Heliyon 9 (2023) e17405

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Predicting the potential impacts of climate change on the endangered endemic annonaceae species in east africa

Elijah Mbandi Mkala[a,b,c], Virginia Mwanzia[d], Johh Nzei[a,b,c], Wyclife Agumba Oluoch[e], Boniface K. Ngarega[b,c,f], Vincent Okello Wanga[a,b,c], Milicent Akinyi Oulo[a,b,c], Boniface K. Ngarega[b,c,f], Fredrick Munyao[a,b,c], Flory Mkangombe Kilingo[g], Penninah Rono[a,b,c], Emmanuel Nyongesa Waswa[a,b,c], Elizabeth Syowai Mutinda[a,b,c], Clintone Onyango Ochieng[a,b,c], Geoffrey Mwachala[h], Guang-Wan Hu[a,b,*], Qing-Feng Wang[a,b], Jacinta Kaweze Katunge[a,b,c], Calmina Izabayo Victoire[a,b,c]

[a] *CAS Key Laboratory of Plant Germplasm Enhancement and Specialty Agriculture, Wuhan Botanical Garden, Chinese Academy of Sciences, Wuhan, 430074, China*
[b] *Sino-Africa Joint Research Center, Chinese Academy of Sciences, Wuhan, CN-430074, China*
[c] *University of Chinese Academy of Sciences, Beijing, CN-100049, China*
[d] *Lukenya University, Athi River, P.O Box 90-90128, Mtito Andei, Kenya*
[e] *Center for Development Research – ZEF, University of Bonn, Genscherallee 3, 53113, Bonn, Germany*
[f] *Centre for Integrative Conservation, Xishuangbanna Tropical Botanical Garden, Chinese Academy of Sciences, Menglun, 666303, China*
[g] *UNEP-TONGJI Institute of Environmental Science and Sustainable Development (IESD), Tongji University, Siping Road 1239, Shanghai, 200092, PR China*
[h] *East African Herbarium, National Museums of Kenya, P. O. Box 451660-0100, Nairobi, Kenya*

ARTICLE INFO

Keywords:
Climate change
Conservation management
Ecological niche modeling
Threatened species

ABSTRACT

Globally, endemic species and natural habitats have been significantly impacted by climate change, and further considerable impacts are predicted. Therefore, understanding how endemic species are impacted by climate change can aid in advancing the necessary conservation initiatives. The use of niche modeling is becoming a popular topic in biological conservation to forecast changes in species distributions under various climate change scenarios. This study used the Australian Community Climate and Earth System Simulator version 1 (ACCESS-CM2) general circulation model of coupled model intercomparison project phase 6 (CMIP6) to model the current distribution of suitable habitat for the four threatened Annonaceae species endemic to East Africa (EA), to determine the impact of climate change on their suitable habitat in the years 2050 (average for 2041–2060) and 2070 (average for 2061–2080). Two shared socio-economic pathways (SSPs) SSP370 and SSP585 were used to project the contraction and expansion of suitable habitats for *Uvariodendron kirkii*, *Uvaria kirkii, Uvariodendron dzomboense* and *Asteranthe asterias* endemic to Kenya and Tanzania in EA. The current distribution for all four species is highly influenced by precipitation, temperature, and environmental factors (population, potential evapotranspiration, and aridity index). Although the loss of the original suitable habitat is anticipated to be significant, appropriate habitat expansion and contraction are projections for all species. More than 70% and 40% of the original habitats of *Uvariodendron dzombense* and

* Corresponding author. Chinese Academy of Sciences, Wuhan Botanical Garden, Wuhan, 430074, China.
E-mail address: guangwanhu@wbgcas.cn (G.-W. Hu).

https://doi.org/10.1016/j.heliyon.2023.e17405
Received 20 February 2023; Received in revised form 15 June 2023; Accepted 15 June 2023
Available online 21 June 2023
2405-8440/

Uvariodendron kirkii are predicted to be destroyed by climate change, respectively. Based on our research, we suggest that areas that are expected to shrink owing to climate change be classified as important protection zones for the preservation of Annonaceae species.

1. Introduction

Currently, climate change and anthropogenic factors are the major factors that influence species distribution and habitat on natural ecosystems worldwide [1–4]. Due to temporal reproductive isolation, climate change is known to have an impact on the extinction and regional distributions of different species [5–7]. Because of these complicated changes, species withdraw to locations with conducive macro- and microclimatic conditions [8]. The negative consequences of increased environmental stress become even more concerning when we consider the dynamic changes that are currently occurring in the native ranges of endemic species and the fraction of plant species that may become extinct [9–12]. A thorough understanding of species distribution is usually required before it can be reintroduced in any ecosystem and habitat conservation initiative [13–15]. The loss of any species could have a large impact on ecosystem stability and function [16]. Changes in the distribution ranges of plant species and vegetation patterns, on the other hand, will affect how climate change is experienced across the landscape [17,18]. Thus, for the management of vulnerable species, it is crucial to comprehend how species are distributed within their ecological habitat for developing conservation strategies [19,20].

East Africa is well known for the higher number of Afromontane forests called 'The Eastern Arc Mountains. At least 800 vascular plant species are endemic, with trees accounting for about 10% of these [21,22]. Hundreds of plant species are likewise endangered. Most Eastern Arc endemics are closed-forest specialists with ancient connections to species from West Africa, Madagascar, and even South America and Southeast Asia [23,24]. The existence of endemic floristic features gives this location a unique relict ecosystem that preserves the evolutionary history. The endemic relict flora is thought to be particularly susceptible to climate changes due to its low biotic complexity, which is typically followed by marginal extinction at the warm border of the range and increase at the cold edge [25]. As a result, climate change may endanger the geographical range and habitat appropriateness of many species with high extinction risk, particularly relicts of the Arcto-Tertiary forest, by eradicating their current habitat [26]. Due to the occurrence of indigenous plant species in mountainous regions, EA has high ecological importance. Some of the species that flourish in this area include the Annonaceae species. These species are in grave danger of extinction because they offer important medical characteristics, making their habitat extremely susceptible to exploitation by humans. In addition, overexploitation alters interspecies relationships at various trophic levels, which could have a cascading effect on an ecosystem [27]. The conservation of these species must consider how the distribution of the species may be impacted by various natural and human-caused causes under various climate change scenarios.

The species *Uvariodendron kirkii* Verdc. Ann, *Uvaria kirkii* Oliv. Ex Hook. f., and *Asteranthe asterias* (S. Moore) Engl. & Diels belong to the family Annonaceae and are endemic to Kenya, and Tanzania (EA) [28–30]. Additionally, three newly described and named endemic threatened species (*Uvariodendron mbagoi* Dagallier & Couvreur, *Uvariodendron dzomboense* Dagallier, Q. Luke & Couvreur, and *Uvariodendron schmidtii* Q. Luke, Dagallier & Couvreur) have been discovered in the above-aforementioned regions [31]. The description of these new species emphasized how abundant the endemic species are in this area. Their natural habitat is subtropical or tropical dry forests. Following IUCN criteria, *Uvariodendron kirkii* is listed as vulnerable (VU) while *Uvaria kirkii* and *A. asterias* as near threatened (NT). These species are exploited for medicinal and economic uses [29,32–39]. Thus potential primary sources of new herbal products and medicines [40,41], contributing significantly to human health and the economy in developing countries [42,43]. Effective conservation measures can guarantee the long-term viability of species [27,44,45].

One of the fundamental strategies for protecting plant species is habitat restoration, which necessitates correct knowledge of species distributions in each ecosystem both current and in the future [46,47]. Therefore, one of the primary problems for ecologists is to comprehend how species interact with the environment and predict how they will change. To avoid the extinction of threatened species in response to climate change [48–50]. As a result, predicting viable habitats under climate change gives critical information for the conservation of rare and endangered species.

The major issues facing biological science are the estimation of species diversity and the explanation of evolutionary processes [51]. Environmental factors and climate change have a significant impact on how species disperse, migrate, evolve, adapt, and go extinct [49,52]. Species Distribution Modeling (SDM) is a geographically explicit approach that integrates species occurrence data with environmental variables to produce spatially explicit and thorough maps that are useful for identifying regions that require the most conservation and management solutions [53,54]. SDM is a strong approach that has been used to predict past distributions of relict species in relevant regions, forecast their current prospective distribution range, and predict susceptibility to future climate change [55]. This model is valuable for anticipating conservation regions (particularly zones for species protection, restoration, translocation, and reintroductions) and for addressing questions about niche evolution trends [56]. To the best of our knowledge, no research has been conducted to investigate how global climate change might affect the distribution of threatened endemic Annonaceae species. Therefore, we utilized the power of algorithms in SDMs to develop a model to show the relationship between the species occurrence points and environmental predictors, and further project into future scenarios [57–59]. We shall apply two shared socio-economic pathways (SSPs) SSP370 and SSP585 to project the species distribution for the years 2050 (average for 2041–2060) and 2070 (average for 2061–2080) [60]. The predictions will be made using Coupled Model Intercomparison Project 6 (CMIP6) using the Australian Community Climate and Earth System Simulator version 1 (ACCESS) general circulation model (GCM), a technique for setting the land surface temperatures within a global climate model [61]. This will enable us to; (a) investigate how climate change will affect the distribution of different endemic species under different climate change scenarios, (b) identify more vulnerable endemic species under changing climate scenarios to prioritize conservation on a national scale, and (c) find potentially suitable areas for species whose main habitats are under threat from future climate conditions.

2. Methodology

2.1. The study area

The Eastern Arc Mountains are home to an estimated larger number of indigenous flowering vascular plants that are vulnerable to climate change. Many synoptic weather stations in East Africa have recorded rising temperatures over the past several decades. The mean annual temperatures in the study area range from 12.4 to 24.1 C (mean, 20.7 C; WorldClim interpolated climatology; Hijmans et al. [62]. The Eastern Arc Mountains have a greater number of indigenous flowering vascular plants that are vulnerable to climate change. Increasing temperatures have been reported at several synoptic weather stations in East Africa during the previous decades. The warmest months are November through March, with the mean daily maximum on lower slopes topping 34 °C. The coolest months are June through August when the mean daily minimum drop below 5 °C at high elevations. The slopes near the Indian Ocean are several degrees cooler than comparable altitudes elsewhere. The temperature of the air in the understory varies with the distance from the forest border and the amount of solar radiation that penetrates the canopy.

3. Materials and techniques

3.1. Species distribution and bioclimatic information

Distribution data for *Uvariodendron kirkii, Uvaria kirkii*, *Uvariodendron dzomboense,* and *Asteranthe asterias* were obtained from the Global Biodiversity Information Facility (GBIF), (http://www.gbif.org/; assessed on June 5, 2022) using the *gbif* function of the dismo package [62]. All entries were validated using record identifiers, and herbarium information. Six hundred and one geo-referenced occurrence points for the four species were acquired, and their accuracy was carefully examined visually in Microsoft Excel spreadsheet version 16.66.1. The merged distribution data set were cleaned for inaccuracies such as coordinates projected in water bodies were discarded (not used in this analysis). The spThin package in R was used to spatially thin the occurrence points to a distance of 5 km between each point to prevent spatial biases [63], since historical distribution data is typically skewed toward places that are convenient to reach, leading to significant geographic sampling bias [62]. We performed spatial thinning of 5 km because the number of species reported in this study is low. After all, the species are threatened and endemic to specific locations. Thus, performing spatial

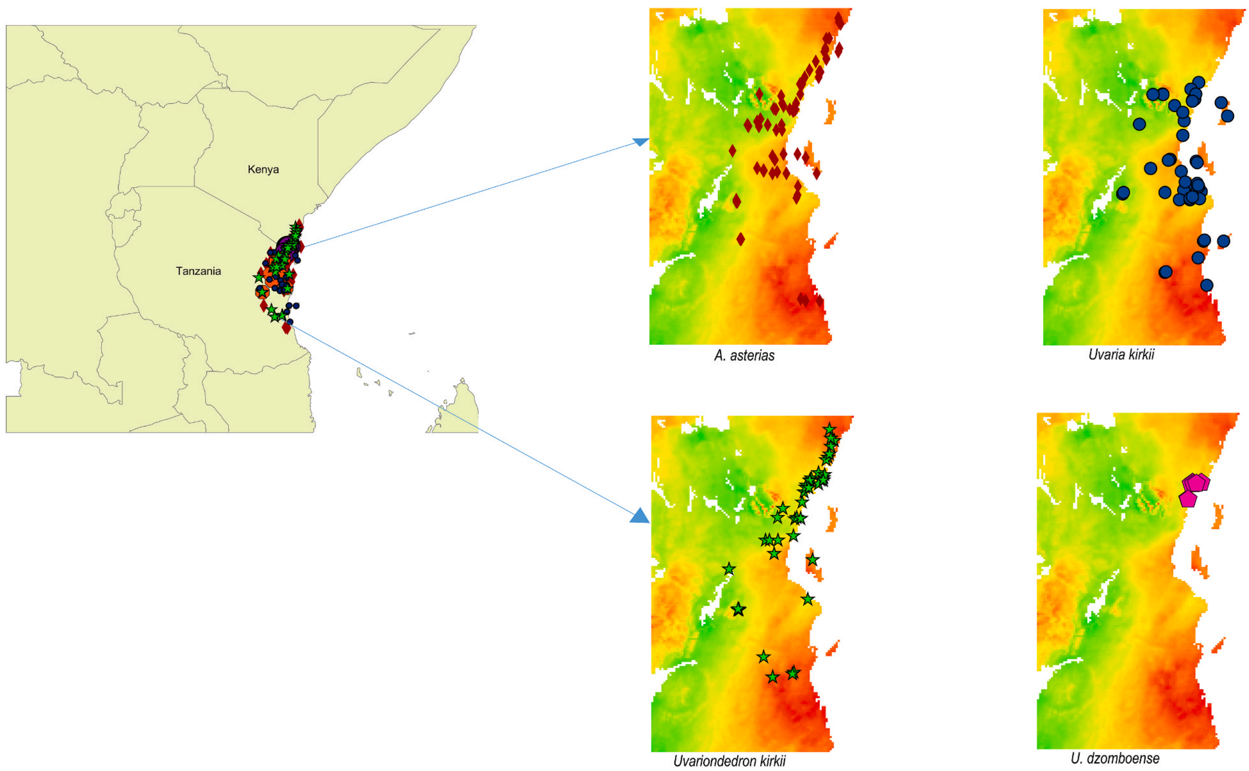

Fig. 1. Maps showing the distribution points for the four Annonaceae species; distributed in Kenya and Tanzania.

thinning over 5 km would result in less data being used for this analysis. Finally, two hundred and forty-two occurrence points (89 for *A. asterias*, 61 for *Uvariodendron kirkii*, and 82 for *Uvaria kirkii* and 10 for *Uvariodendron dzomboense*) were retained for further analyses (Fig. 1). Notably, we only included *Uvariodendron dzomboense* from the three newly discovered threatened species. We left *U. mbagoi*, and *U. schmidti* in this study because they recorded less than ten correct occurrence points (most of the coordinates reported were of the same location points this could lead bias our results). The bioclimatic variables (19) were obtained from the Worldclim database (www.worldclim.org; accessed on June 12, 2022) at a spatial resolution of 2.5 arc-min (roughly 5 km at the equator), using the *getData* function in raster package version 3.5.15 integrated into the R environment [62,64]. Four additional environmental factors including population density, land cover, aridity index (AI), and evapotranspiration (ET)) were incorporated in the analysis because they are likely to affect species distribution and their suitable habitat. In addition, land cover was included as a variable in the model, and was considered as a categorical in the model and hence not evaluated as a continuous variable in the model. The two shared socio-economic pathways (SSPs) SSP370 and SSP585 were used to project the species distribution for the years 2050 (average for 2041–2060) and 2070 (average for 2061–2080) [60]. The predictions were made using Coupled Model Intercomparison Project 6 (CMIP6) for the Australian Community Climate and Earth System Simulator version 1 (ACCESS) general circulation model (GCM), a technique for setting the land surface temperatures within a global climate model (Ackerley and Dommenget, 2016). To obtain the 19 bioclimatic variables from the combined data. We used ArcGIS to extract the 19 bioclimatic variables from the downloaded compilation. We also used ArcGIS to define the projection of our extent before using them in our analysis.

3.2. Environmental variable considerations

While minimizing inter-variable correlation to reduce the impact of highly linked variables, we selected 23 parameters while reserving 10 variables that are likely to have a direct physiological effect on the species. Considering the pairwise correlation between the predictors, we used two correlation metrics to analyze the relative variable importance for all bioclimatic variables for the species independently (Pearson Correlation and Area under the Curve (AUC)) to analyze the relative variable importance for all bioclimatic variables for the four Annonaceae species. This is significant since these species are found in the tropical region, and their significant water loss and conservation are linked to the environmental condition of the region, thus this element was taken into account. We chose the environmental predictors that were most likely to limit the species distribution from among the factors that passed the two correlation measurements. These factors included population density, aridity index (AI), and evapotranspiration (ET). To minimize inter-variable correlation we performed variance inflation factor (VIFstep: $r = 10$) using the *usdm* r package in R [65]. This process was repeated until all VIF scores were under 10. The variables analyzed for the environment were selected to reflect the circumstances faced by the species. The four interactive bioclimatic variables mean temperature of the wettest quarter (bio 8), mean temperature of the driest quarter (bio 9), precipitation of the warmest quarter (bio18), and precipitation of the coldest quarter (bio19) were not excluded before this analysis. Thus, included these variables in our analysis, which did not contain any unusual spatial patterns were retained in our analysis. The bioclimatic variables were then used for the subsequent analysis. Among the 23 variables analyzed, 13 were retained and considered to have a direct physiological effect on the species (Table S1-S4). The relative variable contribution of the selected variables to the models was accessed among the three species independently using Pearson Correlation and Area under the

Table 1
Mean model performance of the species according to MaxEnt, generalized linear model, boosted regression trees, Random Forest and support vector machines algorithms for the AUC, correlation (COR), and TSS, as well as the deviance, are reported. The average value for each method is displayed.

Species	Methods	AUC	COR	TSS	Deviance
Uvariodendron kirkii	**Rf**	0.94	0.64	0.82	0.18
	Maxent	0.94	0.43	0.83	0.41
	glm	0.93	0.36	0.79	0.22
	brt	0.93	0.55	0.77	0.21
	svm	0.73	0.37	0.6	0.3
Total Average		**0.89**	**0.47**	**0.76**	**0.26**
Asteranthe asterias	**Rf**	0.96	0.65	0.86	0.2
	Maxent	0.93	0.49	0.76	0.46
	glm	0.9	0.43	0.71	0.3
	brt	0.94	0.61	0.8	0.27
	svm	0.85	0.42	0.67	0.35
Total Average		**0.91**	**0.52**	**0.76**	**0.31**
Uvaria kirkii	**Rf**	0.89	0.56	0.76	0.2
	Maxent	0.89	0.37	0.69	0.46
	glm	0.84	0.23	0.61	0.27
	brt	0.89	0.43	0.73	0.24
	svm	0.8	0.4	0.69	0.3
Total Average		**0.86**	**0.39**	**0.69**	**0.37**
Uvariodendron dzombense	Rf	0.99	0.7	0.99	0.04
	Maxent	0.98	0.42	0.98	0.14
	glm	0.98	0.27	0.97	0.05
	brt	0.98	0.32	0.97	0.06
	svm	0.99	0.29	0.99	0.09
Total Average		**0.98**	**0.4**	**0.98**	**0.076**

curve (AUC) metrics. The data sources and code used (GitHub link) for this analysis are included in the supplementary material (S. A1 and S.A2).

3.3. Modeling technique

Several modeling techniques have been applied in the modeling processes to assess species distribution and habitat preferences [66, 67]. These algorithms completely depend on the level of complexity, appropriateness, predictive power, and capability to incorporate presence-only data because of limited access to absence data. In this study, we used five modeling methods; Generalized Linear Models (GLM), Boosted Regression Trees (BRT), Multivariate Adaptive Regression Splines (MARS), Maximum Entropy (MaxEnt), and Random Forest (RF) for their performance [68] in R environment [65], to identify the methods with the highest statistical accuracy. The models were then ensembled per species using the sdm package version and weighted average (Table 1) [65].

3.4. Model evaluation

For all models, evaluation data was gathered using the *getEvaluation* function from sdm package in the R environment. To evaluate the predictive effectiveness of the ecological niche modeling, we measured the area under the receiver operating characteristic curve (AUC-ROC) and the true skills statistic (TSS) (Table 1; Fig. S2) [69–71]. TSS was used to see if our results confirm with AUC- ROC. AUC values varying from 0 to 1 with 0.5–0.6 indicate poor model performance, 0.7–0.9 represent good performance, and >0.9 show excellent model performance [56]. TSS values below 0.40 indicate poor model performance, 0.40 to 0.75 indicate good model performance, and above 0.75 indicate outstanding model performance [56]. The TSS measure also ranges from - 1 to +1 [72]. These methods are the true measure of excellent results and have been widely used to calibrate and identify fundamental model requirements in numerous studies [73,74]. Each modeling approach was tested 2 times, using 30% of the data for testing and 70% of the data for training. We ran 20 ecological niche models (ENMs) with 2 algorithms and 10 replicates for each species' dataset to evaluate the models. Model averaging was carried out by weighting individual model projections by their AUC values after excluding models with an AUC of below 0.6 an approach that has shown to be very resilient [75]. An ensemble model was created using a TSS-weighted average [69].

3.5. Changes in distribution within binary models

The current and future output raster files were converted to binary file format using SDMTools extension in ArcGIS version 10.8 [64], using 10% training points criteria as the most precise and cautious threshold for differentiating between suitable and unsuitable regions [76,77]. The binary maps were therefore used to access the suitability habitat change for the two SSPs and periods, by calculating the difference between the SSPs and the current maps to generate change maps including stable habitat, habitat gain, habitat loss, and unsuitable habitat SDMTools extension in ArcGIS version 10.8 [64].

4. Results

4.1. Species distribution map in east africa

The colours represent the species distribution in the background map of East Africa as indicated with arrows: green (*Uvariodendron kirkii*), brown (*Asteranthe asterias*), blue *(Uvaria kirkii*) and pink (*Uvariodendron dzombense*).

4.2. Bioclimatic variables affecting suitable habitat distribution of the species

According to vif scores, variables; evapotranspiration (ET), aridity index (AI), population density (population), mean diurnal range (Mean of monthly (maximum temperature - minimum temperature)) (bio 2), isothermality (bio 3), temperature seasonality (bio4), Minimum Temperature of Coldest Month (bio6), the maximum temperature of the warmest month (bio 5), temperature annual range (bio7), mean temperature of warmest quarter (bio 10), annual precipitation (bio 12), precipitation of the wettest month (bio 13), precipitation of the driest month (bio14), precipitation seasonality (bio15), precipitation of driest quarter (bio 17), Precipitation of Warmest Quarter (bio18), Precipitation of Coldest Quarter (bio19) were selected variably among the species for building the models (Table S1-S4). The AUC values and TSS values above (0.7) indicated the models performed (Table 1). In addition, the relative variable contribution varied across the species and between correlation metrics and the AUC metric (Table S1-S4). Based on the averaged correlation metric the current distribution model for *Asteranthe asterias* indicated a greater contribution of bio19 (34.9%), followed by bio15 (26.3%) and AI (14.2%), for *Uvariodendron kirkii*; bio19 (48.9%)) bio15 (13.9%), and AI (19.2%), for *Uvaria kirkii*; population (30.2%), bio7 (19.9%), bio14 (15.1) and bio15 (14.9%), for *U. dzombense*; bio6 (68.4%), evapotranspiration (33.3%), bio4 (33.6%) and population (26.7.2%) were the major contributors to the model (Table S5). The combined metric relative contribution of the variables is shown (Fig.S1).

4.3. Model performance according to the algorithms applied

Species distribution models for current distribution predicted regions of climatic suitability for *Asteranthe asterias, Uvariodendron*

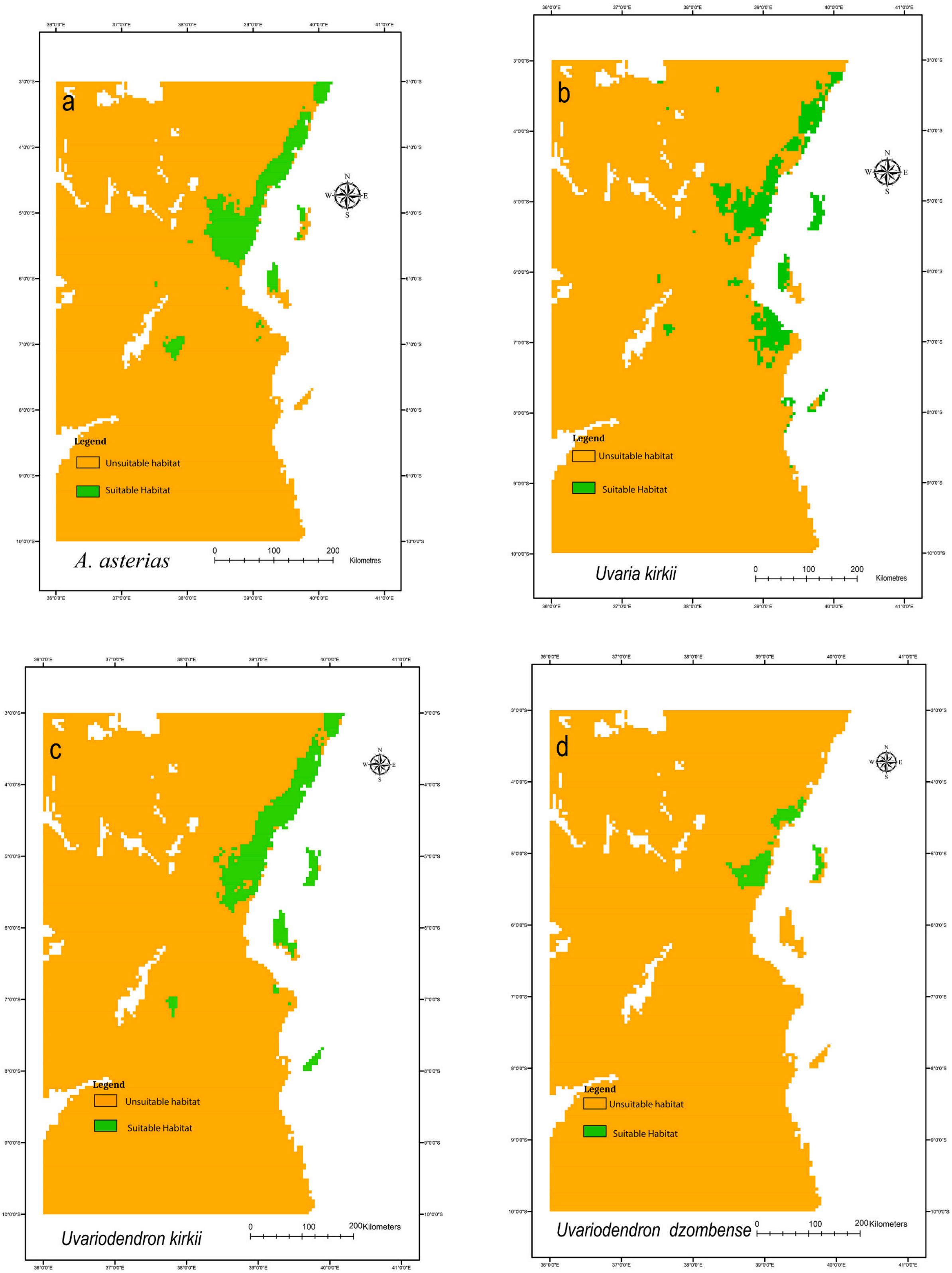

Fig. 2. Currently projected habitat suitability maps indicate the distribution of the species along Kenya and Tanzanian coastlines.

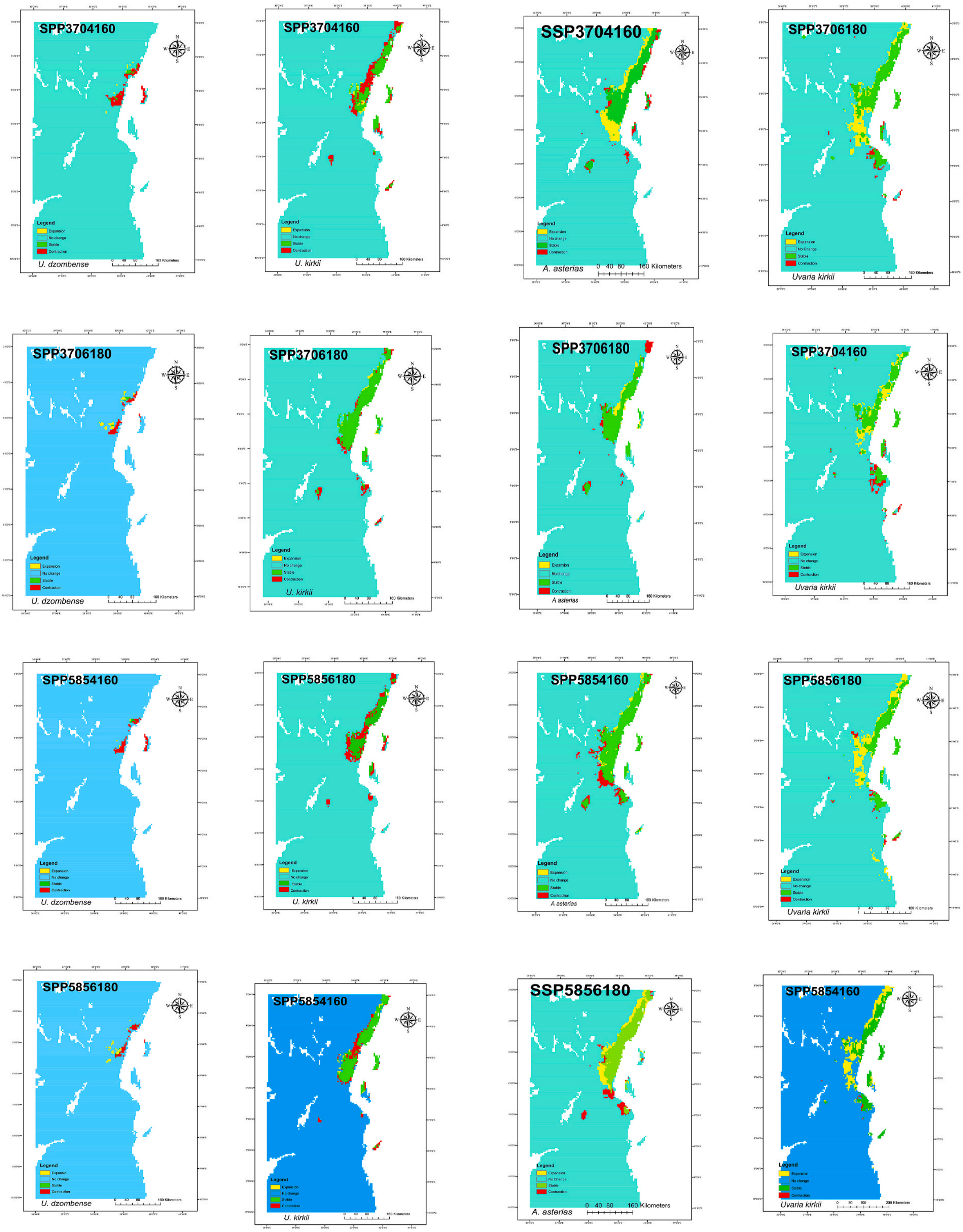

Fig. 3. The projected future suitable habitat distribution areas for the four *Annonaceae* species in East Africa (Kenya and Tanzania) projected using SSPs scenarios (SSP370 and SSP585) for the averaged years in 2050 (average for 2041–2060) and 2070 (average for 2061–2080). Suitable habitats for the species are shown; with green color, unsuitable habitats (contraction) with red color, and expansion is shown with yellow color. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

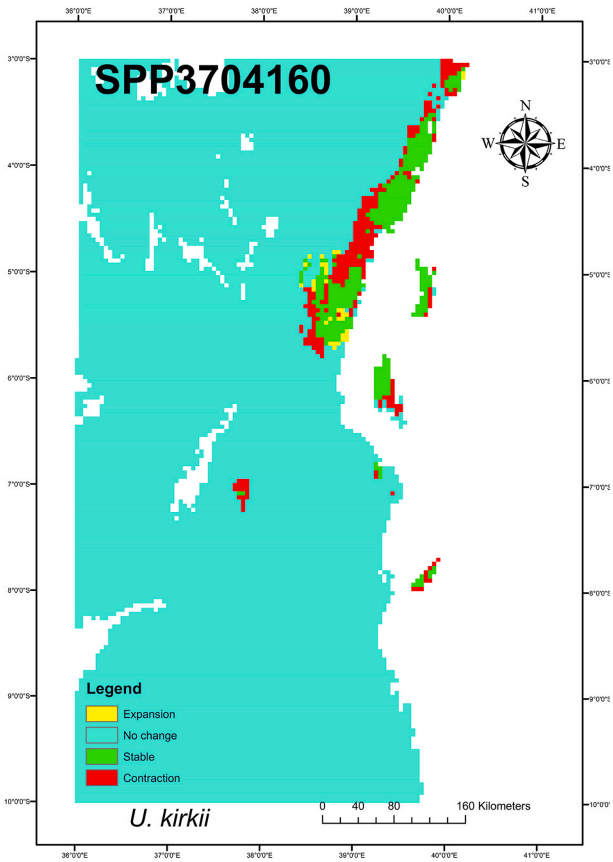

Fig. 3. (*continued*).

kirkii, U. dzombense, and *Uvaria kirkii* with 100% run success for 20 models. The AUC score for each of the species modeling was above 0.8, indicating that models of these data sets performed better than a randomly chosen absence site indicating a high model performance (Table 1). The best algorithms, which performed perfectly well for all species, were the Maxent, Random forest, and boosted regression trees. The other two methods support vector machines and generalized linear model performed poorly (Fig.S2).

4.4. *The current potential suitable habitats areas for the four annonaceae species*

(Fig. 2). The models project higher distribution in Tanzania, especially for *Asteranthe asterias* (Fig. 2a), *Uvaria kirkii* (Fig. 2b), *Uvariodendron kirkii* (Fig. 2c) compared to *Uvariodendron dzombense* (Fig. 2d). Suitable habitats for the species are indicated with green color and no occupancy is indicated with brown color.

4.5. *The projected habitat distribution change for the annonaceae species*

Changes in habitat suitability in the future for the four Annonaceae species is projected in (Fig. 3). Notably habitat suitability change is projected in both SSPs. The future projections indicate that *Uvariodendron dzombense* will be highly affected by climate change in the future, followed by *U. kirkii*, *A. asterias,* and lastly by *Uvaria kirkii*, scenarios for *U. dzombense,* indicate more habitat loss (color red) in both Kenya and Tanzania than habitat gain (yellow color). For the *U. kirkii*, it will also experience high habitat loss at the periphery and the center between Kenya and Tanzania, and there will be more habitat loss in SSP5854160 and SSP5856180. In addition, habitat gain for *U. kirkii* is projected in all scenarios at the periphery of Kenya and shall be minimal. The projection for the *A. asterias* indicates more habitat loss (contraction) also at the periphery of Tanzania compared to Kenya in SSP5854160 and SSP5856180 compared to SSP3704160 and SSP3706180 (Table S6). However, the future projection indicates a persistent gain of suitable habitats compared to habitat loss in SSPs (SSP3704160 and SSP5856180) compared to SSPs (SSP3706180 and SSP5854160). Lastly, the projections for *Uvaria kirkii* indicate in all SSPs it will experience persistent gain of suitable habitats in Tanzania compared to Kenya. The percentage habitat loss is projected to be above 70% for *Uvariodendron dzombense*, whereas *Uvariodendron kirkii* (30%)*, A. sterias* (14%), and *Uvaria kirkii* (6.25%) in both SSP370 and SSP585 (2050). *Uvaria kirkii* and *A. sterias* suitable habitats are likely not to be affected by climate change compared to the *Uvariodendron dzombense* and *Uvariodendron kirkii* species, which indicate high contraction. The percentage of expansion of *Uvaria kirkii* was found to be highest (35.5%), followed by *A. sterias* (16.5%) when compared with *Uvariodendron dzombense* and *Uvariodendron kirkii* in all averaged SSPs (Fig. S3). Finally, the species habitat projection further indicates to have future greater habitat suitability areas in Kenya compared to Tanzania. In addition, they will colonize new areas in the west and north of Kenya and Tanzania respectively.

4.6. Ecological niche

The four species' two-dimensional ecological niche maps were created using the *niche* function in sdm package version 1.1–8 and the first two most contributing predictor variables (Fig. 4). The map indicates the distribution of the species in the environmental space. The ecological niche model showed significant correlations between the predicted environmental suitability and the actual distribution of the simulated species, which was constructed using the locations of the original occurrence, indicating good model performance (Fig. 4).

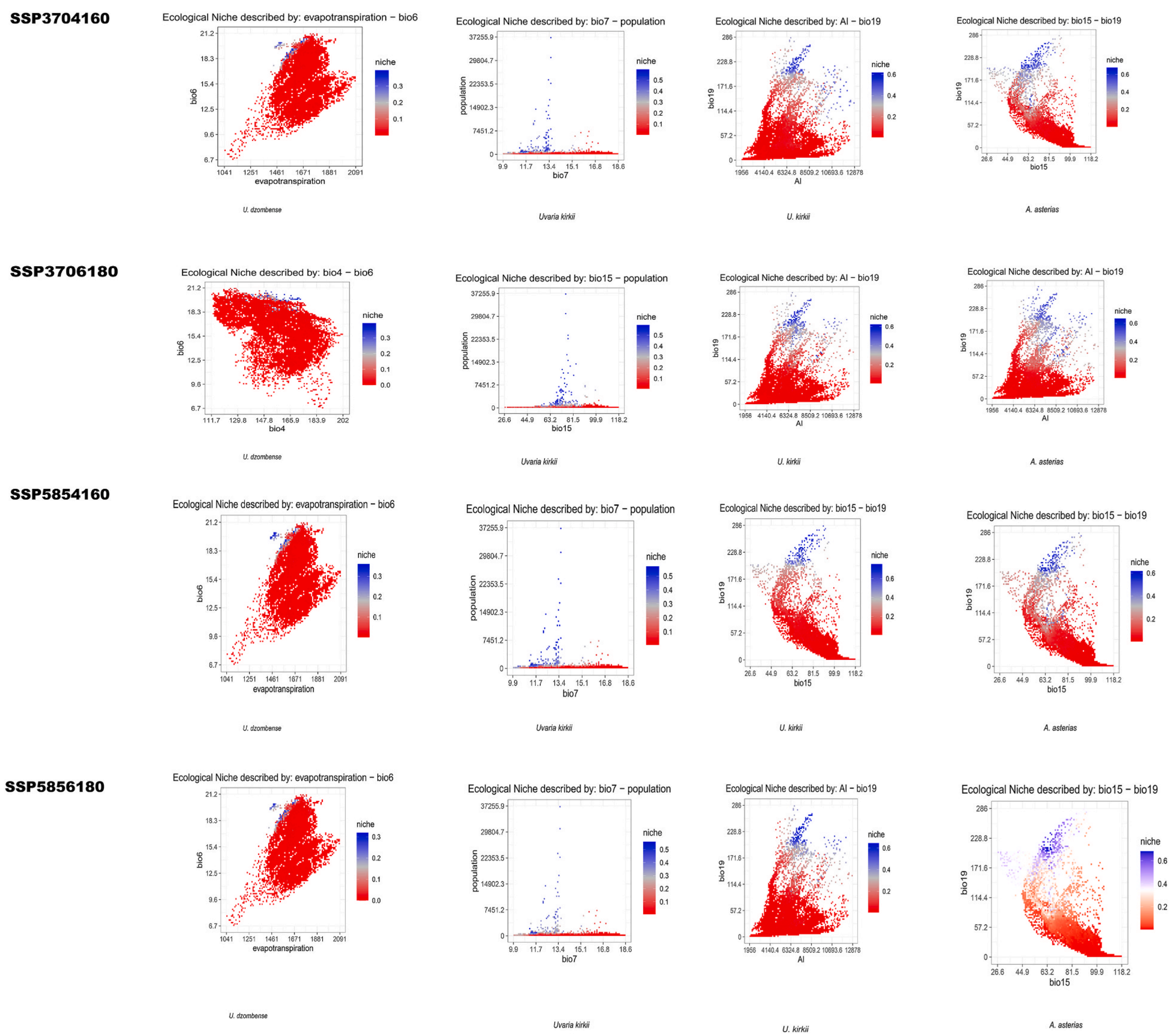

Fig. 4. The two-dimensional ecological niche visualization for *Uvariodendron dzombense, Uvaria kirkii, Uvariodendron kirkii*, and *Uvaria kirkii*, using the most contributing variables; Isothermality (bio6), evapotranspiration, mean Diurnal Range (bio4), temperature annual range (bio7), population, precipitation seasonality (bio15), aridity index (AI), and precipitation of the coldest quarter (bio19). The availability of combinations of environmental variable space (with a scale between 0 and 286) globally is indicated by the red outline, and the grey and blue color mixtures projected the suitable environmental space habitable by the species. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

5. Discussion

5.1. Model performance evaluation for predicting species distribution

We can conclude from our findings that the models used in this study are useful for identifying suitable habitats for the four endemic Annonaceae plant species distributed in EA. The models accurately predicted the current and future distribution of these species. Many studies have demonstrated the use of species distribution models to identify suitable areas for the presence of plant species [78,79]. However, using simply bioclimatic variables could lead to biased conclusions [80], as human activities and dispersal restrictions are important factors in forecasting the future ranges of these species [81]. Research has demonstrated that SDMs are almost accurate models to predict the geographic distribution of rare and endemic species even when considering future climate change, despite certain uncertainties [82–84]. Even while such data are occasionally lacking in places like our research area (for example other aspects like productivity, dispersal, etc.) are unexplored in this study, the accuracy of SDMs depends on the quality of the data, especially when accounting for human activities and interactions with other species. In addition to the conventional bioclimatic factors, added additional environmental variables to our models in this work to boost their accuracy.

5.2. Environmental factor's effects on habitat suitability

Precipitation and temperature are two climatic variables that are known to have a significant impact on plant community dynamics due to their wide spatial and temporal variability, particularly in the Afromontane region in EA [85,86]. Our modeling approach shows that the distribution of the four Annonaceae species was highly influenced by min temperature of the coldest month (bio6), precipitation of the coldest Quarter (bio19), temperature seasonality (bio4), precipitation seasonality (bio15), bio6 (68.4%), bio19 (34.9%), bio4 (33.6%), bio15 (26.3%), respectively. The higher contribution of temperature than precipitation highlights these preferences. Recent research by Wilson et al. [87] also showed that temperature, water availability, humidity, rainfall, wind, and precipitation are typically critical environmental variables for delimiting vegetation types and species distribution in Africa. Besides, precipitation and temperature variables, in this study population, aridity index (AI), and evapotranspiration (ET) play a significant role in the distribution patterns of the Annonaceae species. Previous research has identified anthropogenic activities as additional factors that may influence species distribution ranges [88,89]. There are several other ecological factors that, alone or in combination with climate change, influence species distribution patterns, for example, rapid population growth has resulted in excessive logging, conversion of forestlands to farmland, urban development programs, and over-exploitation [90,91]. Similar ecological disturbances have been documented in EA, where mining and agricultural products account for the majority of people's income [92,93]. These ecological factors, along with climate change, may be sufficient to explain the distribution pattern of the endemic Annonaceae species along the EA coastline. This is consistent with previous studies, which reported that land use patterns, population growth, tourist industry expansion, infrastructure development, conversion of natural forest to monocropping vegetation, and short generation times can reshape species diversity [94]. The species habitat suitability in this study was also selective to the climatic variables thus the indicated difference in variable contribution (Fig.S2), which rhymes with the previous findings [95,96].

5.3. Effect of climate change on the annonaceae species range

We also investigated the prospective influence of climate change on the distribution of suitable Annonaceae habitats. Our simulations showed that the range of the four Annonaceae suitable habitats will expand and decline (Fig. 3). The fluctuation in precipitation and temperature variables because of climate change was predicted to cause different habitat suitability among the species in the projected SSPs. Because of climate change, there is a projected increase in habitat loss for *Uvariodendron dzombense, followed* by *U. kirkii*, *A. asterias,* and lastly by *Uvaria kirkii* in all SSPs. Besides, *A. asterias* and lastly by *Uvaria kirkii* are likely to shift to newly suitable habitat areas rapidly compared to *Uvariodendron dzombense* and *U. kirkii*. Stable environments play a key role in ensuring the species survive adverse conditions. Over the last century, the temperature rise is approximated to be $0.74 + 0.18\ ^\circ C$ and is expected to rise to between $2.0\ ^\circ C$ and $4.5\ ^\circ C$ over the next 100 years [97,98]. Thus, climate change and the expansion of climate belts are likely to allow tropical and subtropical species to expand their ranges significantly [99]. Many species, which are unable to cope with the change will therefore, be compelled to change and adapt to new ecosystems or face threats to extinction [100,101].

5.4. Climatic suitability and species adaptability

In addition, climate suitability and species adaptability are attributed to the loss and gain of species-suitable habitat areas in a specific region over time. The adaptability characteristics help the species to overcome geographic barriers, especially when colonizing new regions and ensuring they can thrive in a wide range of environmental conditions [1,102]. As a result, the expansion of suitable Annonaceae habitats should be prioritized for three reasons. To begin with, Annonaceae species have therapeutic potential [29,36,103], and are important in the region [32,37]. If plant species die in their natural environment due to climate change, it may take a long time to recover their economic importance to Africans and the ecological value of linked biocoenosis [104,105]. Second, our modeling predicts the expansion of suitable habitats based solely on climate data and a few environmental variables; however, other factors such as human activities, geological conditions, and biological interactions may limit this habitat expansion [106]. Third, most of the Annonaceae plant species in EA generally occur in a restricted range thus, Annonaceae habitats are prone to fragmentation due to the loss of their original habitat.

5.5. Environmental conservation and restoration implications

Medicinal plants are essential to ecosystems and have a major impact on human health. Restoration and conservation of medicinal plants have become increasingly important in managing terrestrial ecosystems globally in recent decades. Thus, models of species distribution are helpful tools that aid in the conservation and restoration of rare, and threatened endemic species [46,83,107]. Therefore, our study proposes that the conservation and management measures should largely concentrate on the endemic medicinal Annonaceae species in EA. Furthermore, developing new and updated ecosystem management standards should be seen as a preliminary measure to understanding the adaptability of the species under future climate change scenarios. For example, aided migration could be an alternative for evaluating the adaptability of the species in various locations than its existing range. It is obvious that human interference, particularly changes in land use, may amplify the adverse effects of climate change, which are undoubtedly getting worse. According to recent research, human activities have an impact on plant distribution in addition to climate, and they must be taken into account before beginning conservation efforts.

6. Conclusion

Based on two shared socioeconomic pathways (SSPs)—SSP370 and SSP585—our analysis projected the probable distribution of *Uvariodendron kirkii*, *Uvaria kirkii*, *Uvariodendron dzomboense*, and *Asteranthe asterias* for the present and the future (2050 and 2070). Kenya and Tanzania are among the biodiversity hotspots in EA, with a diverse and rich species variety, serving as the ideal habitat. However, the observed decrease in biodiversity is due to several climate change-related factors. Our findings indicated that as the climate changes in the next years, the potential distribution range of habitats that are good for *Uvariodendron dzombense* and *Uvariodendron kirkii* will continue to shrink. The expansion will be greater for *Uvaria kirkii* and *Asteranthe asterias*. This study is unique in that it defines ideal growing regions for the Annonaceae species. As a result, the maps created might be viewed as the target species baseline data. To maintain its current classification as endangered and prevent its potential extinction in the future, this species would need an all-encompassing conservation strategy. Such conservation methods would require coordinated efforts from many stakeholders, including the forest departments, governmental organizations, research institutes, and the local population.

Source of funding

The International Partnership Program of the Chinese Academy of Sciences (151853KYSB20190027), the National Natural Sciences Foundation of China (31970211), and the Sino-Africa Joint Research Center, CAS (SAJC202101), financially supported this work.

Author contribution statement

E.M.M, V.M, J.N, W.A. O, B. K. N, V·O·W, M.A, F.M: Performed experiments, wrote the paper, analyzed and interpreted the data.
E.M.M, F.M.K, P·K, E.N·W, E.S.M, C, O·O, J.K.M, C·I·V: Performed experiments, contributed reagents and wrote the paper.
E.M.M., G.M, G.-W.H, and Q.-F.W: Conceived and designed the experiments.

Data availability statement

Data will be made available on request.

Additional information

Supplementary content related to this article has been published online at [URL].

Declaration of competing interest

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

Acknowledgements

We thank Dr. Gbadamassi G.O. Dossa from the Center for Integrative Conservation, Xishuangbanna Tropical Botanical Garden, Chinese Academy of Sciences, China for his support; for his guidance, and teaching us the importance of reproducibility and use of GitHub as a repository to store our data (Codes) that can be accessed free by the public.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e17405.

References

[1] K. Abbass, M.Z. Qasim, H. Song, M. Murshed, H. Mahmood, I. Younis, A Review of the Global Climate Change Impacts, Adaptation, and Sustainable Mitigation Measures, Environmental Science and Pollution Research, 2022, pp. 1–21.
[2] A. Alcalde-Calonge, F.J. Sáez-Martínez, P. Ruiz-Palomino, Evolution of research on circular economy and related trends and topics. A thirteen-year review, Ecol. Inf. (2022), 101716.
[3] H.-O. Pörtner, D.C. Roberts, H. Adams, C. Adler, P. Aldunce, E. Ali, et al., Climate Change 2022: Impacts, Adaptation and Vulnerability, IPCC Sixth Assessment Report, 2022.
[4] Z. Soilhi, N. Sayari, N. Benalouache, M. Mekki, Predicting current and future distributions of *Mentha pulegium* L. in Tunisia under climate change conditions, using the MaxEnt model, Ecol. Inf. 68 (2022), 101533.
[5] S.M. Aguillon, T.O. Dodge, G.A. Preising, M. Schumer, Introgression, Curr. Biol. 32 (2022) R865–R868.
[6] Y. Fourcade, M.F. WallisDeVries, M. Kuussaari, C.A. van Swaay, J. Heliölä, E. Öckinger, Habitat amount and distribution modify community dynamics under climate change, Ecol. Lett. 24 (2021) 950–957.
[7] L. Bosso, S. Smeraldo, D. Russo, M.L. Chiusano, G. Bertorelle, K. Johannesson, et al., The rise and fall of an alien: why the successful colonizer *Littorina saxatilis* failed to invade the Mediterranean Sea, Biol. Invasions 24 (2022) 3169–3187.
[8] J.H. Seider, Investigating the Role of Climate Warming on Vegetation Productivity and Shrub Distributions in the Beaufort Delta Region of Canada, 2021.
[9] O.A. Idris, P. Opute, I.R. Orimoloye, M.S. Maboeta, Climate change in Africa and vegetation response: a bibliometric and spatially based information assessment, Sustainability 14 (2022) 4974.
[10] P.E. Menezes-Silva, L. Loram-Lourenço, R.D.F.B. Alves, L.F. Sousa, S.E.d.S. Almeida, F.S. Farnese, Different ways to die in a changing world: consequences of climate change for tree species performance and survival through an ecophysiological perspective, Ecol. Evol. 9 (2019) 11979–11999.
[11] S.D. Morris, M.R. Kearney, C.N. Johnson, B.W. Brook, Too hot for the devil? Did climate change cause the mid-Holocene extinction of the Tasmanian devil Sacrophilus harrisii from mainland Australia? Ecography 2022 (2022).
[12] F. Khajoei Nasab, A. Mehrabian, H. Mostafavi, A. Neemati, The influence of climate change on the suitable habitats of Allium species endemic to Iran, Environ. Monit. Assess. 194 (2022) 169.
[13] J. Castro, F. Morales-Rueda, F.B. Navarro, M. Löf, G. Vacchiano, D. Alcaraz-Segura, Precision restoration: a necessary approach to foster forest recovery in the 21st century, Restor. Ecol. 29 (2021), e13421.
[14] M.M. Yuan, X. Guo, L. Wu, Y. Zhang, N. Xiao, D. Ning, et al., Climate warming enhances microbial network complexity and stability, Nat. Clim. Change 11 (2021) 343–348.
[15] R.E. Young, G.D. Gann, B. Walder, J. Liu, W. Cui, V. Newton, et al., International principles and standards for the ecological restoration and recovery of mine sites, Restor. Ecol. 30 (2022), e13771.
[16] J. Cavender-Bares, F.D. Schneider, M.J. Santos, A. Armstrong, A. Carnaval, K.M. Dahlin, et al., Integrating remote sensing with ecology and evolution to advance biodiversity conservation, Nat. Ecol. Evol. 6 (2022) 506–519.
[17] Y. Sun, Y. Sun, S. Yao, M.A. Akram, W. Hu, L. Dong, et al., Impact of climate change on plant species richness across drylands in China: from past to present and into the future, Ecol. Indicat. 132 (2021), 108288.
[18] G. Di Pasquale, A. Saracino, L. Bosso, D. Russo, A. Moroni, G. Bonanomi, et al., Coastal pine-oak glacial refugia in the Mediterranean basin: a biogeographic approach based on charcoal analysis and spatial modelling, Forests 11 (2020) 673.
[19] F. Vessella, M.C. Simeone, B. Schirone, Quercus suber range dynamics by ecological niche modelling: from the Last Interglacial to present time, Quat. Sci. Rev. 119 (2015) 85–93.
[20] F. Khajoei Nasab, A. Mehrabian, H. Mostafavi, Mapping the current and future distributions of Onosma species endemic to Iran, J. Arid. Land 12 (2020) 1031–1045.
[21] V.M. Ngumbau, Q. Luke, M. Nyange, V.O. Wanga, B.M. Watuma, Y.M. Mbuni, et al., An annotated checklist of the coastal forests of Kenya, East Africa, PhytoKeys 147 (2020) 1.
[22] B.M. Watuma, S. Kipkoech, D.K. Melly, V.M. Ngumbau, P.C. Rono, F.M. Mutie, et al., An annotated checklist of the vascular plants of taita hills, Eastern Arc mountain, PhytoKeys 191 (2022) 1.
[23] N. Burgess, T.M. Butynski, N.J. Cordeiro, N. Doggart, J. Fjeldså, K. Howell, et al., The biological importance of the Eastern Arc Mountains of Tanzania and Kenya, Biol. Conserv. 134 (2007) 209–231.
[24] S. Kipkoech, B.M. Watuma, V.M. Ngumbau, An Annotated Checklist of the Vascular Plants of Taita Hills, Eastern Arc Mountain, 2022.
[25] P.J. Platts, Spatial Modelling, Phytogeography and Conservation in the Eastern Arc Mountains of Tanzania and Kenya, 2012.
[26] H. Yousefzadeh, N. Amirchakhmaghi, B. Naseri, F. Shafizadeh, G. Kozlowski, Ł. Walas, The impact of climate change on the future geographical distribution range of the endemic relict *tree Gleditsia caspica* (Fabaceae) in Hyrcanian forests, Ecol. Inf. 71 (2022), 101773.
[27] T. Strydom, M.D. Catchen, F. Banville, D. Caron, G. Dansereau, P. Desjardins-Proulx, et al., A roadmap towards predicting species interaction networks (across space and time), Phil. Trans. Roy. Soc. B 376 (2021), 20210063.
[28] C.K. Kaingu, J.A. Oduma, J.M. Mbaria, S.G. Kiama, Effects of *Croton menyharthii* and *Uvariodendron kirkii* extracts on ovarian corpora lutea and reproductive hormones, Discov. Phytomed. J. Nat. Prod. Res. Ethnopharmacol. 4 (2017) 21–25.
[29] R. Christopher, Plant species of the genus *Uvaria*: ethnobotanical uses, biological activities and phytochemistry, Nat. Prod. Res. 36 (2022) 2946–2961.
[30] T.L. Couvreur, M. Botermans, B.J. van Heuven, R.W. van der Ham, Pollen morphology within the Monodora clade, a diverse group of five African Annonaceae genera, Grana 47 (2008) 185–210.
[31] L.-P.M. Dagallier, F.M. Mbago, W.Q. Luke, T.L. Couvreur, Three new species of *Uvariodendron* (Annonaceae) from coastal East Africa in Kenya and Tanzania, PhytoKeys 174 (2021) 107.
[32] J.C. Lovett, C.K. Ruffo, R.E. Gereau, J.R. Taplin, Field Guide to the Moist Forest Trees of Tanzania, Society for Environmental Exploration London, UK, 2006.
[33] K.E. Wairimu, Evaluation of contractile effects of *Uvariodendron kirkii* (verdec), in: Extracts on Isolated Uterine Strips of Female Wistar Rats, Egerton University, 2021.
[34] O.T. Osuntokun, Efficacy, properties and therapeutic use of some major medicinal plants for human health, Biopestic.: Bot. Microorg. Improv. Agric. Human Health 179 (2021).
[35] V.S. Parmar, K.S. Bisht, A. Malhotra, A. Jha, W. Errington, O.W. Howarth, et al., A benzoic acid ester from Uvaria narum, Phytochemistry 38 (1995) 951–955.
[36] C.K. Ruffo, A. Birnie, B. Tengnäs, Edible Wild Plants of Tanzania, 2002.
[37] T. Plants, Useful Tropical Plants, Ken Fern. tropical.theferns.Info, 2022, 5/24/2022.
[38] M.H. Nkunya, Unusual metabolites from some Tanzanian indigenous plant species, Pure Appl. Chem. 77 (2005) 1943–1955.
[39] C. Kihampa, C.C. Joseph, M.H. Nkunya, S.M. Magesa, A. Hassanali, M. Heydenreich, et al., Larvicidal and IGR activity of extract of Tanzanian plants against malaria vector mosquitoes, J. Vector Borne Dis. 46 (2009) 145.
[40] S.-L. Chen, H. Yu, H.-M. Luo, Q. Wu, C.-F. Li, A. Steinmetz, Conservation and sustainable use of medicinal plants: problems, progress, and prospects, Chin. Med. 11 (2016) 1–10.
[41] A.K. Shakya, Medicinal plants: future source of new drugs, Int. J. Herb. Med. 4 (2016) 59–64.
[42] R. Okigbo, U. Eme, S. Ogbogu, Biodiversity and conservation of medicinal and aromatic plants in Africa, Biotechnol. Mol. Biol. Rev. 3 (2008) 127–134.
[43] A. Sharma, S. Khanna, G. Kaur, I. Singh, Medicinal plants and their components for wound healing applications, Future J. Pharmaceut. Sci. 7 (2021) 1–13.
[44] J.D.W. Lako, K.L.L. Sube, C.S.G. Lumori, J.P. Yengkopiong, J.A.M. Utong, S.A. Binyason, et al., Diversity and distribution of medicinal plants in the republic of South Sudan, World J. Adv. Res. Rev. 7 (2020) 18–31.
[45] S.D. Johnson, A.L. Hargreaves, M. Brown, Dark, bitter-tasting nectar functions as a filter of flower visitors in a bird-pollinated plant, Ecology 87 (2006) 2709–2716.

[46] S. Mahmoodi, M. Heydari, K. Ahmadi, N.R. Khwarahm, O. Karami, K. Almasieh, et al., The current and future potential geographical distribution of *Nepeta crispa* Willd., an endemic, rare and threatened aromatic plant of Iran: implications for ecological conservation and restoration, Ecol. Indicat. 137 (2022), 108752.
[47] A.R. Marshall, C.E. Waite, M. Pfeifer, L.F. Banin, S. Rakotonarivo, S. Chomba, et al., Fifteen Essential Science Advances Needed for Effective Restoration of the World's Forest Landscapes, vol. 378, The Royal Society, 2022, 20210065.
[48] S. Khanal, R. Timilsina, M. Behroozian, A.T. Peterson, M. Poudel, M.S.S. Alwar, et al., Potential impact of climate change on the distribution and conservation status of *Pterocarpus marsupium*, a Near Threatened South Asian medicinal tree species, Ecol. Inf. 70 (2022), 101722.
[49] A.A. Hama, N.R. Khwarahm, Predictive mapping of two endemic oak tree species under climate change scenarios in a semiarid region: range overlap and implications for conservation, Ecol. Inf. (2022), 101930.
[50] J. Sharma, R. Singh, S. Garai, S.M. Rahaman, M. Khatun, A. Ranjan, et al., Climate change and dispersion dynamics of the invasive plant species *Chromolaena odorata* and *Lantana camara* in parts of the central and eastern India, Ecol. Inf. 72 (2022), 101824.
[51] W. Zhang, R.W. Bussmann, J. Li, B. Liu, T. Xue, X. Yang, et al., Biodiversity hotspots and conservation efficiency of a large drainage basin: distribution patterns of species richness and conservation gaps analysis in the Yangtze River Basin, China, Conserv. Sci. Pract. 4 (2022), e12653.
[52] S. Zotos, M. Stamatiou, I.N. Vogiatzakis, Elusive species distribution modelling: the case of Natrix natrix cypriaca, Ecol. Inf. 71 (2022), 101758.
[53] M. Kearney, W. Porter, Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges, Ecol. Lett. 12 (2009) 334–350.
[54] C.J. Marsh, Y. Gavish, M. Kuemmerlen, S. Stoll, P. Haase, W.E. Kunin, SDM profiling: a tool for assessing the information-content of sampled and unsampled locations for species distribution models, Ecol. Model. (2023) 110–170.
[55] M. Sanz-Arnal, C. Benítez-Benítez, M. Miguez, P. Jiménez-Mejías, S. Martín-Bravo, Are Cenozoic relict species also climatic relicts? Insights from the macroecological evolution of the giant sedges of *Carex* sect. *Rhynchocystis* (Cyperaceae), American Journal of Botany, 109(1), 115-129, Am. J. Bot. 109 (2022) 115–129.
[56] A.T. Peterson, J. Soberón, R.G. Pearson, R.P. Anderson, E. Martínez-Meyer, M. Nakamura, et al., Ecological niches and geographic distributions (MPB-49), in: Ecological Niches and Geographic Distributions (MPB-49), Princeton University Press, 2011.
[57] J.R. Barker, H.J. MacIsaac, Species distribution models: administrative boundary centroid occurrences require careful interpretation, Ecol. Model. 472 (2022), 110107.
[58] J. Franklin, Mapping Species Distributions: Spatial Inference and Prediction, Cambridge University Press, 2010.
[59] A. Guisan, W. Thuiller, Predicting species distribution: offering more than simple habitat models, Ecol. Lett. 8 (2005) 993–1009.
[60] M. Meinshausen, Z.R. Nicholls, J. Lewis, M.J. Gidden, E. Vogel, M. Freund, et al., The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500, Geosci. Model Dev. (GMD) 13 (2020) 3571–3605.
[61] D. Ackerley, D. Dommenget, Atmosphere-only GCM (ACCESS1. 0) simulations with prescribed land surface temperatures, Geosci. Model Dev. (GMD) 9 (2016) 2077–2098.
[62] R.J. Hijmans, S. Phillips, J. Leathwick, J. Elith, dismo: species distribution modeling, R package version 1 (2017) 1.
[63] M.E. Aiello-Lammens, R.A. Boria, A. Radosavljevic, B. Vilela, R.P. Anderson, spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models, Ecography 38 (2015) 541–545.
[64] R.C. Team, R: A Language and Environment for Statistical Computing, 2013.
[65] B. Naimi, M.B. Araújo, sdm: a reproducible and extensible R platform for species distribution modelling, Ecography 39 (2016) 368–375.
[66] H. Ali, J.U. Din, L. Bosso, S. Hameed, M. Kabir, M. Younas, et al., Expanding or shrinking? range shifts in wild ungulates under climate change in Pamir-Karakoram mountains, Pakistan, PLoS One 16 (2021), e0260031.
[67] Z. Koma, A.C. Seijmonsbergen, M.W. Grootes, F. Nattino, J. Groot, H. Sierdsema, et al., Better together? Assessing different remote sensing products for predicting habitat suitability of wetland birds, Divers. Distrib. 28 (2022) 685–699.
[68] S.J.E. Velazco, F. Galvao, F. Villalobos, P. De Marco Junior, Using worldwide edaphic data to model plant species niches: an assessment at a continental extent, PLoS One 12 (2017), e0186025.
[69] O. Allouche, A. Tsoar, R. Kadmon, Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS), J. Appl. Ecol. 43 (2006) 1223–1232.
[70] X. Wen, G. Zhao, X. Cheng, G. Chang, X. Dong, X. Lin, Prediction of the Potential Distribution Pattern of the Great Gerbil (*Rhombomys Opimus*) under Climate Change Based on Ensemble Modelling, Pest Management Science, 2022.
[71] Y. Zhao, J. Romero, M. Mohammadian, Issues related to modelling and parameter settings of models for ecological systems the case of distribution of thorny devil, in: 2022 2nd International Conference on Innovative Practices in Technology and Management, ICIPTM), 2022, pp. 669–674.
[72] L.J. Beaumont, E. Graham, D.E. Duursma, P.D. Wilson, A. Cabrelli, J.B. Baumgartner, et al., Which species distribution models are more (or less) likely to project broad-scale, climate-induced shifts in species ranges? Ecol. Model. 342 (2016) 135–146.
[73] Y. Lei, Y. Ying, Stochastic proximal AUC maximization, J. Mach. Learn. Res. 22 (2021) 1–45.
[74] S. Smeraldo, L. Bosso, V.B. Salinas-Ramos, L. Ancillotto, V. Sánchez-Cordero, S. Gazaryan, et al., Generalists yet different: distributional responses to climate change may vary in opportunistic bat species sharing similar ecological traits, Mamm Rev. 51 (2021) 571–584.
[75] M. Marmion, M. Parviainen, M. Luoto, R.K. Heikkinen, W. Thuiller, Evaluation of consensus methods in predictive species distribution modelling, Divers. Distrib. 15 (2009) 59–69.
[76] E.M. Mkala, E.S. Mutinda, V.O. Wanga, M.A. Oulo, W.A. Oluoch, E.N. Waswa, et al., Modeling impacts of climate change on the potential distribution of three endemic *Aloe* species critically endangered in East Africa, Ecol. Inf. 71 (2022), 101765.
[77] L. Ancillotto, E. Mori, L. Bosso, P. Agnelli, D. Russo, The Balkan long-eared bat (*Plecotus kolombatovici*) occurs in Italy-first confirmed record and potential distribution, Mamm. Biol. 96 (2019) 61–67.
[78] J. Ehrlén, W.F. Morris, Predicting changes in the distribution and abundance of species under environmental change, Ecol. Lett. 18 (2015) 303–314.
[79] V. Srivastava, V. Lafond, V.C. Griess, Species Distribution Models (SDM): Applications, Benefits and Challenges in Invasive Species Management, CABI Reviews, 2019, pp. 1–13.
[80] E. Kaky, F. Gilbert, Assessment of the extinction risks of medicinal plants in Egypt under climate change by integrating species distribution models and IUCN Red List criteria, J. Arid Environ. 170 (2019), 103988.
[81] F. Shabani, M. Ahmadi, L. Kumar, S. Solhjouy-fard, M.S. Tehrany, F. Shabani, et al., Invasive weed species' threats to global biodiversity: future scenarios of changes in the number of invasive species in a changing climate, Ecol. Indicat. 116 (2020), 106436.
[82] M. Gogol-Prokurat, Predicting habitat suitability for rare plants at local spatial scales using a species distribution model, Ecol. Appl. 21 (2011) 33–47.
[83] E.M. Mkala, M. Jost, S. Wanke, B.K. Ngarega, A. Hughes, E.S. Mutinda, et al., How vulnerable are holoparasitic plants with obligate hosts to negative climate change impacts? Ecol. Inf. 69 (2022), 101636.
[84] S. Ranjitkar, J. Xu, K.K. Shrestha, R. Kindt, Ensemble forecast of climate suitability for the Trans-Himalayan Nyctaginaceae species, Ecol. Model. 282 (2014) 18–24.
[85] P.T. Lyam, J. Duque-Lazo, J. Schnitzler, F. Hauenschild, A.N. Muellner-Riehl, Testing the forest refuge hypothesis in sub-Saharan Africa using species distribution modeling for a key savannah tree species, Senegalia Senegal (L.) Britton, Front. Biogeogr. 12 (2020).
[86] Y. van der Hoek, C. Sirami, E. Faida, V. Musemakweli, D. Tuyisingize, Elevational distribution of birds in an Eastern African montane environment as governed by temperature, precipitation, and habitat availability, Biotropica 54 (2022) 334–345.
[87] J.R. Wilson, L.C. Foxcroft, S. Geerts, M.T. Hoffman, S. MacFadyen, J. Measey, et al., The role of environmental factors in promoting and limiting biological invasions in South Africa, in: Biological Invasions in South Africa, Springer, Cham, 2020, pp. 355–385.
[88] J.S. Park, Spatial heterogeneity of environmental factors related to the invasion of *Hypochaeris radicata* in South Korea, Ecol. Inf. 71 (2022) 101–784.
[89] B. Zahoor, X. Liu, L. Kumar, Y. Dai, B.R. Tripathy, M. Songer, Projected shifts in the distribution range of Asiatic black bear (Ursus thibetanus) in the Hindu Kush Himalaya due to climate change, Ecol. Inf. 63 (2021), 101312.

[90] W.D. Newmark, W.D. Newmark, Conserving Biodiversity in East African Forests: a Study of the Eastern Arc Mountains, vol. 155, Springer Science & Business Media, 2002.
[91] C. van Weelden, J.R. Towers, T. Bosker, Impacts of climate change on cetacean distribution, habitat and migration, Clim. Change Ecol. 1 (2021).
[92] J.M. Maitima, S.M. Mugatha, R.S. Reid, L.N. Gachimbi, A. Majule, H. Lyaruu, et al., The linkages between land use change, land degradation and biodiversity across East Africa, Afr. J. Environ. Sci. Technol. 3 (2009).
[93] X.T. Tiamgne, F.K. Kalaba, V.R. Nyirenda, Mining and socio-ecological systems: a systematic review of Sub-Saharan Africa, Resour. Pol. 78 (2022), 102947.
[94] H.Y.S.H. Nugroho, F. Nurfatriani, Y. Indrajaya, T.W. Yuwati, S. Ekawati, M. Salminah, H. Baral, Mainstreaming ecosystem services from Indonesia's remaining forests, Sustainability 14 (2022), 12124.
[95] N.M. Fyllas, T. Koufaki, C.I. Sazeides, G. Spyroglou, K. Theodorou, Potential impacts of climate change on the habitat suitability of the dominant tree species in Greece, Plants 11 (2022) 1616.
[96] K. Omar, I. Elgamal, Can we save critically endangered relict endemic plant species? A case study of Primula boveana Decne ex Duby in Egypt, J. Nat. Conserv. 61 (2021).
[97] S. Solomon, D. Qin, M. Manning, K. Averyt, M. Marquis, Climate Change 2007-the Physical Science Basis, in: Working Group I Contribution to the Fourth Assessment Report of the IPCC, vol. 4, Cambridge university press, 2007.
[98] F. Zhou, M. Yao, X. Fan, G. Yin, X. Meng, Z. Lin, Evidence of warming from long-term records of climate and permafrost in the hinterland of the qinghai–tibet plateau, Front. Environ. Sci. 10 (2022), 836085.
[99] T.H. Oliver, M.D. Morecroft, Interactions between climate change and land use change on biodiversity: attribution problems, risks, and opportunities, Wiley Interdiscip. Rev.: Clim. Change 5 (2014) 317–335.
[100] R.T. Corlett, D.A. Westcott, Will plant movements keep up with climate change? Trends Ecol. Evol. 28 (2013) 482–488.
[101] T. Makki, H. Mostafavi, A.A. Matkan, H. Aghighi, R. Valavi, Y.E. Chee, et al., Impacts of climate change on the distribution of riverine endemic fish species in Iran, a biodiversity hotspot region, Freshw. Biol. (2023).
[102] C. Bellard, W. Thuiller, B. Leroy, P. Genovesi, M. Bakkenes, F. Courchamp, Will climate change promote future invasions? Global Change Biol. 19 (2013) 3740–3748.
[103] J.V.D. Gomes, A.S. Borges, B.R. Athaydes, K.K.P. Gomes-Copeland, D. Silveira, P.O. Magalhães, et al., Anti-Helicobacter pylori potential, antioxidant capacity, and anti-inflammatory activity of Xylopia sericea A. St.-Hil.(Annonaceae) leaves, Phytomedicine 2 (2022), 100214.
[104] A. Hussein, S. Workeneh, Modeling the Impacts of Climate Changes on the Distribution of *Aloe Vera* Species in Ethiopia, 2021.
[105] M. Zalewski, E. Kiedrzyńska, I. Wagner, K. Izydorczyk, J.M. Boczek, T. Jurczak, et al., Ecohydrology and adaptation to global change, Ecohydrol. Hydrobiol. 21 (2021) 393–410.
[106] C. Berger, M. Bieri, K. Bradshaw, C. Brümmer, T. Clemen, T. Hickler, et al., Linking scales and disciplines: an interdisciplinary cross-scale approach to supporting climate-relevant ecosystem management, Climatic Change 156 (2019) 139–150.
[107] L. Namitha, A. Achu, C.S. Reddy, S.S. Beevy, Ecological modelling for the conservation of *Gluta travancorica* Bedd.-An endemic tree species of southern Western Ghats, India, Ecol. Inf. 71 (2022), 101823.