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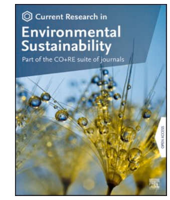

Potential distribution of crop wild relatives under climate change in Sri Lanka: implications for conservation of agricultural biodiversity

Sujith S. Ratnayake [a,b], Champika S. Kariyawasam [a,b,*], Lalit Kumar [c], Danny Hunter [d], A.S. U. Liyanage [e]

[a] Ecosystem Management, School of Environmental and Rural Science, University of New England, Armidale, NSW 2351, Australia
[b] Ministry of Environment and Wildlife Resources, Battaramulla 10120, Sri Lanka
[c] East Coast Geospatial Consultants, Armidale, NSW 2350, Australia
[d] Senior Scientist, Alliance of Bioversity International and CIAT, Rome, Italy
[e] Plant Genetic Resources Centre, Department of Agriculture, Gannoruwa, Peradeniya 20400, Sri Lanka

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ABSTRACT

The global population is growing rapidly and food production needs to be stepped up substantially to supply the additional demand expected by projected increased population. Further, climate change is expected to exert considerable pressure on global agriculture and food production. Crop wild relatives (CWR), which possess large untapped genetic diversity, can provide vital genetic material for future crop improvement. At present, this important category of plants is at risk due to anthropogenic climate change and other human-mediated changes i.e., habitat destruction. Therefore, it is important to study and understand the vulnerability of CWR to climate change, their potential distribution, and range dynamics for their conservation. Here we use Maxent algorithm to simulate the potential distribution across nine CWR species belonging to four crop genera, *Cinnamomum*, *Piper*, *Vigna* and *Oryza* in Sri Lanka and investigate how the predicted potential suitable areas change under climate change. Our findings indicate that species response to climate change varies among species studied, even within the same genus. Many species are predicted to decrease their suitable habitat by 2050, suggesting that these species are highly vulnerable to climate change impacts. The study identifies potential CWR rich areas in the country for future in situ conservation. Our findings facilitate decision-makers to make evidence-based decision-making for better management of CWR in Sri Lanka.

1. Introduction

Negative consequences of recent global climate changes are exerting extensive impacts on species and ecosystems of the world (IPCC, 2014; Walther et al., 2002); climate-induced impacts on earth biota are well recognized by the scientific community. Earth's temperature has increased substantially (approx. by 0.6 °C) over the last 10 decades with considerable variability (Millennium Ecosystem Assessment, 2005). Importantly, the rate of global warming has increased slightly from 1976 (i.e., 0.17 °C/decade), compared with the previous years, particularly over land areas (Folland et al., 2001). Climate change has the potential to lead to a considerable impact on global agriculture that continues to influence food production and food systems worldwide (Al et al., 2008). Knowledge, understanding and proper evaluations of climate change-related impacts can be limited, particularly in developing countries (Kariyawasam et al., 2019b). Besides, the global population is increasing rapidly; it will remain growing and is anticipated to reach nearly 10 billion by 2050 (Searchinger et al., 2019). To supply the expected increased demand, global food production needs to be increased by 50% compared to the present (Chakraborty and Newton, 2011). Attaining sustainable development goal 2: achieve zero hunger by 2030, could be a challenging goal. Therefore, scientists have attempted to achieve food security targets using wild relatives of important crops.

Crop wild relatives (CWR) are an important category of wild plants closely related to cultivated crops that have the potentiality to provide genetic material to develop new improved crop varieties with higher yield and climate change tolerance (Maxted et al., 2006; Vincent et al., 2019; Zair et al., 2018). Banana is a commercially improved crop using two wild relatives of banana, *Musa acuminata* and *Musa balbisiana* (Bakry et al., 2009; Kallow et al., 2020). Crop wild relatives possess

* Corresponding author at: Ecosystem Management, School of Environmental and Rural Science, University of New England, Armidale, NSW 2351, Australia.
E-mail addresses: rratnaya@une.edu.au (S.S. Ratnayake), ckariyaw@myune.edu.au (C.S. Kariyawasam), d.hunter@cgiar.org (D. Hunter).

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multiple utility values i.e., significant potential nutritional value; yet, the real potential of many species have not been explored and remain understudied (Singh et al., 2020). Also, the relative utility of this important resource is hampered as they are rare in ex situ collections (Castañeda-Álvarez et al., 2016). Even in situ, these species are not widely available; they are under-exploited and rarely protected (Vincent et al., 2019). Climate change has already exerted considerable pressure on global crop production and output will continue to decline, particularly in developing countries (Parry et al., 2004; Ray et al., 2015). Crop wild relatives are a vital resource that has the potential to address this challenge as they possess beneficial traits and superior trait diversity that can be utilized for crop improvements (i.e., higher nutritional value, pest and disease tolerance). Further, they are adapted to survive in a wide range of habitats under varying environmental conditions (Maxted and Kell, 2009; Padulosi et al., 2011; Phillips et al., 2017; Yadav et al., 2015). The value of CWR is marked by their wide use in crop improvements in adapting to various challenges such as climate change, diseases, over the recent few decades (i.e., 185 CWR taxa into 29 crops), predominantly for crops such as wheat, rice, barley, cassava, potato and tomato (Dempewolf et al., 2017; Hunter and Heywood, 2011; Maxted and Kell, 2009). Agriculture and food security are likely to be threatened in the future by the spread of crop pests and pathogens in the future as these biotic agents are predicted to change their potential ranges due to climate change impacts (Bebber et al., 2013; Garrett et al., 2006). In this context, the potential utilization of CWR genetic traits against biotic stresses is highly important and can be utilized for crop improvements to minimize impacts (Dempewolf et al., 2014).

Climate change impacts on the potential distribution of CWR, both spatially and temporally, and such impacts may vary among taxa at the species level (Vincent et al., 2019). Niche-based species distribution models (SDMs) can estimate the distribution pattern range dynamics of species across the geographic space using species' occurrence data and a suite of environmental predictors (Elith and Leathwick, 2007). Such information is vital for assessing potential risks and prioritizing them for conservation actions (van Treuren et al., 2020). SDMs can also be used to identify potentially suitable habitats for the targeted species in areas which are inaccessible, unexplored or not occupied by them (Franklin, 2009; González-Orozco et al., 2020; Kariyawasam et al., 2019a). However, the species' realized niche or the area occupied by the species can be smaller than the fundamental niche that represents species' full potential area of occupancy, due to natural barriers, human and other biotic influences (Phillips et al., 2006). Therefore, what the niche models estimate as the potentially suitable area can be slightly larger than the actual area occupied by the species. Thus, the possible implications should be considered while incorporating outcomes of SDMs into real-world applications.

In Sri Lanka, there are around 645 CWR species (Liyanage, 2010). Several agriculturally important CWR species in the country are freely grown in the wild without any management intervention. These species possess huge potential to contribute to the country's food security, human nutrition and poverty alleviation. However, their survival under the challenges of climate change is not extensively studied and understood. Genetic erosion of CWR species in Sri Lanka is a serious issue in the last few decades and their conservation is mostly restricted to ex situ conservation; though, the persistence of some species under ex situ conditions is not certain (Liyanage, 2010). Therefore, risk assessment of CWR is important to identify those species at greater risk and prioritize those for conservation planning. In this study, we model nine priority CWR species in Sri Lanka, belonging to four crop genera, *Cinnamomum, Piper*, *Vigna* and *Oryza.* Under climate change, we aim to (i) examine the spatial and temporal distribution of CWR species (ii) assess the potentially suitable areas acquired by them and (iii) identify high conservation value areas for in situ conservation around Sri Lanka. This information will provide baseline data to help understand CWR species vulnerability under climatic changes and provide information to formulate strategies for their conservation.

2. Materials and methods

2.1. Species occurrence data

Based on data collected through continuous field surveys and inventories, the Plant Genetic Resources Centre (PGRC) in Sri Lanka, prioritized 31 wild relatives of food crops for active conservation (Liyanage, 2010). The present study considered 26 species after eliminating species with small numbers of occurrences (Table S1). This database contained 869 occurrence records (representing 1998–2007 period) belonging to five crop genera (crop groups), namely *Cinnamomum, Musa, Oryza, Piper and Vigna*.

Duplicate occurrences were removed using ENM tools version 1.3 (http://enmtools.blogspot.com/2011/03/enmtools-13-is-out.html). Sampling bias is a common problem in presence-only data as data collections are biased towards easily accessible areas (Phillips et al., 2006). Thus, spatial thinning (spatial filtering) was carried out using the R package, "spThin" to reduce the effects of sampling bias that removes a minimum number of records while retaining the maximum possible number for model building (Aiello-Lammens et al., 2015). We decided the thinning geographic distance of 1 km as the study area is slightly heterogeneous (Boria et al., 2014). Addressing sampling bias through spatial thinning reduces model overfitting and improves model performance better than background manipulation (i.e., use of bias files) (Boria et al., 2014; Kramer-Schadt et al., 2013). In addition, Wisz et al. (2008) have highlighted that the performance of modeling techniques is low and not robust to small sample sizes ($n < 30$). Spatial thinning resulted in nine species belonging to four crop groups with more than 30 minimum occurrences which are located 1 km apart from each other (i.e., distribution is not restricted) for further analysis (Fig. 1; Table S2). Thus, the number of CWR species in each crop genus was comprised of *Cinnamomum* ($n = 1$), *Piper* ($n = 3$), *Vigna* ($n = 1$) and *Oryza* ($n = 4$). The small numbers of occurrences represented by some of the species are not due to low sampling effort but due to highly localized geographic distribution and as such, the presence points represent the species range.

2.2. Environmental variables

Nineteen bioclimatic variables at a high spatial resolution (30 arc *sec* or $\sim 1\ km^2$) for current (1960–1990) and future climate were taken from the WorldClim dataset (https://www.worldclim.org/) to identify the most responsive variables for CWR distribution (Hijmans et al., 2005). In addition, land cover and topographical covariates: elevation (dem), soil and aspect were considered. We did not consider anthropogenic impacts as CWR species occur naturally and thus the level of human influences on their distribution is relatively low. Global land cover data were downloaded at a 300 m resolution from the European Space Agency GlobCover Portal (http://due.esrin.esa.int/page_globcover.php) and resampled to the 30 arc sec resolution. We obtained dem, aspect and soil data of a similar resolution used in a study by Kadupitiya et al. (2018). Removing highly correlated variables was undertaken using the 'removeCollinearity' function of the freely available package 'virtualspecies' (version 1.4–4) in the R platform (Leroy et al., 2016) (Fig. S1). Variables with reduced collinearity at the threshold value of 0.7 (Pearson Correlation Coefficient < 0.7) were selected (Dormann et al., 2013). The selected 11 variables of reduced collinearity are shown in Table 1. For future projections, we used the MIROC5, the fifth version of the Model for Interdisciplinary Research on Climate (Watanabe et al., 2010). MIROC5 has been well tested for South Asia and confirmed that it better simulates climate variability in the region and makes a reliable prediction (Mishra et al., 2014; Sharmila et al., 2015; Sperber et al., 2013). Representative Concentration Pathways (RCPs) signify the projected levels of greenhouse gas (GHG) emissions which are largely driven by socio-economic factors and climate policy (IPCC, 2014). We selected RCP 4.5 (intermediate GHG emissions) and 8.5 (high GHG emissions) scenarios for two time periods, 2050 and 2070.

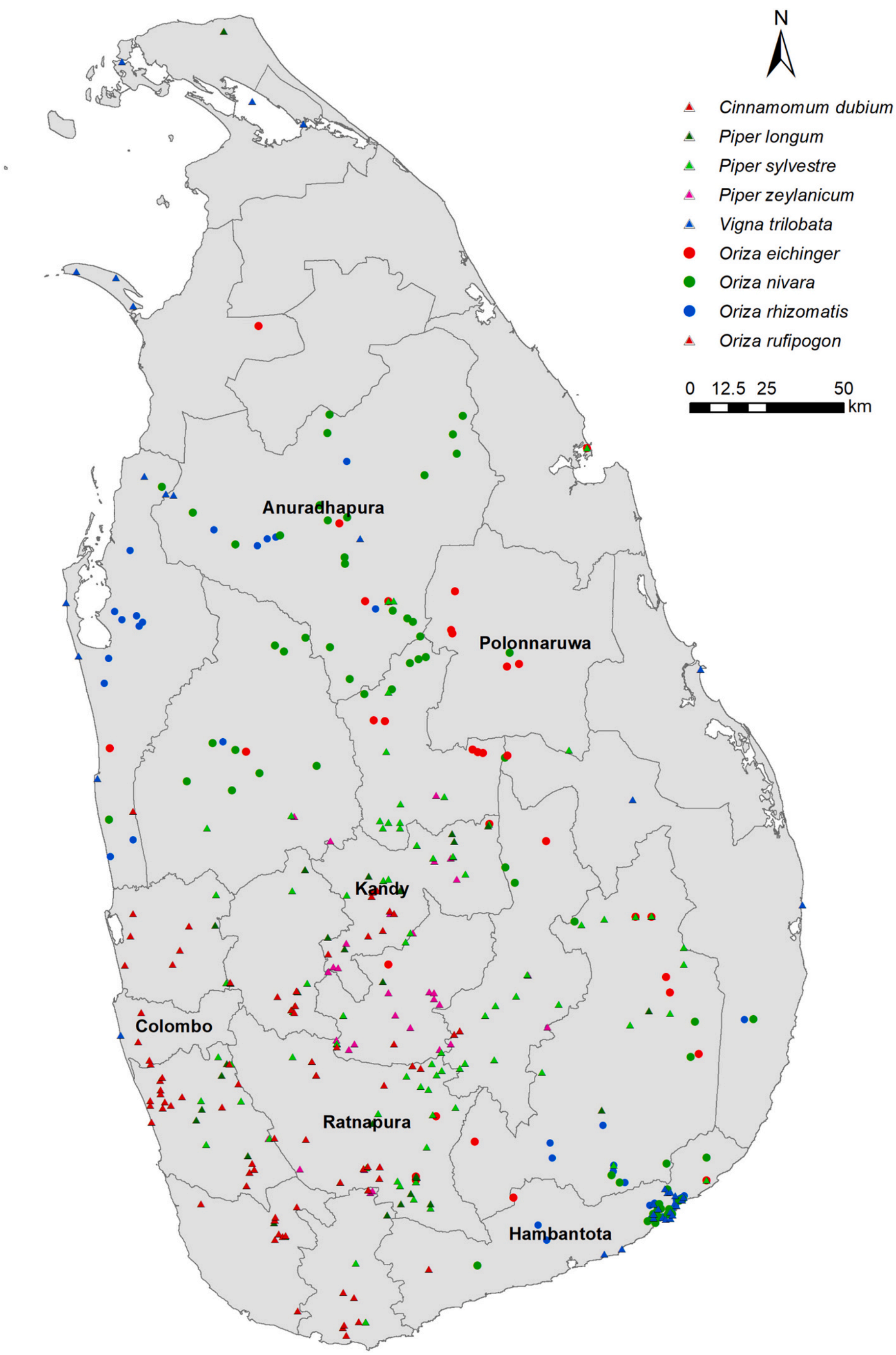

Fig. 1. Distribution of occurrence records of the nine crop wild relative species used in this study.

2.3. Maxent modeling

For model building, we selected the machine learning program, Maximum Entropy Species Distribution Modeling (Maxent; version 3.4.1) (https://biodiversityinformatics.amnh.org/open_source/maxent/) which is based on the maximum entropy principle to understand the potential distribution of selected CWR species in Sri Lanka (Phillips et al., 2006). The selection of Maxent in the current study was due to several reasons: (i) Maxent is a robust modeling technique that mostly outperforms many other super modeling methods (Elith et al., 2011; Merow et al., 2013; Phillips and Dudík, 2008); (ii) Maxent uses presence-only species occurrences and also both continuous and categorical environmental predictors as input data; (iii) Maxent performs well across all sample sizes including samples of small numbers of occurrences; however, it needs to be interpreted with caution (Baldwin, 2009; Hernandez et al., 2006; Wisz et al., 2008) and (iv) Maxent results can be easily visualized into a binary prediction (i.e. suitable and unsuitable) using a selected threshold. A combination of feature types influences the predictive performance of the Maxent algorithm (Phillips and Dudík, 2008). The five feature types existing are linear (L), quadratic (Q), product (P), threshold (T), and hinge (H). The selection of feature classes depends on the number of presence records available (Merow et al., 2013). The Maxent algorithm determines the combination of feature classes to use if default "auto features"' is selected. We used all feature types for the species that exceeded 80 presence records; L, Q and H with 15–79 records (Merow et al., 2013; Phillips and Dudík, 2008). Five replicates were selected with bootstrapping

Table 1
Selected variables for maxent modeling.

No	Variable	Unit	Symbol
1	Mean Diurnal Range (Mean of monthly (max temp - min temp))	Celsius (°C)	bio_2
2	Maximum temperature of the warmest month	Celsius (°C)	bio_5
3	Minimum temperature of the coldest month	Celsius (°C)	bio_6
4	Annual precipitation	Millimeters (mm)	bio_12
5	Precipitation of driest month	Millimeters (mm)	bio_14
6	Precipitation seasonality	Millimeters (mm)	bio_15
7	Precipitation of coldest quarter	Millimeters (mm)	bio_19
8	Global Land Cover	N/A	landcover
9	Elevation	Meters	dem
10	Soil	N/A	soil
11	Aspect	Degrees	aspect

(sampling with replacement) as species occurrence numbers are generally sparse (Phillips et al., 2006). Models were run with 1000 maximum iterations, allocating sufficient time for convergence to make a smooth prediction. Random test percentage was set to 20%, allowing 80% of the occurrence data for model training. We modeled multiple species with varying numbers of occurrences. Therefore, species-specific tuning is not practical and thus we let the other parameters remain at default values. Default settings have been proven as good across a range of species and occurrence numbers (Phillips and Dudík, 2008). Maxent algorithms built on current climate data were projected to the future scenarios and the resulting average output ASCII rasters were visualized in ArcMap (version 10.4.1) for analysis.

2.4. Model performance

Model performance was assessed through widely used accuracy measures: threshold-independent Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve and threshold–dependent True Skill Statistic (TSS) (Allouche et al., 2006; Fielding and Bell, 1997; Phillips et al., 2006). In addition, confusion matrix derived measures, sensitivity (correctly classified presences as a percentage) and specificity (correctly classified absences as a percentage) were examined (Fielding and Bell, 1997). The AUC values not less than 0.7 implies moderate model performance while the AUC values exceeding 0.9 implies good performance (Peterson et al., 2011; Swets, 1988). TSS values greater than 0.4 indicate moderate performance while the values greater than 0.8 indicate good performance (Pramanik et al., 2018).

2.5. Potential area of prediction

Maximizing the sum of the sensitivity and specificity threshold was used to develop binary maps of presence and absence (suitable and not suitable) under the current climate and climate change scenarios for 2050 and 2070. This is a recognized threshold selection approach for presence-only data with pseudo-absences as this approach has been proven to produce consistent results across a range of datasets (Liu et al., 2016). Presence-absence (suitable-not suitable) maps were developed using this threshold approach and suitable area of each species was calculated using the Field Calculator tool in ArcMap. The percentage change of suitable area was estimated for 2050 and 2070 under RCP4.5 and 8.5 scenarios in relation to the current climate. The classified species layers were combined in ArcMap to develop a cumulative species richness map ('heat map'), representing the distribution of all evaluated CWR species, by overlaying potential suitability areas of all species. The combined raster map was classified into six species richness classes depending on the number of species that overlapped: none (0 species), very low (1 species), low (2 species), moderate (3 species), high (4 species) and very high (≥5 species).

3. Results

Models of nine CWR species showed acceptable predictive accuracy for further study (Table S3). The significance of the highly contributing variables for the potential distribution of CWR varied among the species; however, a few variables were more common predictors than others among the species evaluated (Fig. S2). This variable importance is mostly consistent with the results of the Jackknife test as well. In many models, soil, precipitation of driest month (bio_14), annual precipitation (bio_12) and dem performed relatively better than the other variables. The overall contribution of precipitation variables was significant in all models. Also, the contribution of soil variable determining the potential species distribution was found to be high across all models.

The potential habitat preferences of individual CWR species under current climate and future scenarios are presented in Fig. 2. In many species, the calculated projected suitable areas decrease from the current climate to 2070 under two emissions scenarios (Fig. 3; Table 2). Many models predict a decrease in the likely suitable area by 2050 and increase again by 2070 under RCP4.5 (low emissions scenario). However, under RCP8.5 (high emissions scenario), these species are in rapid continuous decline and six species will lose more than 80% of their suitability areas by 2070. On the contrary, *P. sylvestre* is projected to increase in the potentially suitable area from the current climate to the future, until 2070 under all scenarios and predicted to gain considerable area (126–167% gain). The map showing cumulative species richness across nine CWR species under current climate and future scenarios, produced by overlapping potential habitat suitability of each species, is presented in Fig. 4. The projected map under current climatic conditions implies a region of potential CWR species richness in the south-west wet zone of Sri Lanka, around Ratnapura, Kandy and Nuwara Eliya districts; however, this greater richness diminishes in the future under climate change scenarios.

4. Discussion

In species distribution modeling, the use of ecologically meaningful variables is important to obtain realistic, reliable and precise prediction (Mod et al., 2016). This study found that precipitation variables, particularly precipitation of the driest month (bio_14) and annual precipitation (bio_12) are vital in determining the distribution of CWR species in Sri Lanka. The performance of soil variable is exceptionally high across all models; however, it is not a predictor that is influenced by climate change and thus, the relative influence of soil variable determining the potential distribution of these species is low (Ratnayake et al., 2020). We consider that the models were significantly improved by incorporating this variable. Overall, the model performance was good across the selected species. Generally, species that had small sample sizes with limited distribution gave relatively high AUC values (Evangelista et al., 2008; Van Proosdij et al., 2016; Yang et al., 2013); thus, the high AUC values we received in our models could be due to the highly specialized ecological niches of these species.

Phillips et al. (2017) have stated that CWR species are generally found in diverse habitats with a broader range of environmental settings as they can withstand climatic extremes. However, our results do not support these findings. We found a greater number of evaluated species (eight species out of nine) are predicted to decline in their potentially suitable habitats by 2050, suggesting these species are quite vulnerable to the impacts of climate change. The results also imply that RCP8.5 has a greater impact on the potential distribution of these species and their richness under changing climatic conditions. Thus, CWR may be less adapted as they are not cultivated in many environmental conditions. Further, based on the experience of ecogeographic surveys, Liyanage

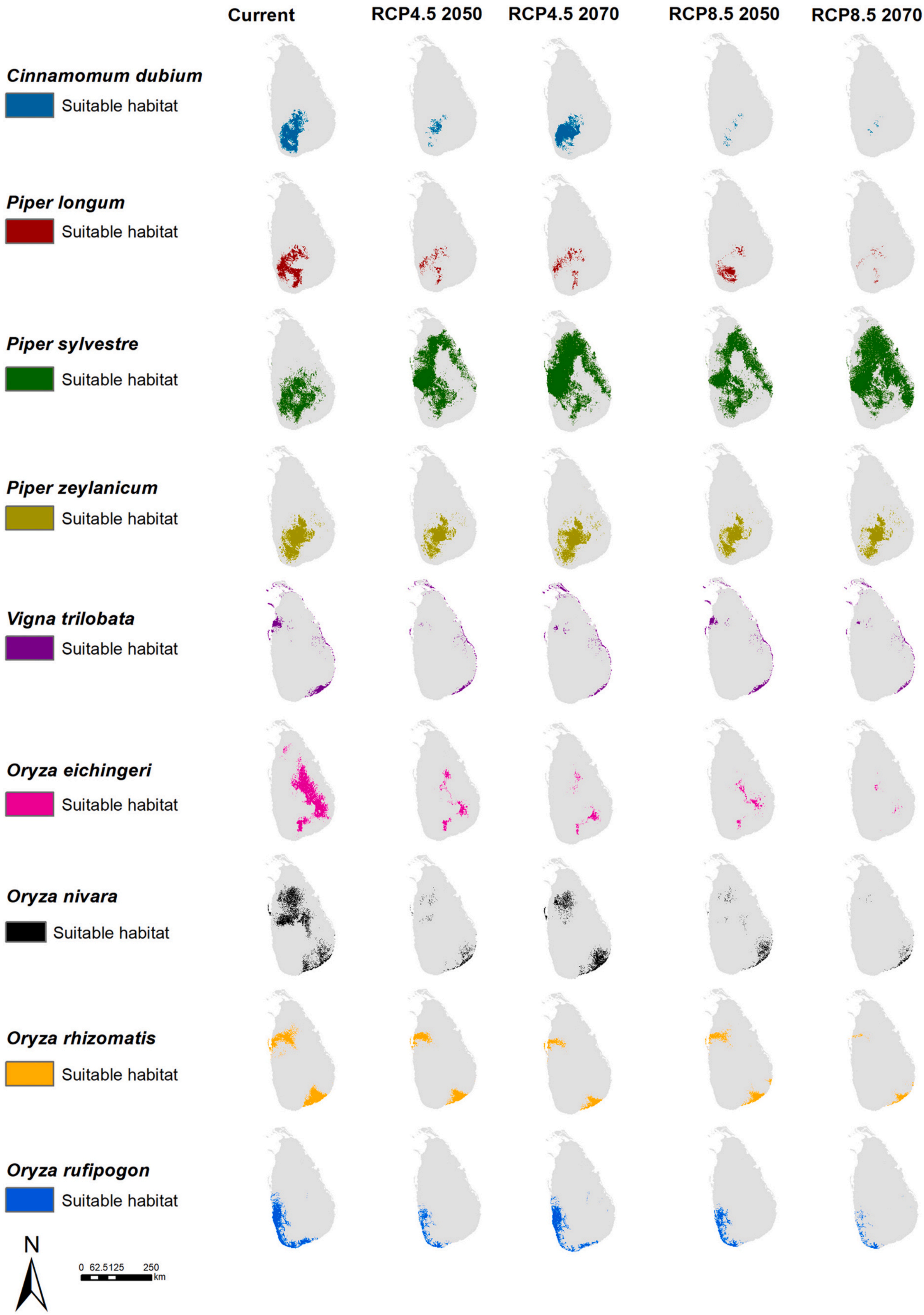

Fig. 2. Maps showing the potential suitable habitats of nine crop wild relative species in Sri Lanka under current climate and RCP4.5 and 8.5 scenarios for 2050 and 2070.

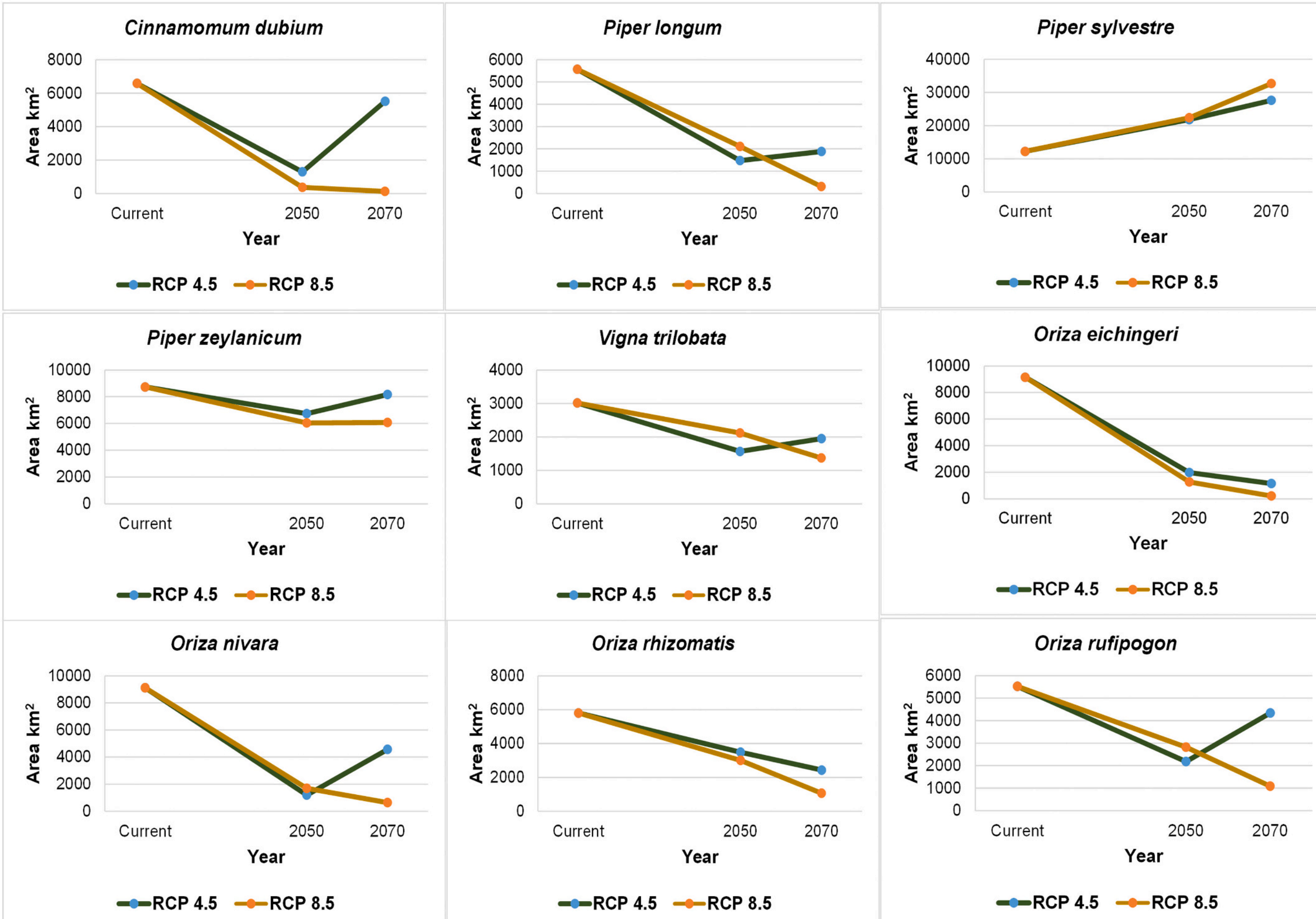

Fig. 3. Graphical illustration to show how potentially suitable area (km^2) of nine crop wild relative species change under current climate and RCP4.5 and 8.5 scenarios for 2050 and 2070.

Table 2
Potentially suitable area (km^2) of nine crop wild relative species under current climate and RCP4.5 and 8.5 scenarios for 2050 and 2070 (percentage changes are given within brackets relevant to current climate).

No	Species	Current	RCP4.5 for 2050	RCP4.5 for 2070	RCP8.5 for 2050	RCP8.5 for 2070
1	*Cinnamomum dubium*	6581	1296 (−80)	5512 (−16)	366 (−94)	121 (−98)
2	*Piper longum*	5571	1477 (−73)	1885 (−66)	2107 (−62)	311 (−94)
3	*Piper sylvestre*	12,214	21,806 (79)	27,620 (126)	22,333 (83)	32,660 (167)
4	*Piper zeylanicum*	8736	6737 (−23)	8173 (−6)	6041 (−31)	6068 (−31)
5	*Vigna trilobata*	3014	1567 (−48)	1948 (−35)	2114 (−30)	1370 (−55)
6	*Oryza eichingeri*	9155	1978 (−78)	1147 (−87)	1273 (−86)	207 (−98)
7	*Oryza nivara*	9118	1195 (−87)	4569 (−50)	1694 (−81)	638 (−93)
8	*Oryza rhizomatis*	5804	3489 (−40)	2432 (−58)	3001 (−48)	1058 (−82)
9	*Oryza rufipogon*	5526	2183 (−60)	4342 (−21)	2821 (−49)	1084 (−80)

(2010) reports that the majority of CWR species in Sri Lanka have restricted geographic distributions. For instance, *Cinnamomum* species are confined to the wet zone of the country and *Piper* species are mostly distributed in the wet and intermediate zones (Table S1). Based on an experimental study, Jablonski et al. (2002) has stated that the reproductive responses of CWR (i.e., fruits and seeds production) are much less than crops, at higher levels of CO_2. Thus, climate change and associated atmospheric CO_2 increase may influence the success of CWR in the future. Also, the species response to climate change can vary and it can be highly taxon-specific (Fei et al., 2017). For instance, our results suggest that the pattern of shift of *Piper sylvestre* under climate change is different from other species. Also many species potentially decline their habitat distribution until 2050 and increase again until 2070, particularly under RCP4.5 scenario. Thus, species may not show the same pattern of suitable habitats change under climate change. Literature shows that some species have shown differences in their pattern of range shifts when drastic climatic changes occurred in the past (Root et al., 2003). A study by Jarvis et al. (2008) has shown that climate change strongly reduces the potential habitat suitability of wild relatives of peanut (*Arachis*), potato (*Solanum*) and cowpea (*Vigna*), leading to fragmentation of suitable areas. Phillips et al. (2017) have reported a range shift of CWR species in Norway with likely increased richness in the future under climate change. Also in complex ecological systems, climate change can cause multifaceted, non-sequential and perhaps unpredictable changes (Walther, 2010). Climate change can result in a decline in the availability of crop pollinators that provide valuable ecosystem services for crop production (Giannini et al., 2017).

Our findings suggest that the southwest wet zone is rich in CWR species compared with the other parts of the country under the present climate (Fig. 4). Occurrences of a majority of the CWR species (26 species listed in Table S1) considered in this study are located in this

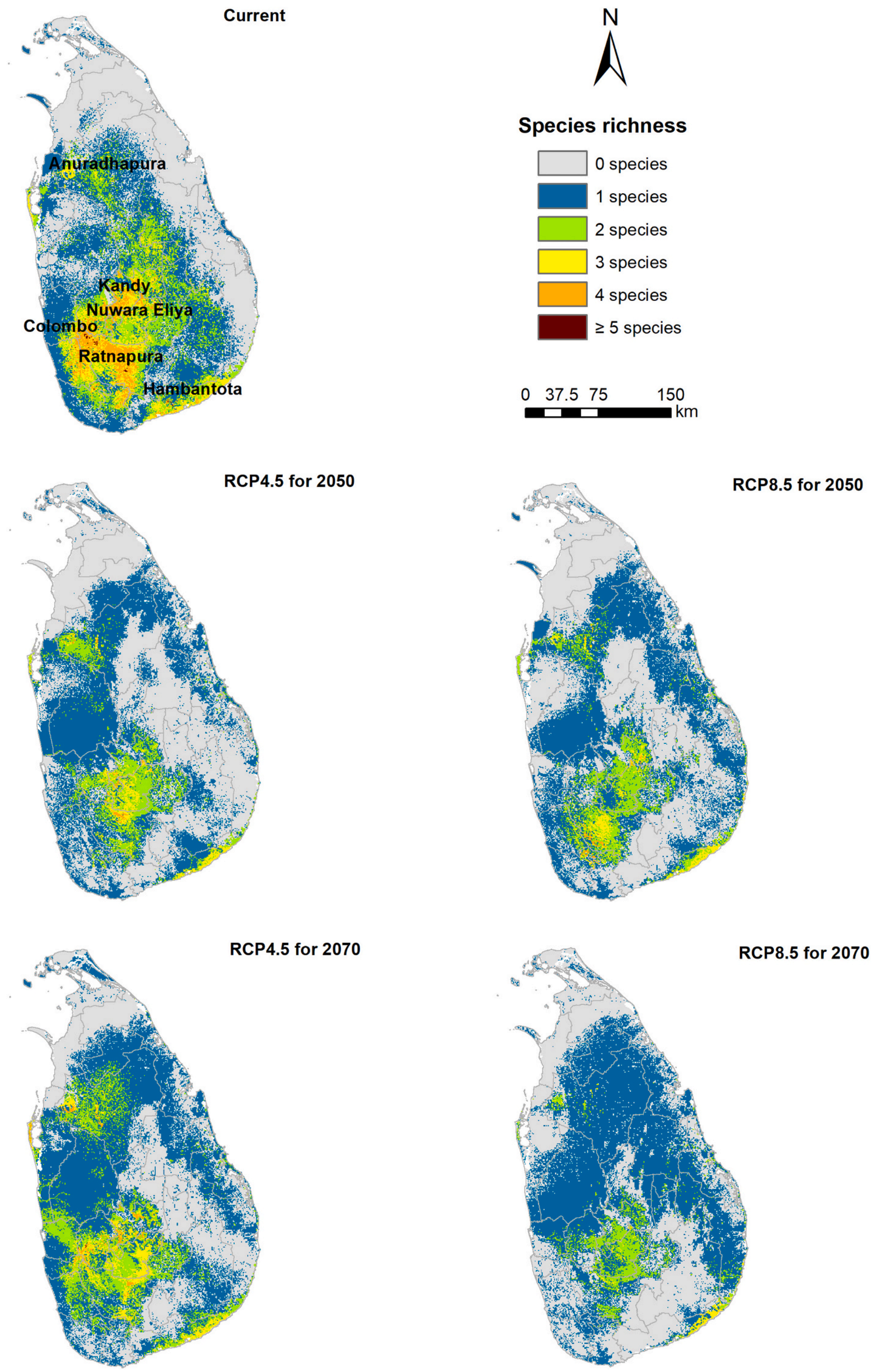

Fig. 4. Potential species richness of evaluated nine crop wild relative species under current climate and RCP4.5 and 8.5 scenarios for 2050 and 2070.

region. The southwest wet zone of Sri Lanka is considered as a global biodiversity hotspot with a greater level of endemism (Myers et al., 2000). Range-restricted endemic species are extremely vulnerable to climate changes as they are not adapted to tolerate a variety of climatic conditions (Bai et al., 2018). The species' existence in southwest Sri Lanka is increasingly threatened by human interventions due to growing population pressure in this area (Gunawardene et al., 2007; Myers et al., 2000). Further, this region is a hotspot of invasive plants richness (Kariyawasam et al., 2019a) and thus, this may cause additional competition to the survival of native CWR species in this region in the future. Invasive species can cause potentially severe impacts under climate change with negative implications for the survival of native flora (Kariyawasam et al., 2021). In this context, the sustainability of CWR in the future and utility of them in agriculture development activities in Sri Lanka in the future is uncertain. This situation calls for the requirement of a well-organized program for CWR conservation and management, including supportive policies (Castañeda-Álvarez et al., 2016; Hunter and Heywood, 2011; Maxted et al., 2020).

Systematic conservation planning is mandatory for the persistence of biodiversity as species' existence on earth is potentially challenged by climatic changes, extensive habitat destructions and many other human–mediated disturbances (Margules and Pressey, 2000; Root et al., 2003). The safeguarding of existing populations of CWR in Sri Lanka is critically important as many species have highly localized geographic distribution and they are susceptible to climate changes and decline in their habitat suitability in the future. These CWR species consist of valuable untapped genetic potential that can be utilized in future crop improvement programs in the country, as well as possessing genetic traits that might be beneficial globally. Thus, the potential distribution maps developed by this study are valuable tools for guiding the implementation of appropriate conservation strategies. Further, they can be used for prioritizing the priority areas for in situ conservation, i.e., establishment of CWR reserves. Species whose conservation status has been assessed as 'Least Concern' by the red listing process should not be overlooked while developing conservation measures (van Treuren et al., 2020). For instance, *P. zeylanicum* is a 'Least Concern' species, but our findings imply that this species is predicted to decline in its potential habitat suitability in the future. We also found that the majority of our CWR occurrences are located outside the protected area system. These populations do not have any form of legal protection and they are potentially at increased risk from anthropogenic impacts, i.e., habitat destruction. Thus, the value of biodiversity outside protected areas system needs to be taken into account in future national conservation planning, particularly for CWR conservation (Kariyawasam et al., 2020). Even in protected areas, the consideration given for CWR conservation is much less compared with fauna and timber crops (Liyanage, 2010). In addition, the distribution maps are vital for designing future CWR exploration activities as they indicate the areas with a greater possibility of species occurrence. Conservation and management strategies should address the recovery requirements of individual species as species show differences to the impacts of climate change. CWR species that are at immediate risk of extinction should be given high-priority for conservation. Wild rice is a potentially important genetic resource for improving disease resistance in crops. For instance, 18 accessions of *O. nivara* found in Sri Lanka between 2006 and 2008 showed resistance to Brown Plant Hopper, which is one of the main rice pests in the country. Further, wild rice species, *O. nivara* and *Oryza rufipogon* are extremely important in crop improvement programs as they easily hybridize with cultivated rice species (Hunter and Heywood, 2011).

If urgent conservation actions are not taken to safeguard these species, some of them might be lost forever. Authorities have not yet recognized and utilized the potential benefits of these species for agricultural development, particularly in developing countries, which hinders their conservation. Protection of existing CWR localities will preserve the genetic diversity that can be used for future agricultural development activities in the country. This would make a substantial contribution towards food security, poverty alleviation and elimination of malnutrition in Sri Lanka in the future.

5. Conclusion

The study findings reveal that climate change can lead to a reduction in the potentially suitable areas of the majority of the evaluated CWR species in Sri Lanka. A majority of the evaluated species show high levels of vulnerability to climate changes, except *P. sylvestre* that is predicted to increase its range. This may have negative consequences for agriculture and food systems in Sri Lanka, leading to food insecurity. The study findings highlight the importance of the conservation of existing habitats of priority CWR species and provides implications for their ex situ conservation. The study also provides important baseline data to help conservation planners in preparing species recovery plans for high-risk species to ensure their better management.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crsust.2021.100092.

References

Aiello-Lammens, M.E., Boria, R.A., Radosavljevic, A., Vilela, B., Anderson, R.P., 2015. spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. Ecography 38 (5), 541–545.

Al, W., Orking, G.R., Clima, O., 2008. Climate Change and Food Security: A Framework Document. Food and Agriculture Organization of the United Nations Rome, Italy.

Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). J. Appl. Ecol. 43 (6), 1223–1232.

Bai, Y., Wei, X., Li, X., 2018. Distributional dynamics of a vulnerable species in response to past and future climate change: a window for conservation prospects. PeerJ 6, e4287.

Bakry, F., Carreel, F., Jenny, C., Horry, J.-P., 2009. Genetic improvement of banana. In: Breeding Plantation Tree Crops: Tropical Species. Springer, pp. 3–50.

Baldwin, R., 2009. Use of maximum entropy modeling in wildlife research. Entropy 11 (4), 854–866.

Bebber, D.P., Ramotowski, M.A., Gurr, S.J., 2013. Crop pests and pathogens move polewards in a warming world. Nat. Clim. Chang. 3 (11), 985–988.

Boria, R.A., Olson, L.E., Goodman, S.M., Anderson, R.P., 2014. Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. Ecol. Model. 275, 73–77. https://doi.org/10.1016/j.ecolmodel.2013.12.012.

Castañeda-Álvarez, N.P., et al., 2016. Global conservation priorities for crop wild relatives. Nat. Plants 2 (4), 1–6.

Chakraborty, S., Newton, A.C., 2011. Climate change, plant diseases and food security: an overview. Plant Pathol. 60 (1), 2–14.

Dempewolf, H., Eastwood, R.J., Guarino, L., Khoury, C.K., Müller, J.V., Toll, J., 2014. Adapting agriculture to climate change: a global initiative to collect, conserve, and use crop wild relatives. Agroecol. Sustain. Food Syst. 38 (4), 369–377.

Dempewolf, H., Baute, G., Anderson, J., Kilian, B., Smith, C., Guarino, L., 2017. Past and future use of wild relatives in crop breeding. Crop Sci. 57 (3), 1070–1082.

Dormann, C.F., et al., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36 (1), 27–46.

Elith, J., Leathwick, J., 2007. Predicting species distributions from museum and herbarium records using multiresponse models fitted with multivariate adaptive regression splines. Divers. Distrib. 13 (3), 265–275.

Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E., Yates, C.J., 2011. A statistical explanation of MaxEnt for ecologists. Divers. Distrib. 17 (1), 43–57.

Evangelista, P.H., Kumar, S., Stohlgren, T.J., Jarnevich, C.S., Crall, A.W., Norman III, J. B., Barnett, D.T., 2008. Modelling invasion for a habitat generalist and a specialist plant species. Divers. Distrib. 14 (5), 808–817.

Fei, S., Desprez, J.M., Potter, K.M., Jo, I., Knott, J.A., Oswalt, C.M., 2017. Divergence of species responses to climate change. Sci. Adv. 3 (5), e1603055.

Fielding, A.H., Bell, J.F., 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environ. Conserv. 24 (1), 38–49.

Folland, C.K., et al., 2001. Observed climate variability and change. In: Houghton, J.T., et al. (Eds.), Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, p. 881.

Franklin, J., 2009. Mapping species distributions: Spatial inference and prediction. In: Ecology, Biodivesity and Conservation. Cambridge University Press, Cambridge.

Garrett, K.A., Dendy, S.P., Frank, E.E., Rouse, M.N., Travers, S.E., 2006. Climate change effects on plant disease: genomes to ecosystems. Annu. Rev. Phytopathol. 44, 489–509.

Giannini, T.C., Costa, W.F., Cordeiro, G.D., Imperatriz-Fonseca, V.L., Saraiva, A.M., Biesmeijer, J., Garibaldi, L.A., 2017. Projected climate change threatens pollinators and crop production in Brazil. PLoS One 12 (8), e0182274.

González-Orozco, C.E., Galán, A.A.S., Ramos, P.E., Yockteng, R., 2020. Exploring the diversity and distribution of crop wild relatives of cacao (*Theobroma cacao* L.) in Colombia. Genet. Resour. Crop. Evol. 1–15.

Gunawardene, N.R., et al., 2007. A brief overview of the Western Ghats–Sri Lanka biodiversity hotspot. Curr. Sci. 93 (11), 1567–1572.

Hernandez, P.A., Graham, C.H., Master, L.L., Albert, D.L., 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. Ecography 29 (5), 773–785.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25 (15), 1965–1978.

Hunter, D., Heywood, V., 2011. Crop Wild Relatives: A Manual of in situ Conservation. Earthscan, London; Washington, DC.

IPCC, 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva, Switzerland.

Jablonski, L.M., Wang, X., Curtis, P.S., 2002. Plant reproduction under elevated CO2 conditions: a meta-analysis of reports on 79 crop and wild species. New Phytol. 156 (1), 9–26.

Jarvis, A., Lane, A., Hijmans, R.J., 2008. The effect of climate change on crop wild relatives. Agric. Ecosyst. Environ. 126 (1–2), 13–23.

Kadupitiya, H.K., De Silva, S.H.S.A., Dilshani, D.G.S., Weerasinghe, P., 2018. Distribution of soil organic carbon in Sri Lanka: A GIS based modeling approach. Trop. Agric. 166 (3), 91–106.
Kallow, S., et al., 2020. Regulation of seed germination by diurnally alternating temperatures in disturbance-adapted banana crop wild relatives (*Musa acuminata*). Seed Sci. Res. 30 (4), 238–248.
Kariyawasam, C.S., Kumar, L., Ratnayake, R.S.S., 2019a. Invasive plant species establishment and range dynamics in Sri Lanka under climate change. Entropy 21 (6), 571. https://doi.org/10.3390/e21060571.
Kariyawasam, C.S., Kumar, L., Ratnayake, S.S., 2019b. Invasive plants distribution modeling: a tool for tropical biodiversity conservation with special reference to Sri Lanka. Trop. Conserv. Sci. 12, 1–12. https://doi.org/10.1177/1940082919864269.
Kariyawasam, C.S., Kumar, L., Ratnayake, S.S., 2020. Potential risks of plant invasions in protected areas of Sri Lanka under climate change with special reference to threatened vertebrates. Climate 8 (4), 51. https://doi.org/10.3390/cli8040051.
Kariyawasam, C.S., Kumar, L., Ratnayake, S.S., Wijesundara, D., 2021. Potential risks of invasive alien plant species on native plant biodiversity in Sri Lanka due to climate change. Biodiversity 1–11.
Kramer-Schadt, S., et al., 2013. The importance of correcting for sampling bias in MaxEnt species distribution models. Divers. Distrib. 19 (11), 1366–1379. https://doi.org/10.1111/ddi.12096.
Leroy, B., Meynard, C.N., Bellard, C., Courchamp, F., 2016. Virtualspecies, an R package to generate virtual species distributions. Ecography 39 (6), 599–607.
Liu, C., Newell, G., White, M., 2016. On the selection of thresholds for predicting species occurrence with presence-only data. Ecol. Evolut. 6 (1), 337–348.
Liyanage, A.S.U., 2010. Eco-Geographic Survey of Crop Wild Relatives. In Situ Conservation of Crop Wild Relatives through the Enhanced Information Management and Field Application Project. Plant Genetic Resources Centre, Peradeniya, Sri Lanka.
Margules, C.R., Pressey, R.L., 2000. Systematic conservation planning. Nature 405 (6783), 243.
Maxted, N., Kell, S., 2009. Establishment of a Global Network for the in situ Conservation of Crop Wild Relatives: Status and Needs, 266. FAO Commission on Genetic Resources for Food and Agriculture, Rome, Italy.
Maxted, N., Ford-Lloyd, B.V., Jury, S., Kell, S., Scholten, M., 2006. Towards a definition of a crop wild relative. Biodivers. Conserv. 15 (8), 2673–2685.
Maxted, N., Hunter, D., Ríos, R.O., 2020. Plant Genetic Conservation. Cambridge University Press.
Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36 (10), 1058–1069.
Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-Being: Synthesis. Island Press, Washington, DC.
Mishra, V., Kumar, D., Ganguly, A.R., Sanjay, J., Mujumdar, M., Krishnan, R., Shah, R.D., 2014. Reliability of regional and global climate models to simulate precipitation extremes over India. J. Geophys. Res.-Atmos. 119 (15), 9301–9323.
Mod, H.K., Scherrer, D., Luoto, M., Guisan, A., 2016. What we use is not what we know: environmental predictors in plant distribution models. J. Veg. Sci. 27 (6), 1308–1322.
Myers, N., Mittermeier, R.A., Mittermeier, C.G., Da Fonseca, G.A., Kent, J., 2000. Biodiversity hotspots for conservation priorities. Nature 403 (6772), 853. https://doi.org/10.1038/35002501.
Padulosi, S., Heywood, V., Hunter, D., Jarvis, A., 2011. Underutilized species and climate change: Current status and outlook. In: Yadav, S.S., Redden, R.J., Hatfield, J.L. (Eds.), Crop Adaptation to Climate Change. Blackwell Publishing Ltd, Oxford, UK, pp. 507–521.
Parry, M.L., Rosenzweig, C., Iglesias, A., Livermore, M., Fischer, G., 2004. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Glob. Environ. Chang. 14 (1), 53–67.
Peterson, A.T., Soberón, J., Pearson, R.G., Anderson, R.P., Martínez-Meyer, E., Nakamura, M., Araújo, M.B., 2011. Ecological Niches and Geographic Distributions (MPB-49), 56. Princeton University Press, New Jersey.
Phillips, J., Brehm, J.M., van Oort, B., Asdal, Å., Rasmussen, M., Maxted, N., 2017. Climate change and national crop wild relative conservation planning. Ambio 46 (6), 630–643.
Phillips, S., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modelling of species geographic distributions. Ecol. Model. 190, 231–259.
Phillips, S.J., Dudík, M., 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31 (2), 161–175.
Pramanik, M., Paudel, U., Mondal, B., Chakraborti, S., Deb, P., 2018. Predicting climate change impacts on the distribution of the threatened *Garcinia indica* in the Western Ghats, India. Clim. Risk Manag. 19, 94–105.
Ratnayake, R.S.S., Kumar, L., Kariyawasam, C.S., 2020. Neglected and underutilized fruit species in Sri Lanka: prioritisation and understanding the potential distribution under climate change. Agronomy 10 (1), 34. https://doi.org/10.3390/agronomy10010034.
Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6 (1), 1–9.
Root, T.L., Price, J.T., Hall, K.R., Schneider, S.H., Rosenzweig, C., Pounds, J.A., 2003. Fingerprints of global warming on wild animals and plants. Nature 421 (6918), 57–60.
Searchinger, T., Waite, R., Hanson, C., Ranganathan, J., Dumas, P., Matthews, E., Klirs, C., 2019. Creating a Sustainable Food Future: A Menu of Solutions to Feed Nearly 10 billion People by 2050. Final Report. WRI, Washington, D.C., USA.
Sharmila, S., Joseph, S., Sahai, A., Abhilash, S., Chattopadhyay, R., 2015. Future projection of Indian summer monsoon variability under climate change scenario: an assessment from CMIP5 climate models. Glob. Planet. Chang. 124, 62–78.
Singh, A., Dubey, R.K., Bundela, A.K., Abhilash, P.C., 2020. The trilogy of wild crops, traditional agronomic practices, and UN-sustainable development goals. Agronomy 10 (5), 648. https://doi.org/10.3390/agronomy10050648.
Sperber, K.R., et al., 2013. The Asian summer monsoon: an intercomparison of CMIP5 vs. CMIP3 simulations of the late 20th century. Clim. Dyn. 41 (9–10), 2711–2744.
Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. Science 240 (4857), 1285–1293.
Van Proosdij, A.S., Sosef, M.S., Wieringa, J.J., Raes, N., 2016. Minimum required number of specimen records to develop accurate species distribution models. Ecography 39 (6), 542–552.
van Treuren, R., Hoekstra, R., Wehrens, R., van Hintum, T., 2020. Effects of climate change on the distribution of crop wild relatives in the Netherlands in relation to conservation status and ecotope variation. Glob. Ecol. Conserv. e01054.
Vincent, H., et al., 2019. Modeling of crop wild relative species identifies areas globally for in situ conservation. Commun. Biol. 2 (1), 1–8.
Walther, G.-R., 2010. Community and ecosystem responses to recent climate change. Philosoph. Trans. Royal Soc. B: Biol. Sci. 365 (1549), 2019–2024.
Walther, G.-R., et al., 2002. Ecological responses to recent climate change. Nature 416 (6879), 389–395.
Watanabe, M., et al., 2010. Improved climate simulation by MIROC5: mean states, variability, and climate sensitivity. J. Clim. 23 (23), 6312–6335.
Wisz, M.S., Hijmans, R.J., Li, J., Peterson, A.T., Graham, C., Guisan, A., Group N.P.S.D.W, 2008. Effects of sample size on the performance of species distribution models. Divers. Distrib. 14 (5), 763–773.
Yadav, S.S., Hunter, D., Redden, B., Nang, M., Yadava, D., Habibi, A.B., 2015. Impact of climate change on agriculture production, food, and nutritional security. Crop. Wild Relativ. Clim. Change 1–23.
Yang, X.-Q., Kushwaha, S., Saran, S., Xu, J., Roy, P., 2013. Maxent modeling for predicting the potential distribution of medicinal plant, *Justicia adhatoda* L. in Lesser Himalayan foothills. Ecol. Eng. 51, 83–87.
Zair, W., Maxted, N., Amri, A., 2018. Setting conservation priorities for crop wild relatives in the Fertile Crescent. Genet. Resour. Crop. Evol. 65 (3), 855–863.