past species

distributions (Nogués-Bravo, 2009; Bruni et al., 2024), predict future range shifts under future climate scenarios (Petitpierre et al., 2016; Ferrier et al., 2016; Peterson et al., 2018), thus providing insights relevant to biodiversity and conservation planning in a changing climate (Phillips et al., 2006a; Elith and Leathwick, 2009). Furthermore, the ecological niche theory provides statistical framework for quantifying a species ecological niche for comparison with the niches of other species (Quiroga and Souto, 2022; Zhou et al., 2023) or among geographically distinct populations within a species (Pili et al., 2020; Borokini et al., 2023). This is important for understanding the degree of similarity of the ecological requirements that support the persistence of co-occurring species that can be used to infer biotic interactions or to predict invasion risks (Warren et al., 2008; Broennimann et al., 2012). Such approaches are particularly valuable for investigating tightly coupled systems, such as herbivores and their host plants, where climate change may alter spatial associations and interaction dynamics.

In this study, we modeled the potential current and future distributions of *G. belina* and 11 of its primary host plants, including *Colophospermum mopane*, *Sclerocarya birrea*, *Orozoa crassinervia, Senegalia nigrescens, Vachellia karroo, Searsia lancea, Carissa macrocarpa, Ozoroa longipes, Protorhus longifolia, Ficus sycomorus*, and *Terminalia sericea* (Table S1). We also described species-environment relationships for each of these 12 species and identified predictor variables that contribute to their ecological niches. Furthermore, we quantified the degree of ecological niche overlap between mopane moth and the 11 selected host plant species. These integrative species distribution models and niche overlap analyses will increase the understanding of climate change effects on mopane moth and its current and predicted future interactions with its host plants. Key findings will advance scientific knowledge of the

ecosystems in Southern Africa, and support conservation management for this culturally significant and economic insect and its floristic habitats.

2. Methods

2.1 Species occurrence records

We downloaded occurrence records for mopane moth and 11 selected host plants in March – April 2026 from the Global Biodiversity Information Facility (GBIF; https://www.gbif.org/) and used functions in the CoordinateCleaner R package version 3.0.1 (Zizka et al., 2019) to remove records outside of their natural ranges, those associated with botanical gardens and museums, and those with taxonomic and other systematic errors. We limited records to those collected from 1945, removed duplicate records, and spatially thinned the occurrence records using a thinning distance of 10 km; the resulting datasets were used for the distribution models and niche overlap analyses (Table S1; Fig S1 a-k).

2.2 Predictor variables

We downloaded 19 bioclimatic predictor variables (1970–2000) from the WorldClim database (version 2; Fick and Hijmans, 2017) to model the potential distribution of mopane moth and the 11 host plant species. These bioclimatic variables represent 30-year normals of mean and variability for temperature and precipitation (Table 2; O'Donnel and Ignizio, 2012). For each of the 12 species, we used vifstep() function in the usdm R package version 2.1-7 (Naimi et al., 2014) to reduce multicollinearity among the predictor variables, resulting in fewer and less correlated predictor variables (Table S1). For predicting future distributions of the 12 species, we downloaded 19 corresponding bioclimatic variables from the EC-Earth3-Veg (Döscher et al., 2022) global circulation model (GCM) with four shared socio-economic pathway scenarios – 1-2.6, (SSP 126), 2-4.5 (SSP 245), 3-7.0 (SSP 370), and 5-8.5 (SSP585) – monthly averages for the

2061-2080 period. The EC-Earth3-Veg was developed by the European Consortium of researchers using various physical domains and system components describing atmosphere, ocean, sea ice, land surface, and dynamic vegetation (Döscher et al., 2022), and integrated into the Coupled Model Intercomparison Project Modelling in Phase 6 (CMIP6; Eyring et al., 2016). Previous studies have shown that the EC-Earth3-Veg is one of the best performing GCMs for modeling and predicting future African climate (Tagele et al., 2026), North Africa and western Asia (Babaousmail et al., 2021), southern Africa (Addisuu et al., 2025).

SSP 126 predicts future climate with reduced greenhouse gas emission based on sustainable development, international cooperation, lower population growth, improved education, and efficient technology, while SSP 245 represents moderate anthropogenic global CO_2 emissions, associated with 4.5 W/m² of radiative forcing, under the assumption that efforts to reduce emissions would be taken (Riahi et al., 2017; Ziehn et al., 2019a, 2019b). SSP 370 represents regional rivalry where economic competition intensifies across countries and regions, resulting in environmental degradation and increased population growth in the Global South; however, SSP 585 represents the highest projected anthropogenic global CO_2 emissions under various socio-economic and demographic trends (Eyring et al., 2016; Ziehn et al., 2019c). Both the current and future 19 bioclimatic predictor variables were downloaded at 1 km spatial resolution using the geodata R package version 0.6-3 (Hijmans et al., 2025).

2.3 Species distribution modeling

We fitted species distribution modeling (SDMs) for the 12 species at 1 km spatial resolution using random forest (RF), boosted regression trees (BRT), generalized linear regression models (GLMs), and maximum entropy (maxent) in sdm R package version 1.2-55 (Naimi and Araújo, 2016; R Core Team, 2026). Machine learning algorithms such as RF, BRT, and Maxent, are used

for classification and prediction and are widely applied in species distribution modeling. Random forests use the bootstrap aggregation (bagging) method to fit an ensemble of hundreds or thousands of small classification or regression trees using small subsets of predictor variables (Breiman, 2001; Hastie et al., 2009; Strobl et al., 2009; Elith, 2019). RF models are noted for high prediction accuracy and reduced risk of model overfitting in SDMs (Strobl et al., 2009; Mi et al., 2017; Elith, 2019). Boosted regression trees (BRT), also known as gradient boosting machines (GBM), uses the boosting method to iteratively build classification or regression trees using subsets of predictor variables and improving the prediction accuracy based on the model deviance of subsequent iterations (De'ath, 2007; Elith et al., 2008). Maxent was built under the assumption that species distribution data is incomplete, thus it predicts the potential distribution of a species by finding the probability distribution of maximum entropy, such that prediction values of an entire study area are computed based on similarity to the predictor values associated with sites of known species occurrences (Phillips et al., 2006a; Phillips and Dudík, 2008). Maxent is particularly preferred for modeling the distributions of species with fewer occurrences (Elith et al., 2006; Phillips et al., 2006b; Phillips and Dudík, 2008). Generalized linear models (GLMs) is a regression-based model that allows for applying linear models to model and predict non-normal data, such as species binary occurrence data, based on predictor variables using a link function (McCullagh and Nelder, 1989; Hastie and Tibshirani, 1990).

We fitted SDMs for the 12 species using 10 replicates each of the four algorithms, using 70% of the occurrence records for model training and the remaining 30% for independent cross validation. We generated 10,000 background points within the geographical ranges for each species as pseudoabsences, except for *Ozoroa longipes* where 5,000 background points were used to improve model prevalence. Model performance was evaluated using the area under the

curve (AUC) of the receiver operating characteristic (ROC) plot (Hanley and McNeil, 1982), True Skill Statistics (TSS; Allouche et al., 2006), and the Boyce Index (Boyce et al., 2002). We used the jackknife test to evaluate the relative importance of the predictor variables and used partial response curves based on the evaluation strip method to describe species-environment relationships for each of the 12 modeled species (Elith et al., 2005; Phillips et al., 2006a). We generated ensemble prediction maps of continuous probabilities of suitability for the 12 species using the weighted average method based on the AUC metric (AUC > 0.7; Araújo and New, 2007). The continuous probabilities of ensemble prediction maps were discretized into binary suitable and unsuitable habitats using model generated thresholds (Table S1). The current predictions of the 12 species were projected into the four climatic scenarios, and the resulting future ensemble predictions were discretized into binary predicted suitable and unsuitable habitats using the same model generated thresholds used for the SDM predictions for the current conditions. We then quantified the difference between habitat suitabilities of the current conditions and each of the projected habitats under the four SSPs. We quantified the frequency and percentage of the suitable raster cells for the current and future potential distributions based on the four climatic scenarios for each of the 12 species.

2.4 Niche overlap analysis

We investigated similarity between the ecological niches of *G. belina* and its 11 host plants using the centroid, overlap, unfilling, and expansion (COUE) framework (Broennimann et al., 2012). The COUE framework uses principal component analysis (PCA) ordination scores for the predictor variable values associated with the species occurrence points to quantify pairwise niche overlap (Petitpierre et al., 2012; Borokini et al., 2023). We calculated Schoener's *D* niche overlap metric, as well as niche stability, expansion, and unfilling measures. In this study, niche overlap

is the degree of similarity in the ecological niches of the 11 host plants (reference niches) and mopane moth (comparison niche), and it ranges from 0 (no overlap) to 1 (total overlap) (Brown and Carnaval, 2019). Niche overlap was decomposed into stability, which represents similarity in the occupied niche spaces of mopane moth and each of the 11 host plants, while expansion illustrated the ecological niches of the 11 host plants not occupied by *G. belina*. Niche unfilling described niche space for *G. belina* that are available and suitable for the 11 host plants that are yet to be occupied (Guisan et al., 2014). We conducted niche equivalency randomization tests (1000 iterations) to generate random niche overlap values and determine the statistical significance of the observed niche overlap measures under both lower and higher *D* assumptions. Niche overlap analysis was conducted in ecospat R package version 4.1.3 (Di Cola et al., 2017) using the same 19 bioclimatic variables (1970–2000) (version 2; Fick and Hijmans, 2017) used for the SDMs.

3. Results

3.1 What variables contribute to the niches of mopane moth and its 11 host plant species?

Precipitation variables contributed more to the ecological niches of the 12 modeled species. Among the top three precipitation variables with the most contributions, BIO15 (precipitation seasonality) was observed for six species (Figure 2). Additionally, variables that describe extreme precipitation conditions, such as BIO14 (precipitation of the driest month), BIO16 (precipitation of the wettest quarter) and BIO18 (precipitation of the warmest quarter) were notable in their contributions to the ecological niches of the 12 species (Figure 2). Interestingly, precipitation variables alone contributed to the niches of *Gonimbrasia belina* and *Colophospermum mopane* (Figure 2). Temperature variables contributed the most to the niches of six species; specifically, BIO8 (mean temperature of the wettest quarter), representing water

and energy balance for productivity, have an overwhelming major contribution appearing among the top three predictors for nine of the 12 species (Figure 2).

3.2 Species-predictor relationships of G. belina and its 11 host plant species

Probability of occurrences for the 12 species varied considerably among the predictor variables. High occurrence probability of *Carissa macrocarpa* was associated with low BIO2 (annual mean temperature diurnal range), BIO3 (isothermality), BIO8 (mean temperature of the wettest quarter), and BIO12 (annual precipitation) values, intermediate values of BIO19 (precipitation of the coldest quarter), and high values of BIO14 (precipitation of the driest month) and BIO18 (precipitation of the warmest quarter) (Figure 3a), while *Colophospermum mopane* probability of occurrence increased with high BIO6 (minimum temperature of the coldest month) and BIO15 (precipitation seasonality) values, but low BIO13 (precipitation of the wettest month) values (Figure 3b). *Ficus sycamorus* potential distribution was associated with low BIO14 and high BIO3 values, but occurrence probabilities had no relationship with the remaining predictors (Figure 3c); the probability of *Ozoroa crassinervia* occurrence increased with low BIO8 and BIO9 (mean temperature of the driest quarter) values and intermediate values of BIO2, BIO3, BIO15, and BIO18 (Figure 3d), while the probability of *Ozoroa longipes* occurrences had negative relationship with BIO3 but positive relationships with BIO15 and BIO19 (Figure 3e). Furthermore, occurrence probabilities of *Protorhus longifolia* were higher with low BIO8 and BIO15, intermediate values of BIO12, BIO14, and BIO19, and high values of BIO9 and BIO18 values (Figure 3f). The potential distribution of *Sclerocarya birrea* was high with low BIO3, BIO9, and BIO18 values and high BIO8 and BIO15 values (Figure 3g), while the probability of *Siarsea lancea* occurrence had negative relationship with BIO2, BIO3, BIO8, BIO12, and BIO14, and increased with BIO9 and BIO19, but had no relationship with BIO15 and BIO18

(Figure 3h). Moreover, the probability of *Senegalia nigrescens* occurrence was higher with the highest values of BIO8, low values of BIO9, and intermediate values of BIO13, BIO15, BIO18 (Figure 3i), while *Terminalia sericea* potential distribution was higher with low BIO3, BIO14, and BIO19 values, intermediate values of BIO8, BIO16 (precipitation of the wettest quarter), and BIO18 values, and high BIO15 values (Figure 3j). Finally, the occurrence probability of *Vachellia karroo* was associated with higher BIO19 values, intermediate BIO14 values, and low BIO12 and BIO15 values while other variables had no relationship (Figure 3k); occurrence probabilities of *Gonimbrasia belina* increased with higher values of BIO15, lower BIO16 and BIO19 values, and intermediate BIO2, BIO3 and BIO9 values (Figure 3l).

3.3 What algorithms perform the best for the SDMs of the 12 species?

Overall, the machine learning algorithms were superior to the GLM in fitting species distribution models (SDMs), based on test AUC values. Random forest performed the best in the SDMs of five species, maximum entropy was the top performer for four species, while boosted regression trees and generalized linear models performed the best for two and one species, respectively (Table 1). However, BRT failed to run for one of the species with less than 30 occurrences. Additionally, Boyce Index ranged from 0.37 for *P. longifolia* to 0.87 for *F. sycomorus* (Table 1).

3.4 How will climate change influence range shifts in mopane moth and its 11 host species?

Eight of the 12 modeled species, including *G. belina*, were predicted to lose parts of their suitable habitats by the 2061-2080 period. *G. belina* was predicted to lose a major portion of its range, from 56.46% in current conditions to 32.37% in SSP585, with predicted habitat losses in other climate scenarios, especially in the tropical and subtropical areas of central and eastern Africa, while habitats in the arid ecological zones would be relatively intact (Figure 4, Table S3). *C. macrocarpa* was predicted to lose habitat suitability throughout the species range under all

future climatic SSPs (10.92% to 25.97%) with SSP585 having the greatest habitat loss, while the range of *F. sycomorus* was predicted to shrink from 69.93% to 62.81% in SSP 585 with losses expected in the northern edges of the species range in the semi-arid regions of western and northern Africa (Figure 4, Table S3). Our models predicted a major loss of suitable habitat for *O. crassinervia* from 71.91% in current conditions to 22.7% in SSP585, but the species might find climate refugia in the southern edge of its range; however, the optimistic future climatic scenario, i.e., SSP126, was predicted to result in the loss of more than half of current habitat suitability for the species (Figure 4, Table S3). *P. longifolia* was predicted to experience minor loss in habitat suitability, from 19.83% to 18.3% in SSP126 and 19.67% in SSP370, mainly concentrated in the northern edges of the species range, but minor habitat gains were expected in the southern edge of the species range in Southern Africa (Figure 4, Table S3). More than half of *S. lancea*'s current habitat suitability was predicted to be lost by 2061-2080 (from 78.03% in current conditions to 33.79% in SSP585), while *T. sericea* was predicted to lose a major portion of its range from 72.92% to 30.03% in SSP585, with climatic refugia for the species limited to the Kalahari Desert and Okavango Basin and portions of the southeastern Africa (Figure 4, Table S3). *V. karroo* would lose a moderate portion of its range, from 78.69% in current conditions to 57.87% in SSP585, with losses predicted in other future climate SSPs; most of the species' suitability in southern Africa would remain intact with large losses limited to the northern end of the species range (Figure 4, Table S3).

Conversely, four species including *C. mopane, O. longipes, S. birrea*, and *S. nigrescens*, were predicted to gain more suitable habitats by 2061-2080. The suitable habitat of *C. mopane* was expected to increase from 60.35% to between 65.96% in SSP370 to 69.35% in SSP585 (Figure 4, Table S3). While some habitat losses were expected in the northeastern portion of the

species range, major gains were predicted in central and southern portions of the species range (Figure 4, Table S3). Likewise, the range-restricted *O. longipes* was predicted to experience habitat gains mainly in the northwestern side of its range, from 82.62% to 99.37% under SSP585 as with other SSPs, while *S. birrea* was predicted to gain more suitable habitat from 81.67% in current conditions to 92.70% in SSP585 and moderate gains in other SSPs, with habitat gains expected in the southern, central, and eastern ranges while a small loss was expected in the lower Guinean forest ecosystem (Figure 4, Table S3). Finally, *S. nigrescens* was expected to expand its range under warming climatic conditions, from 74.5% in current state to 79.32% in SSP245 but up to 92.74% in SSP370; predicted habitat gains were spatially distributed across southern, central, and eastern ranges, while habitat loss was expected in small areas of the southern and eastern portions of the species range (Figure 4, Table S3).

3.5 Niche overlap between mopane moth and its 11 host plants?

We observed a low ($D \leq 0.3$) to moderate (D=0.4–0.6) niche overlap between the niches of mopane moth and its 11 host plants; Schoener's *D* values ranged from 0.06 in *O. longipes* to 0.65 in *T. sericea* (Table 2; Figure 5). There was statistically significant support for the niche overlap results under low *D* assumption between nine host plants and mopane moth, however, the observed niche overlap values for two species – *F. sycomorus* and *O. crassinervia* – and mopane moth were not significantly different from null *D* distributions (Table 2; Figure 5). The decomposition of the niche overlap showed nonsignificant but relatively high niche stability ranging between 0.26 and 0.98 between each of the 11 host plants and mopane moth, while niche expansion was generally low across most pairwise comparisons, except in *O. longipes* (0.72), *P. longifolia* (0.74), and *C. macrocarpa* (0.46) but all niche expansion values were nonsignificant.

Niche unfilling was low across most pairwise analyses and only significant in *C. mopane* and *S. nigrescens* (both unfilling=0.00, $p<0.001$) (Table 2; Figure 5).

4. Discussion

Climate-driven changes in habitat suitability is expected to reshape the spatial distributions and biotic interactions between the mopane moth (*Gonimbrasia belina*) and its host plants across sub-Saharan Africa. Our results showed that predictor variables representing climatic variability and water-energy balance constrain and contribute the most to the ecological niches of the 12 species. Furthermore, precipitation variables contribute more strongly than temperature predictors to the niches of the mopane moth and its principal host, *Colophospermum mopane*, highlighting the dominant role of water availability and seasonality in structuring this plant-insect interaction. Machine-learning algorithms, particularly random forests and maximum entropy, consistently outperformed the other modelling approaches, confirming their reliable performance in predicting the distributions of species of different ecological attributes and occurrence sample sizes. Future climate projections further revealed contrasting responses among the modeled taxa, with four species predicted to expand their climatically suitable ranges while the remaining eight species, including the mopane moth, are projected to experience varying degrees of range contraction; although, climatically stable refugia persist for all species especially in the southern region of Africa. Finally, niche overlap analyses demonstrated generally low to moderate climatic niche similarity between the mopane moth and its host plants, coupled with high niche stability, suggesting that future persistence of this ecologically and economically important herbivore will not only depend on the continued availability of host plants but also on its ability to track suitable climatic conditions under ongoing climate change.

4.1 Current and predicted future distributions of G. belina and its host plants

Species distribution modeling show that climatic variables representing seasonality, diurnal variability, and water-energy balance contribute the most to the niches of the 12 species. These results support the predictions of the fundamental water-energy balance hypothesis which proposed that species distributions are jointly constrained by water availability and thermal energy required to sustain physiological performance, primary productivity, and population persistence (O'Brien, 1998; Hawkins et al., 2003). Although precipitation variables contributed more to the niches of *G. belina* and *C. mopane*, temperature variables, particularly mean temperature of the wettest quarter (BIO8), were important for many of the remaining host plants, indicating that the interaction between seasonal moisture availability and thermal conditions determines habitat suitability of these species. Precipitation variability and seasonal rainfall patterns strongly influence soil moisture availability, vegetation productivity, and the timing of biological processes in water-limited ecosystems, while temperature is an important driver of phenological timing and developmental processes in interacting species (Knapp et al., 2002; Ogutu et al., 2015; Kharouba et al., 2018; Kalisa et al., 2019). The importance of precipitation seasonality (BIO15) further reflects the dependence of both the mopane moth and several host plants on timing and predictability of seasonal rainfall, which can influence leaf flushing, larval food availability, and reproductive phenology. Likewise, the contribution of variables describing precipitation of the driest month and the wettest or warmest quarters emphasize the ecological significance of climatic seasonality and variability rather than averages in shaping species distributions (Stewart et al., 2021; Karger et al., 2023).

The shapes of the response curves of the occurrence probabilities along the gradients of the predictor variables varied considerably among species, reflecting differences in their relationships with environmental variables, their tolerance limits and climatic niche breadths.

Species may occupy different positions along environmental gradients and may exhibit different response shapes depending on the climatic conditions associated with their occurrence records (Austin, 2007, 2002, 1987; Austin and Smith, 1989) Species exhibiting Gaussian unimodal relationships have optimal persistence at intermediate climatic values, consistent with ecological niche theory (Austin, 2007; Austin and Smith, 1989). Species exhibiting inverse relationship with precipitation variability tend to prefer water all year round and may be found in riparian or wet microclimatic habitats, in contrast to other species, especially, deciduous species, that prefer seasonality of water availability, with high precipitation tied to key physiological functions or life events. Most of the modeled species have high probability of occurrence in areas with low diurnal or seasonal temperature fluctuations, which may indicate their sensitivity to wide temperature variability and extreme weather events that may characterize future climates. Predictors showing little or no response likely represent environmental gradients that do not substantially limit species distributions within the current climatic space, although a weak response does not necessarily mean that the environmental variable has no biological importance (Austin, 2007, 2002).

Our study has shown that climate change is expected to produce both biodiversity winners and losers across Africa, depending on species' ecological characteristics and their capacity to persist under changing climatic conditions (Thuiller et al., 2005; Bellard et al., 2012; Newbold et al., 2020). In this study, *C. mopane*, *O. longipes*, *S. birrea*, and *S. nigrescens* were projected to expand their climatically suitable habitat, whereas the remaining host plants and the mopane moth were predicted to undergo varying degrees of habitat contraction, particularly under the high-emission SSP585 scenario. We observed that the four species predicted to expand their ranges are associated with intermediate to high BIO15 values; this variable, representing

precipitation seasonality, is expected to increase in the future in warmer climates. Therefore, species that are pre-adapted to fluctuating and seasonal water availability will persist under future climate changes. The observed range expansions for *C. mopane* and *S. birrea* in this study is consistent with previous studies that reported increased habitat suitability for these species, even under a different GCM from the one used in this study (Jinga et al., 2022; Kapuka et al., 2022; Jinga and Manyangadze, 2026). Suitable habitat for *S. birrea* subsp. *caffra* was projected to increase by approximately 26-42% by 2050 and 30-45% by 2070, while those of *C. mopane* were predicted to double in southern Africa under climate change (Jinga et al., 2022; Kapuka et al., 2022). Species that are predicted to gain habitat suitability in the future may possess traits enhance environmental resilience, including wider niche breadth and climatic tolerances, phenotypic plasticity, conservative water-use strategies, effective hydraulic regulation, drought tolerance, flexible phenological responses, and the capacity to maintain growth and reproduction under fluctuating resource availability (Nicotra et al., 2010; Valladares et al., 2014; Anderegg et al., 2018). The projected range expansion of *C. mopane* and *S. birrea*, both well known for their adaptation to seasonally dry African savannas is consistent with their ecological capacity to tolerate water limitation and persist under increasingly arid conditions (Makhado et al., 2014; Krug, 2017; Wigley et al., 2026). However, the predicted contraction of mopane moth and several of its host plants indicate range shrinkage in areas where future climatic conditions go beyond their tolerance limits. However, since SDMs are fitted using environmental conditions in the realized niche, a species may still persist in areas where they are predicted to experience climate-induced extirpations if their physiological tolerance limits extend beyond the realized niche, or through phenotypic and phenological plasticity, as well as positive biotic interactions with neighboring plants and below-ground microflora (Wiens et al., 2009; Serafini et al., 2025).

Collectively, these findings support the expectation that climate change responses are strongly species-specific, with some species gaining climatic suitability while others experience range contraction or substantial habitat turnover.

Importantly, all twelve species retained climatically suitable refugia under every future climate scenario, indicating that climate change is more likely to redistribute suitable habitats than eliminate them entirely. These refugial areas are likely to become increasingly important for maintaining viable populations, conserving genetic diversity, and preserving biotic interactions and other ecological processes under changing climatic conditions (Keppel et al., 2012; Morelli et al., 2016). However, climatic suitability alone does not guarantee long-term persistence. Across southern African savannas, increasing drought frequency, wildfire severity and regime changes are expected to alter vegetation structure, productivity, and ecosystem functioning, potentially reducing habitat quality even within areas that are projected to remain climatically suitable (Intergovernmental Panel on Climate Change, 2022, 2023; Pörtner et al., 2022). Furthermore, adaptation to climate change may indirectly intensify human pressure on natural vegetation through increased dependence on fuelwood, charcoal production, and other woodland resources as agricultural productivity declines, accelerating deforestation and habitat degradation (Intergovernmental Panel on Climate Change, 2022; Kissanga et al., 2024). Consequently, the future persistence of the mopane moth and its host plants will depend not only on the availability of climatically suitable habitats but also on maintaining the ecological integrity of these refugial landscapes through integrated climate adaptation, sustainable woodland management, and biodiversity conservation.

4.2 Future of biotic interactions between G. belina and its host plants

Our results suggest that climate change is likely to alter the spatial dynamics of biotic interactions between *G. belina* and its host plants rather than eliminate these interactions entirely. The projected contraction of the climatically suitable range of *G. belina* indicates that portions of its current distribution may exceed the insect's climatic tolerance limits under future warming scenarios. In contrast, the projected persistence and expansion of widely distributed and climate-adapted host species such as *C. mopane* and *S. birrea* suggest that suitable larval food resources will remain available across much of southern Africa and within the insect's range. Consequently, the continued persistence of these host plants could potentially buffer the negative effects of climate change on mopane moth populations, although the future distribution of the insect will ultimately depend on its own climatic requirements and physiological constraints. Moreover, if the host plants exhibit phenological shifts in response to climate change, this may result in significant phenological asynchrony with the life cycle of *G. belina* with negative demographic consequences and threats to established biotic interactions (Van der Putten et al., 2010; Blois et al., 2013).

The niche overlap analyses further provide important insights into the ecological relationships between the mopane moth and its host plants. Schoener's *D* values, ranging from 0.06 to 0.65, indicate low to moderate climatic niche similarity, while significant niche equivalency tests for nine of the eleven host plants demonstrate that these differences are unlikely to have arisen by chance. Rather than indicating identical ecological requirements, the observed low *D* values suggest that the mopane moth and its host plants occupy distinct but partially overlapping climatic spaces, reflecting differences in environmental requirements, physiological responses, and ecological strategies between plants and herbivorous insects. Such ecological niche differences are expected because plants and animals differ in their climatic

requirements and responses to environmental change, while abiotic conditions can simultaneously influence traits and performance across plant-herbivore interactions (Wiens et al., 2010; Peterson et al., 2011; Liu et al., 2020; Hamann et al., 2021). Interestingly, despite *C. mopane* being recognized as the principal larval host and giving the insect its common name, the moderate niche overlap observed between the two species indicates that their climatic niches are not identical. Thus, although the species interact closely through herbivory, their niches are constrained by different ecological factors, which likely explains why the insect is projected to contract while some of its principal host plants expand under future climates. Additionally, low overlap between mopane moth and the host plants means that the insect does not have a specialized relationship with any of the plants. The low *D* significance indicates niche divergences which are associated with different evolutionary histories across taxonomic groups, thus, no co-evolution is implied. The generally high niche stability observed across most pairwise comparisons indicates that the environmental conditions supporting co-occurrence of *G. belina* and its host plants remain relatively similar within the climatic space examined, while using different environmental resources (i.e., low *D* values). High niche stability also suggests stable coexistence in which herbivorous mopane worm feeding does not severely impact the abundance of the host plants, which may be facilitated by species-specific climatic tolerances, host-associated functional traits, and seasonal synchrony between mopane moth development and host-plant resource availability (Visser and Both, 2005; Broennimann et al., 2012; Renner and Zohner, 2018). Nonetheless, we observed lower stability values for *O. longipes* and *P. longifolia* which may indicate weaker or more opportunistic associations with these hosts. The low to moderate niche overlap, together with the high niche stability recorded across several host plants, are consistent with previous evidence that *G. belina* is a generalist, foraging on multiple

host species within its range rather than relying exclusively on *C. mopane* (Sekonya et al., 2020; Meltus et al., 2024).

5. Conclusion

Overall, our species distribution models show that *G. belina* and many of its host plants will lose a large portion of their suitable habitats by 2080 across central and southern Africa, and this may result in noticeable disruptions in the biotic interactions of this insect and its host plants in affected areas. However, stable climatic refugia will remain especially in the southern parts of the distribution ranges of the 12 species, while four host plants will experience range expansions in the same period. Niche overlap analyses show relatively low similarity between *G. belina* and its 11 hosts, indicating that the insect is a generalist that coexists and have widely different ecological requirements from its hosts. This means that mopane moth may form stronger opportunistic biotic interactions with host plants in refugial habitats and with species that adapt to future climate changes. We observed high species occurrence probabilities for intermediate to high precipitation seasonality for the four species that exhibited future range expansions indicating their adaptation to precipitation variability, which is expected to increase in the future. However, climate-induced wildfires and increased reliance on fuelwood for domestic energy may severely impact the habitats of mopane moth and the host plants even in predicted stable areas. Extirpations and demographic bottlenecks for mopane moth will also have profound impacts on the local communities that depend on it for protein and income sources. Therefore, conservation efforts should prioritize the protection of climatically stable refugia, sustainable management of mopane woodlands, restoration of degraded habitats, and the maintenance of diverse host plant communities that support the persistence of mopane moth populations. Climate adaptation efforts that will reduce anthropogenic pressures such as unsustainable harvesting, deforestation, and

uncontrolled wildfires will be essential for maintaining ecosystem resilience under future climates.

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Tables

Table 1. Comparative performance of the four algorithms used for fitting the current and future potential distribution models for mopane moth and the 11 host plants. *RF = Random Forest, BRT = Boosted Regression Trees, GLM = Generalized linear models, Maxent = Maximum Entropy; AUC = Area under curve of the Receiver Operating Characteristic plot, TSS = true skill statistic. NA indicates model failure.*

Species	RF			BRT			GLM			Maxent			Boyce Index
	Training AUC	Test AUC	TSS	Training AUC	Test AUC	TSS	Training AUC	Test AUC	TSS	Training AUC	Test AUC	TSS	
Carissa macrocarpa	1.00	0.86	0.76	0.99	0.86	0.73	0.88	0.68	0.53	0.90	0.72	0.52	0.79
Colophospermum mopane	1.00	0.97	0.9	0.99	0.96	0.9	1.00	0.88	0.79	0.99	0.98	0.95	0.79
Ficus sycomorus	1.00	0.88	0.79	0.99	0.84	0.80	0.99	0.83	0.73	0.94	0.66	0.52	0.87
Ozoroa crassinervia	1.00	0.83	0.68	0.93	0.84	0.72	0.96	0.87	0.75	0.93	0.77	0.63	0.74
Ozoroa longipes	1.00	0.77	0.72	NA	NA	NA	0.86	0.69	0.59	0.86	0.78	0.72	0.64
Protorhus longifolia	1.00	0.98	0.96	0.96	0.96	0.89	1.00	0.95	0.92	0.99	0.98	0.94	0.37
Sclerocarya birrea	1.00	0.73	0.58	0.99	0.66	0.49	0.92	0.79	0.67	0.89	0.84	0.69	0.62
Siersea lancea	1.00	0.84	0.72	0.99	0.84	0.70	0.90	0.79	0.65	0.83	0.67	0.50	0.52
Senegalia nigrescens	1.00	0.80	0.68	0.99	0.83	0.72	0.80	0.54	0.36	0.84	0.56	0.37	0.98
Terminalia sericea	1.00	0.89	0.79	0.91	0.87	0.74	0.88	0.61	0.48	0.89	0.82	0.67	0.66
Vachellia karroo	1.00	0.82	0.68	0.99	0.83	0.72	0.95	0.80	0.64	0.93	0.88	0.77	0.61
Gonimbrasia belina	1.00	0.77	0.64	0.99	0.82	0.68	0.87	0.65	0.49	0.82	0.75	0.57	0.75

Table 2. Results of the niche overlap analysis between mopane moth and the 11 host plants used for food and habitat. *Randomization was based on niche equivalency test with either high or low niche overlap assumptions. D overlap was based on Schoener's D metric.*

Species name	**D overlap**	**Niche stability**	**Niche expansion**	**Niche unfilling**	**Assumption**
Carissa macrocarpa	0.23***	0.54^{ns}	0.46^{ns}	0.00^{ns}	Lower
Colophospermum mopane	0.35***	0.66^{ns}	0.34^{ns}	0.00***	Lower
Ficus sycomorus	0.44^{ns}	0.98^{ns}	0.02^{ns}	0.26^{ns}	Higher
Ozoroa crassinervia	0.24^{ns}	0.82^{ns}	0.18^{ns}	0.01^{ns}	Lower
Ozoroa longipes	0.06***	0.28^{ns}	0.72^{ns}	0.00^{ns}	Lower
Protorhus longifolia	0.18***	0.26^{ns}	0.74^{ns}	0.00^{ns}	Lower
Sclerocarya birrea	0.54***	0.98^{ns}	0.02^{ns}	0.32^{ns}	Higher
Siersea lancea	0.43*	0.73^{ns}	0.27^{ns}	0.03^{ns}	Lower
Senegalia nigrescens	0.53*	0.93^{ns}	0.07^{ns}	0.00***	Lower
Terminalia sericea	0.65**	0.92^{ns}	0.08^{ns}	0.01^{ns}	Lower
Vachellia karroo	0.53**	0.91^{ns}	0.09^{ns}	0.03^{ns}	Lower

***P<0.001, **P<0.01, *P<0.05, ns = not significant

Figures

a) *Carissa macrocarpa*



b) *Colophospermum mopane*



c) *Ficus sycomorus*



d) *Ozoroa crassinervia*



e) *Ozoroa longipes*



f) *Protorhus longifolia*



g) *Sclerocarya birrea*

h) *Siersea lancea*



i) *Senegalia nigrescens*



j) *Terminalia sericea*



k) *Vachellia karroo*



l) *Gonimbrasia belina*





Figure 1. Photos of the 11 host plants (a-k) used by (l) *Gonimbrasia belina* adult moth, with the larval caterpillar, locally known as mopane worm, inserted.

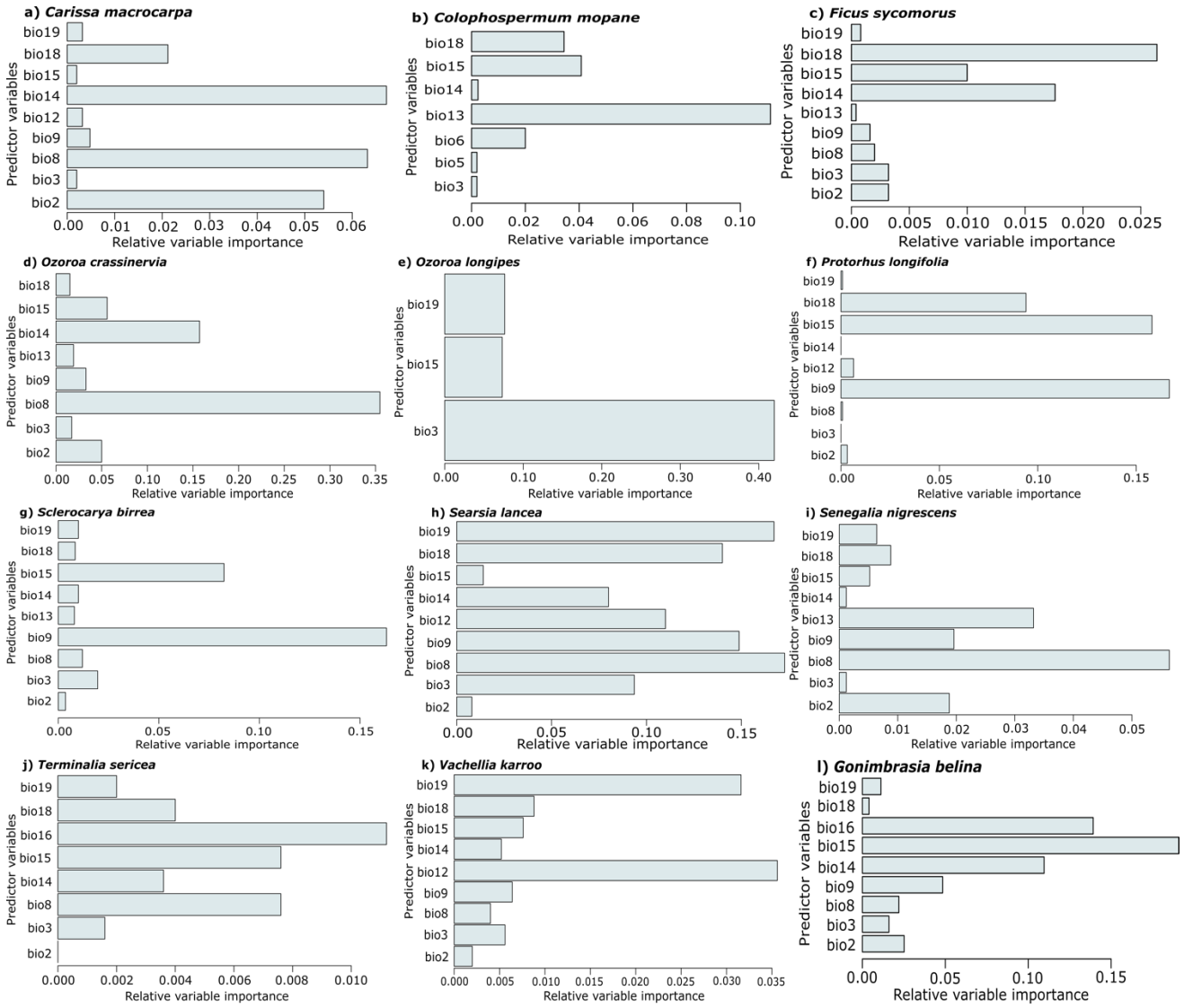


Figure 2. Plots showing the relative contributions of the predictor variables to the predicted distributions of *Gonimbrasia belina* and the 11 host plant species based on the Jackknife analysis. *See Table S2 for the full meaning of the acronyms.*

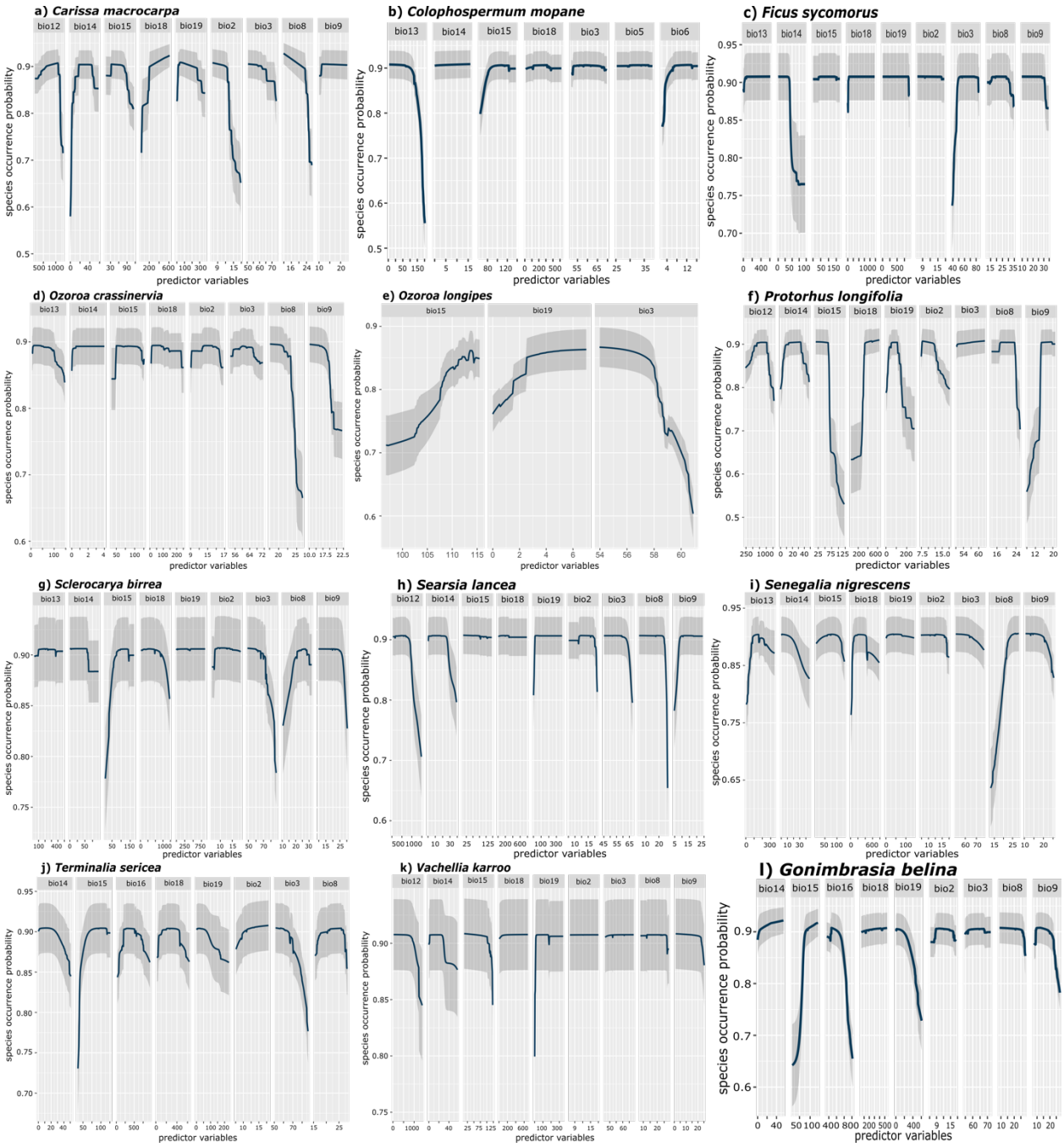


Figure 3. Marginal response plots illustrating the species—environment relationships of the predictor variables used for fitting the distribution models of *Gonimbrasia belina* and the 11 host plant species. *See Table S2 for the full meaning of the acronyms.*

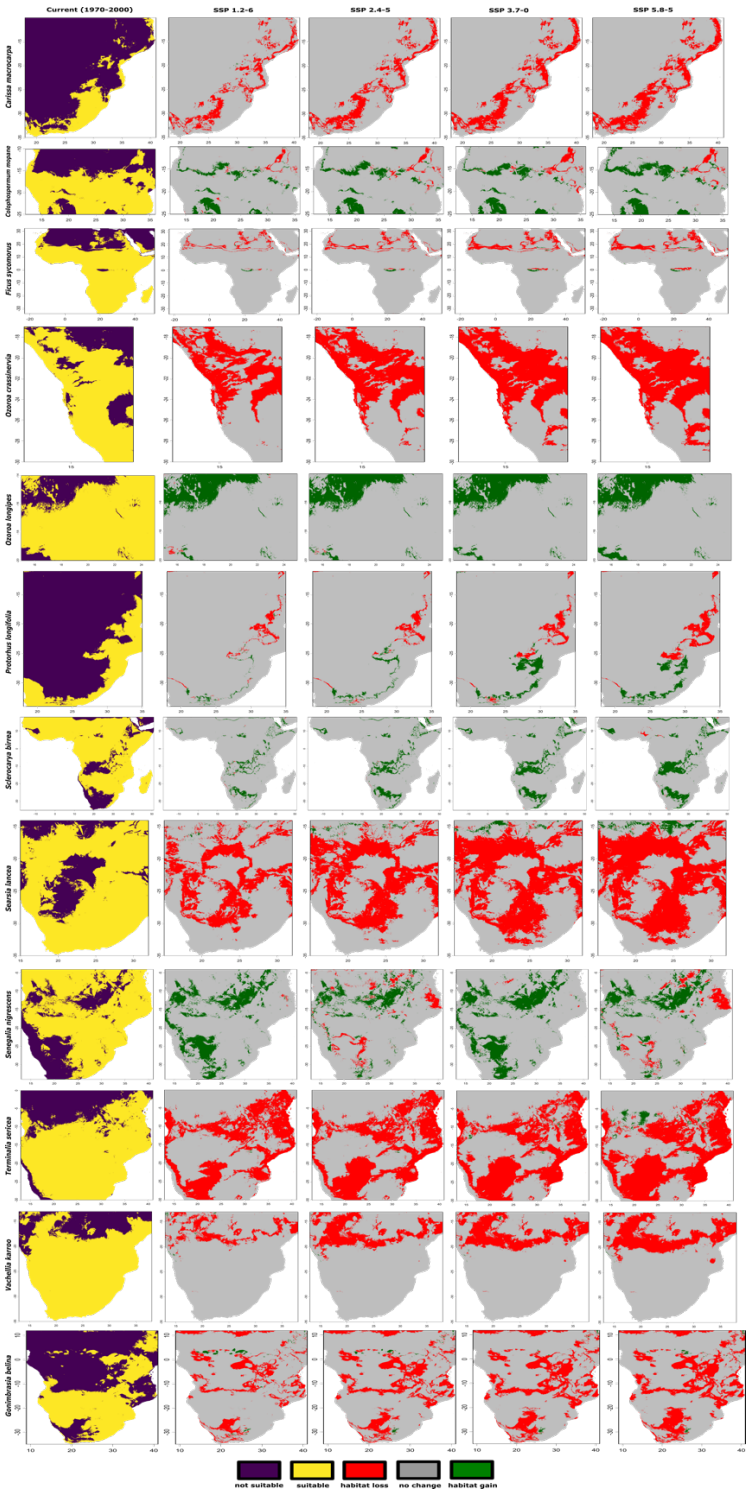


Fig. 4 Plots of binarized habitat suitability maps of *Gonimbrasia belina* and its 11 host plants based on ensemble predictions of the species distribution modeling (left panel), and predicted future habitat suitability changes under EC-Earth-Veg3 general circulation model with four shared socioeconomic pathways: SSPs 1.2-6, 2.4-5, 3.7-0, and 5.8-5 (second to last panels).

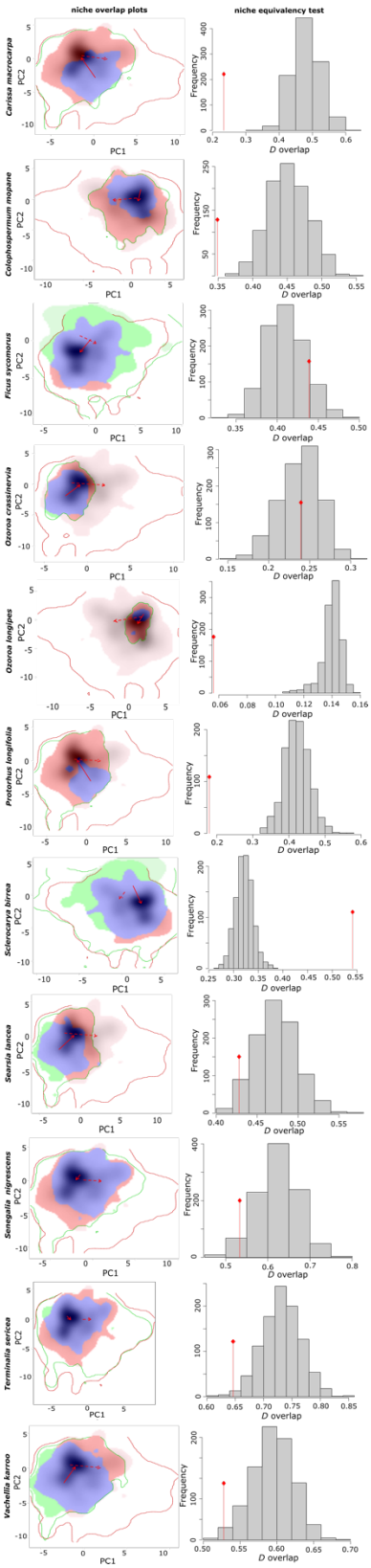


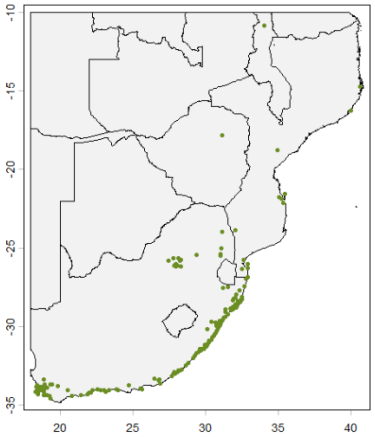
Figure 5. Results of the (a) niche overlap and (b) histograms of the equivalency test between each of the 11 host plants (reference niches) and *Gonimbrasia belina* (comparison

niche) used for food and habitat. ***In the niche overlaps, the blue, red, and green spaces represent areas of niche stability, expansion, and unfilling, respectively. The solid line arrows illustrate the magnitude and direction of centroid shift between the reference and comparison niches, while the dashed line arrows show shifts in the centroids of the overall environmental conditions available to both species. Histogram plots of the equivalency tests show the frequency distributions of the 1000 randomly generated Schoener's D, while the red line with diamond end illustrates the observed niche overlap value for each pairwise analysis. See Table 2 for the D assumptions of equivalency test under which the observed D was statistically significant.***

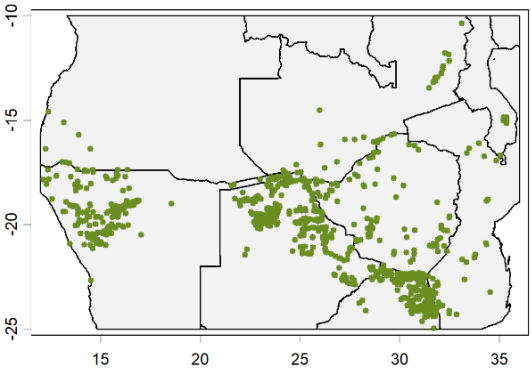
1 **Supplemental Information**

2

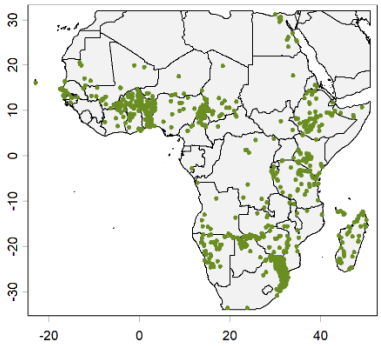
a) ***Carissa macrocarpa***



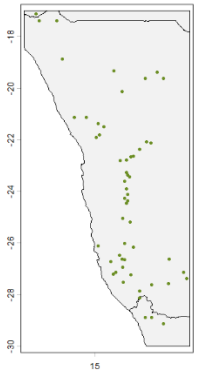
b) ***Colophospermum mopane***



c) ***Ficus sycomorus***

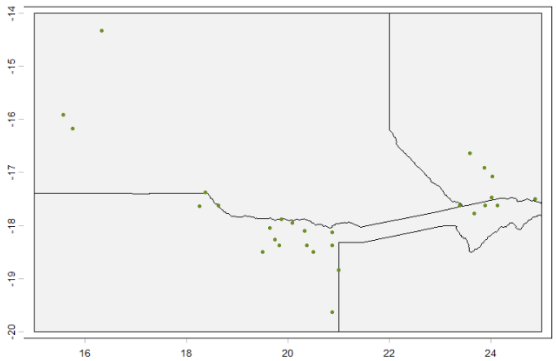


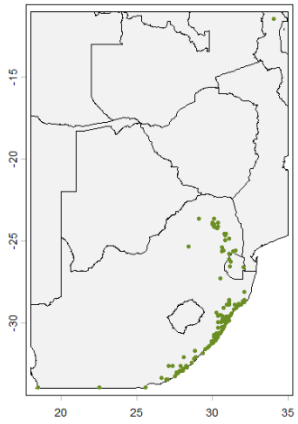
d) ***Ozoroa crassinervia***



e) ***Ozoroa longipes***

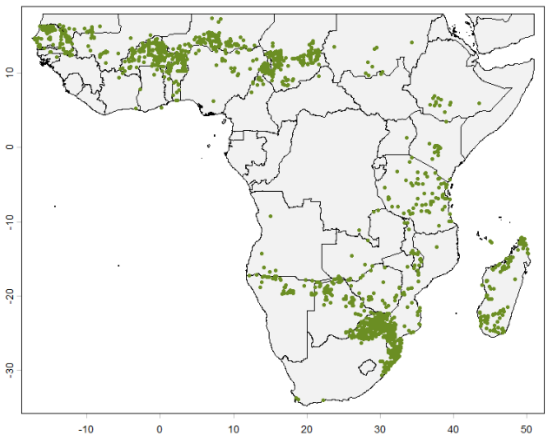
f) ***Protorhus longifolia***



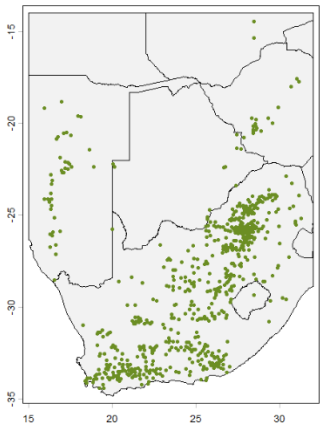


g) ***Sclerocarya birrea***

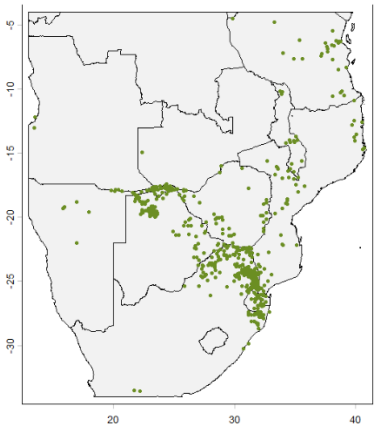
h) ***Searsia lancea***



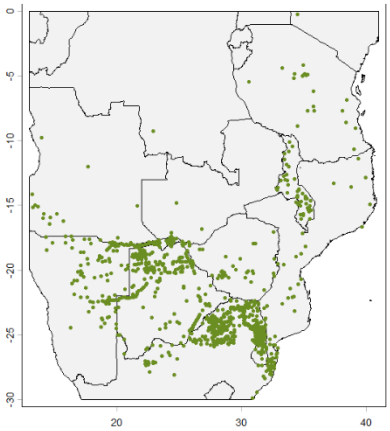
i) ***Senegalia nigrescens***



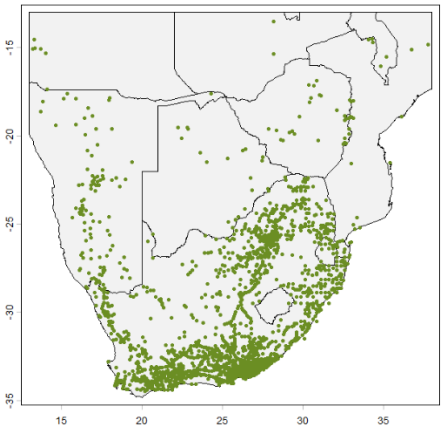
j) ***Terminalia sericea***



k) ***Vachellia karroo***



l) ***Gonimbrasia belina***



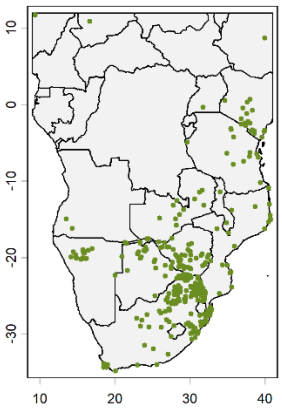


Figure S1. Distribution maps for the 11 host plants (a-k) used by *Gonimbrasia belina* moth (l) for food and habitat. ***The green points represent the occurrence records for each of the species after spatial thinning by 10 km.***

Table S1. List and occurrence data of *Gonimbrasia belina* and its 11 host plants in Africa used for the species distribution modeling, the bioclimatic predictors, and thresholds used to generate binary habitat suitabilities

Species name	Family	Cleaned dataset	Thinned dataset	Bioclimatic predictors†
Carissa macrocarpa (Eckl.) A.DC.	Apocynaceae	1366	157	Bio2, bio3, bio8, bio9, bio12, bio14, bio15, bio18, bio19
Colophospermum mopane (J.Kirk ex Benth.) J.Léonard	Fabaceae	1775	827	Bio3, bio5, bio6, bio13, bio14, bio15, bio18
Ficus sycomorus L.	Moraceae	2114	988	Bio2, bio3, bio8, bio9, bio13, bio14, bio15, bio18, bio19
Ozoroa crassinervia (Engl.) R.Fern. & A.Fern.	Anacardiaceae	74	55	Bio2, bio3, bio8, bio9, bio13, bio14, bio15, bio18
Ozoroa longipes (Engl. & Gilg) R.Fern. & A.Fern.	Anacardiaceae	34	28	Bio3, bio15, bio19
Protorhus longifolia (Bernh.) Engl.	Anacardiaceae	751	115	Bio2, bio3, bio8, bio9, bio12, bio14, bio15, bio18, bio19
Sclerocarya birrea (A.Rich.) Hochst.	Anacardiaceae	3593	1534	Bio2, bio3, bio8, bio9, bio13, bio14, bio15, bio18, bio19
Searsia lancea (L.f.) F.A.Barkley	Anacardiaceae	2173	635	Bio2, bio3, bio8, bio9, bio12, bio14, bio15, bio18, bio19
Senegalia nigrescens (Oliv.) P.J.H.Hurter	Fabaceae	1051	455	Bio2, bio3, bio8, bio9, bio13, bio14, bio15, bio18, bio19
Terminalia sericea Burch. ex DC.	Combretaceae	2299	838	Bio2, bio3, bio8, bio14, bio15, bio16, bio18, bio19
Vachellia karroo (Hayne) Banfi & Galasso	Fabaceae	14562	1574	Bio2, bio3, bio8, bio9, bio12, bio14, bio15, bio18, bio19
Gonimbrasia belina Westwood, 1849*	Saturniidae	688	331	Bio2, bio3, bio8, bio9, bio14, bio15, bio16, bio18, bio19

**Reference insect that depends on the other species for food and habitat*
†See Table S2 for the detailed names of the bioclimatic predictors

Table S2. A list of the 19 bioclimatic variables used for fitting the species distribution models and quantifying the ecological niche overlaps of *Gonimbrasia belina* and its 11 host plants

Bioclimatic variable	Meaning	Scientific unit
Bioclim 1	Annual mean temperature	°C
Bioclim 2	Annual mean temperature diurnal range	°C
Bioclim 3	Isothermality	%
Bioclim 4	Temperature seasonality	°C
Bioclim 5	Maximum temperature of the warmest month	°C
Bioclim 6	Minimum temperature of the coldest month	°C
Bioclim 7	Annual temperature range	°C
Bioclim 8	Mean temperature of the wettest quarter	°C
Bioclim 9	Mean temperature of the driest quarter	°C
Bioclim 10	Mean temperature of the warmest quarter	°C
Bioclim 11	Mean temperature of the coldest quarter	°C

Bioclim 12	Annual precipitation	mm
Bioclim 13	Precipitation of the wettest month	mm
Bioclim 14	Precipitation of the driest month	mm
Bioclim 15	Precipitation seasonality	%
Bioclim 16	Precipitation of the wettest quarter	mm
Bioclim 17	Precipitation of the driest quarter	mm
Bioclim 18	Precipitation of the warmest quarter	mm
Bioclim 19	Precipitation of the coldest quarter	mm

Table S3. Count and percentage of suitable habitat cells based on current and predicted future potential distributions for *Gonimbrasia belina* and its 11 host plants in Africa. ***Threshold represent the model-generated value used to discriminate the continuous probabilities of habitat suitabilities into binary suitable and non-suitable grid cells***

Species name	Threshold	Current model	SSP 126	SSP 245	SSP 370	SSP 585
C. macrocarpa	0.69	1555044 (25.97%)	1008782 (16.85%)	846608 (14.14%)	718083 (11.99%)	653887 (10.92%)
C. mopane	0.84	2937661 (60.35%)	3237377 (66.51%)	3276825 (67.32%)	3210828 (65.96%)	3375828 (69.35%)
F. sycomorus	0.79	27090169 (69.93%)	25654401 (66.23%)	25204755 (65.06%)	24587675 (63.47%)	24330952 (62.81%)
O. crassinervia	0.56	629999 (71.91%)	330726 (37.75%)	255501 (29.16%)	221667 (25.30%)	198873 (22.70%)
O. longipes	0.72	713802 (82.62%)	846468 (97.97%)	850553 (98.44%)	853243 (98.75%)	858581 (99.37%)
P. longifolia	0.61	1008170 (19.83%)	930454 (18.3%)	960624 (18.89%)	1000211 (19.67%)	939112 (18.47%)
S. birrea	0.84	21501313 (81.67%)	22870533 (86.87%)	23614502 (89.69%)	24124175 (91.63%)	24406455 (92.70%)
S. lancea	0.82	3520557 (78.03%)	2392112 (53.02%)	2004441 (44.42%)	1684723 (37.34%)	1524540 (33.79%)
S. nigrescens	0.85	6987059 (74.50%)	8641136 (92.14%)	7438682 (79.32%)	8697997 (92.74%)	7591065 (80.94%)
T. sericea	0.87	7537929 (72.92%)	4063474 (39.31%)	3672294 (35.52%)	3493954 (33.80%)	3104071 (30.03%)
V. karroo	0.81	4593086 (78.69%)	4067409 (69.68%)	3664912 (62.79%)	3542690 (60.69%)	3377943 (57.87%)
G. belina	0.88	9484231 (56.46%)	7209818 (42.92%)	6313235 (37.58%)	5726806 (34.09%)	5437425 (32.37%)

Table S4. Interpretation of the species-environment relationships for the 12 modeled species based on the marginal response curves. ***Interpretations are based on variables for which directional relationship were observed, as plotted in Figure 3.***

Species	Predictor variable	Species-predictor relationship*	Interpretation
Carissa macrocarpa	Annual mean temperature	Low	Preference for low day-night temperature fluctuation and low frost tolerance

	diurnal range (bio2)		
	Isothermality (bio3)	Low	Preference for low temperature variation throughout the year. This is typical of plants growing near the equator
	Mean temperature of the wettest quarter (bio8)	Low	Preference for low temperature in the wettest quarter (June–August). This is a period preceding the flowering season for this species in its native range
	Annual precipitation (bio12)	Low	Combined with its preference for low temperature fluctuation (bio2, bio3) and its mostly coastal geographical distribution, the species may be adapted to maritime climatic conditions which is associated with low precipitation and mild temperatures all year round
	Precipitation of the driest month (bio14)	High	Within the range of this species, January is the driest month during which *C. macrocarpa* fruits (December–May), suggesting important water-energy balance during fruiting
	Precipitation of the warmest quarter (bio18)	High	In its range, warmest quarter (December-February), the species requires high water-energy balance for physiological functions
	Precipitation of the coldest quarter (bio19)	Intermediate	The wettest quarter is also the coldest quarter for *C. macrocarpa*. Combined with preference for low temperature fluctuation (bio2), it shows that the species does not tolerate excess water
Colophospermum mopane	Minimum temperature of the coldest month (bio6)	High	The species does not tolerate low/cold temperature or frost conditions, but also indicating high water-energy balance in this period
	Precipitation of the wettest month (bio13)	Low	The species does not tolerate excess water in January/February when it flowers.
	Precipitation seasonality (bio15)	High	The species prefers seasonality of water availability
Ficus sycomorus	Isothermality (bio3)	High	Preference for high temperature fluctuation throughout the year, which may be associated with the species' wide tropical and subtropical distribution
	Precipitation of the driest month (bio14)	Low	With preference to low precipitation in the driest month, the species is adapted to arid conditions

Ozoroa crassinervia	Annual mean temperature diurnal range (bio2)	Intermediate	Preference for moderate day-night temperature fluctuation
	Isothermality (bio3)	Intermediate	Preference for moderate temperature variation throughout the year.
	Mean temperature of the wettest quarter (bio8)	Low	The species' preference for low temperature in the wettest quarter indicates its tolerance for drought conditions
	Mean temperature of the driest quarter (bio9)	Low	However, the species also does not tolerate extreme drought in the driest quarter
	Precipitation seasonality (bio15)	Intermediate	The species responds well to moderate seasonality of water availability
	Precipitation of the warmest quarter (bio18)	Intermediate	The species grows in alpine areas and rocky slopes and crevices and well-drained soils, which aligns with its preference for moderate water availability in the dry season
Ozoroa longipes	Isothermality (bio3)	Low	Preference for low temperature variation throughout the year, thus requiring yearlong temperature typical of the savanna woodland of south-central Africa. This response may be due to the species' narrow distribution in areas where rivers and other ephemeral waterbodies create microclimates with reduced temperature fluctuations
	Precipitation seasonality (bio15)	High	The species' preference for seasonality of water availability aligns with its habitat conditions
	Precipitation of the coldest quarter (bio19)	High	Requires lots of water in the coldest quarter (June–August) during fruit formation and may be associated with water-energy balance
Ozoroa longipes	Isothermality (bio3)	Low	Preference for low temperature variation throughout the year, thus requiring yearlong temperature typical of the savanna woodland of south-central Africa. This response may be due to the species' narrow distribution in areas where rivers and other ephemeral waterbodies create microclimates with reduced temperature fluctuations
	Precipitation seasonality (bio15)	High	The species' preference for seasonality of water availability aligns with its habitat conditions

Protorhus longifolia	Mean temperature of the wettest quarter (bio8)	Low	The species' preference for low temperature in the wettest quarter indicates its tolerance for drought conditions
	Mean temperature of the driest quarter (bio9)	High	The species is adapted to arid conditions
	Annual precipitation (bio12)	Intermediate	Preference for moderate water availability
	Precipitation of the driest month (bio14)	Intermediate	Species does not adapt to extreme drought and requires some water availability to enhance water-energy balance
	Precipitation seasonality (bio15)	Low	The species requires water availability throughout the year which is associated with its distribution in coastal habitats
	Precipitation of the warmest quarter (bio18)	High	The species needs water even in the warmest quarter and it does not tolerate extreme drought
	Precipitation of the coldest quarter (bio19)	Intermediate	Prefers moderate water availability in the rainy season and it does not tolerate excess water
Sclerocarya birrea	Isothermality (bio3)	Low	Prefers low temperature fluctuation which is typical with the species in tropical and subtropical habitats
	Mean temperature of the wettest quarter (bio8)	High	Indicative of high water-energy balance requirement in the fruiting season
	Mean temperature of the driest quarter (bio9)	Low	While adapted to arid conditions, it prefers ambient conditions in the dry season
	Precipitation seasonality (bio15)	High	The species' preference for seasonality of water availability aligns with its habitat conditions and it may also indicate deciduous behavior
	Precipitation of the warmest quarter (bio18)	Low	Tolerant of arid conditions and it prefers little water in the dry season, which is also indicative of deciduous behavior
Searsia lancea	Annual mean temperature diurnal range (bio2)	Low	Preference for moderate day-night temperature fluctuation which may be associated to its habitat mostly in riparian areas, ephemeral springs, and wetlands

	Isothermality (bio3)	Low	Preference for low temperature variation throughout the year, thus requiring yearlong temperature typical of the savanna woodland of south-central Africa.
	Mean temperature of the wettest quarter (bio8)	Low	The species' preference for low temperature in the wettest quarter indicates its tolerance for drought conditions
	Mean temperature of the driest quarter (bio9)	High	Preference for high temperature in the driest quarter indicative of adaptation to aridity.
	Annual precipitation (bio12)	Low	Pre-adapted to aridity and dry conditions due to secondary access to water in its habitat, despite its evergreen behavior
	Precipitation of the driest month (bio14)	Low	Pre-adapted to aridity and dry conditions due to secondary access to water in its habitat, despite its evergreen behavior
	Precipitation of the coldest quarter (bio19)	High	Requires high water availability during its flowering season which matches the coldest quarter
Senegalia nigrescens	Mean temperature of the wettest quarter (bio8)	High	The species' preference for high temperature in the wettest quarter indicates key physiological or phenological event that require water-energy balance occurs in that season. This is the period the species shift from deciduous phase to flowering
	Mean temperature of the driest quarter (bio9)	Low	Conversely, it does not perform well under extreme arid conditions and this may indicate thermal tolerance limits for the species
	Precipitation of the wettest month (bio13)	Intermediate	Moderate water availability in the wettest month indicates the importance of water during key phenological event but also
	Precipitation seasonality (bio15)	Intermediate	The plant does well under moderate seasonality of water availability hence it may not tolerate extreme precipitation events
	Precipitation of the warmest quarter (bio18)	Intermediate	Since the species is deciduous, it may not require high water content in the dry months
Terminalia sericea	Isothermality (bio3)	Low	Preference for low temperature fluctuation
	Mean temperature of the wettest quarter (bio8)	Intermediate	The species requires ambient conditions in the wettest quarter which is when this species produce fruits

	Precipitation of the driest month (bio14)	Low	Its deciduous behavior indicates no need for water during dry months
	Precipitation seasonality (bio15)	High	Demands for seasonality of water availability indicates the importance of timing for physiological and reproductive functions, as seen in its response to bio8
	Precipitation of the wettest quarter (bio16)	Intermediate	Moderate water during the period it flowers and produces fruits
	Precipitation of the warmest quarter (bio18)	Intermediate	Mild temperature preference in the dry season when it sheds leaves
	Precipitation of the coldest quarter (bio19)	Low	Low tolerance for excess water, a trait found in species adapted to arid or savanna conditions
Vachellia karroo	Annual precipitation (bio12)	Low	Pre-adapted to aridity and dry conditions due to secondary access to water in parts of its range
	Precipitation of the driest month (bio14)	Intermediate	Species does not adapt to extreme drought and requires some water availability to enhance water-energy balance. It does get the needed water from secondary sources near rivers and ephemeral springs
	Precipitation seasonality (bio15)	Low	The species prefers water all year round and this preference may be associated with its riparian habitat and secondary water access
	Precipitation of the coldest quarter (bio19)	High	High demand for water in this period (January–March) aligns with when the species reach peak leaf maturation and parts of the flowering season
Gonimbrasia belina	Annual mean temperature diurnal range (bio2)	Intermediate	Moderate day-night temperature fluctuation
	Isothermality (bio3)	Intermediate	Moderate temperature fluctuation throughout the year indicates physiological limits
	Mean temperature of the driest quarter (bio9)	Intermediate	Tolerance for warm temperatures to moderate limit
	Precipitation seasonality (bio15)	High	Key life cycle events are tied to the seasonality of precipitation which may be used as cue for metamorphic changes

	Precipitation of the wettest quarter (bio16)	Low	This is the period (January-March) when the species transitions from larvae to pupal stage in the ground, hence it requires cool but dry weather conditions. Precipitation in this period, especially February and March can rot the cocoon
	Precipitation of the coldest quarter (bio19)	Low	This is the period (January-March) when the species transitions from larvae to pupal stage in the ground, hence it requires cool but dry weather conditions. Precipitation in this period, especially February and March can rot the cocoon

**Values of predictor variables where the modeled species occurrence probabilities are the highest.*