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Ensemble modeling to predict the impact of future climate change on the global distribution of *Olea europaea* subsp. *cuspidata*

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Climate change is one of the significant factors influencing global species redistribution. As a result, a better understanding of the species' possible range change in future climate conditions is needed. Therefore, this study compiles global geographic occurrence data of a wild olive sub-species, *Olea europaea* subsp. *cuspidate*, and projected potential distribution models in current and future climate scenarios. This study using ensemble modeling predicted that the species will undergo a significant decrease in habitat suitability under future climatic conditions with a contraction ranging from ca. 41 and 42% under RCP4.5 2050 and to about 56 and 61% under RCP8.5 2070 for committee averaging and weighted mean, respectively. More specifically, there will be a decrease in habitat suitability in regions of the southeastern part of the United States in North America; coastal regions in South America; coastal regions in the majority of eastern Africa; coastal parts of Spain, France, Italy, and Greece in Europe; coastal parts of Yemen and Saudi Arabia; the southeastern parts of Pakistan and the southern part of China in Asia; and southwestern and eastern parts of Australia when compared to current habitat suitability. The results of this ensemble modeling could be extremely valuable in identifying cultivation hotspots for the effective restoration and protection of this olive lineage under future climatic conditions.

KEYWORDS

***Olea europaea* subsp. *cuspidata*, species distribution modeling, climate change, global distribution, habitat suitability**

Introduction

Climate change is one of the key components determining the species' range redistribution (Parmesan et al., 2011; Pacifici et al., 2015). As such, changing climatic conditions will likely expand or shrink the species' geographic ranges (Chen et al., 2011; Palmer et al., 2015). Adding to the worries are the consequences of global warming, which are expected to exacerbate in the next 50 years (Ahmad et al., 2019a).

The Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC, 2021) states that the ongoing climate warming has caused the pole-ward shift of numerous plant and animal species in both the southern and the northern hemisphere and the growing season, especially in the northern hemisphere extratropics, has expanded by 2 days each decade since the 1950s. A plethora of research studies have reported that recent anthropogenic-induced ecological changes are responsible for species range shifts (Malhi et al., 2020), changes in phenology (Negi et al., 2021), and species extinctions (Román-Palacios and Wiens, 2020). However, there is still a dearth of information about the biological dynamics of these shifting climatic impacts and documentation of climate change hotspots of vulnerability and resilience (Bellard et al., 2012). Furthermore, rising global temperatures have resulted in significant climatic zone shifts in several areas around the globe, including the substantial expansion of arid climatic zones and the shrinkage of polar climatic zones (IPCC, 2019). As a result, many native species have experienced a substantial shift in their geographical ranges, abundances, and seasonality of activities (Weiskopf et al., 2020). All these negative consequences act as barriers to the management and conservation of biodiversity (Thomas et al., 2004; Butchart et al., 2010; Cook et al., 2012; IPCC, 2012; Pacifici et al., 2017; Pecl et al., 2017; Convention on Biological Diversity, 2020).

As ecology and conservation disciplines require a robust understanding of species distribution and habitat requirements, species distribution models (SDM) are, therefore, one of the essential techniques for spatio-temporal predictions of biodiversity at the biogeographic scale (Alvarado-Serrano and Knowles, 2014; Naimi, 2015; Srivastava et al., 2019). SDM projections can be used to develop sustainable management plans to help minimize the effects of climate change (Pyke and Fischer, 2005; Schorr et al., 2012; Porfirio et al., 2014). However, one major disadvantage of these distribution models is that there are already a large number of modeling algorithms available, and this number is expanding all the time, making it difficult to choose the optimal methodology (Elith et al., 2010; Ahmad et al., 2019b). To overcome this problem, the ensemble modeling technique implemented in the biomod2 package provides a valuable platform for determining the species' current distribution and predicting their future potential Spatio-temporal distributions under changing climatic scenarios (Gillard et al., 2017; Thuiller et al., 2019).

RCPs (representative concentration pathways) represent greenhouse gas emissions, atmospheric concentrations, air pollutant emissions, and land use in the twenty-first century (Vuuren et al., 2011). Based on the mitigation scenarios' trajectory, four (RCPs) have been described (IPCC, 2014). In order to identify suitable habitats for species in the 2050s and 2070s, the model was thus trained using current climate data and projected onto future climate change bioclimatic datasets for all RCPs scenarios. Therefore, to estimate the impact of climate change on species distribution, multiple scenarios based on various RCPs must be examined (Araujo and Rahbek, 2006; Parmesan, 2006; Beaumont et al., 2007; Bellard et al., 2012). This paper is based on the global distribution modeling of *Olea europaea* subsp. *cuspidata* (synonyms—*Olea ferruginea, Olea africana, Olea chrysophylla*) using an ensemble modeling approach. It is a wild species of olive lineage (Green, 2002) and is believed to be of Mediterranean origin (De Candolle, 1882) and a prominent part of Mediterranean vegetation (De Ollas et al., 2019). However, the species is introduced into Australia, New Zealand, and the Pacific islands as a rootstock for cultivated olive (Besnard et al., 2014). Due to over-exploitation, Ethiopia's species is extremely threatened (Negash, 2010). It is used for various purposes, including quality fuel wood and furniture (Negash, 2010), and is also a valuable source of natural antioxidants and bioactive materials (Long et al., 2010). It has numerous medicinal and anti-bacterial properties (Masoko and Makgapeetja, 2015). Therefore, climate change affects livelihoods and economic security, particularly in communities, along with its distribution range. More specifically, we aim to address the following key questions: (1) What is the current distribution of *Olea europaea* subsp. *cuspidata*? (2) What will be the future potential distribution of this species under different climate change scenarios? and (3) what are the key bioclimatic variables affecting the distribution of this species?

Materials and methods

Species distribution data

Occurrence data for *Olea europaea* subsp. *cuspidata* was downloaded primarily from the Global Biodiversity Information Facility (GBIF, 2021) using the gbif function from the dismo package (Hijmans et al., 2020), Botanical Information and Ecology Network Database (BIEN; accessed on 01 August 2021) using the BIEN_occurrence_species function from BIEN package (Maitner et al., 2018) and was further supplemented with intensive field surveys carried by the authors from North Western India and Herbarium records from Forest Research Institute (FRI) Dehradun and various centers of Botanical Survey of India (BSI Dehradun, BSI Kolkatta, and HAWHRC Solan). A total of 4,599 georeferenced occurrence points were obtained from the above-mentioned sources for *Olea europaea* subsp. *cuspidata*. The obtained occurrence dataset was subsequently processed to exclude any locations that fell into the oceans. As a result, 4,461 points were retained. Furthermore, it is a well-known fact that distribution data is frequently skewed toward locations that are geographically user-friendly and easily accessible (Hijmans et al., 2005). This can manifest itself in the form of geographical sample bias (Ahmad et al., 2019a). We employed spatial thinning to minimize spatial autocorrelation and sample bias by dividing the entire region into 10×10 km grid cells and selecting a single occurrence point from each cell with one or more occurrence points. After geographic thinning, the final dataset for modeling the distribution of *Olea europaea* subsp. *cuspidata* in this study consisted of 776 georeferenced points.

Environmental data

We used the current climatic factors from the WorldClim database, version 1.4 (Hijmans et al., 2005) (http://www.worldclim.org) to estimate the global current potential distribution of *Olea europaea* subsp. *cuspidata*. Between 1950 and 2000, these climatic variables indicated the minimum, maximum, and average values of monthly, quarterly, and annual ambient temperatures and precipitation data. These environmental variables had a spatial resolution of 2.5 arc seconds (~4.5 km resolution at the equator). These bioclimatic variables often show a higher degree of collinearity, resulting in poor misleading model performance (Ahmad et al., 2019a). As a result, we used Pearson's correlation analysis to choose only one variable from each pair of strongly associated variables with a correlation coefficient (i.e., $r > 0.75$ or -0.75) before modeling. A total of 10 variables were retained after correlation analysis for modeling the distribution of target species under present climate conditions (Table 1). The Intergovernmental Panel on Climate Change (IPCC) fifth assessment report (AR5) (Moss, 2010) provided Hadley Global Environment Model 2-Earth System (HADGEM2-ES) simulations for two representative concentration pathways (RCP4.5 and RCP8.5) for the two time periods (i.e., 2050 and 2070) for predicting the future potential distribution of the *Olea europaea* subsp. *cuspidata*. RCPs provide climate change trajectories by describing scenarios based on assumptions about socio-economic conditions, greenhouse gas emissions, and the concentration of air pollutants (Albuquerque et al., 2019). The same set of environmental variables used to estimate the current distribution of the examined species was also used to predict their future distributions.

Modeling technique

We performed the ensemble distribution modeling using the nine algorithms implemented in the biomod2 package (Thuiller et al., 2009, 2020). We performed the ensemble distribution modeling using the nine algorithms as implemented in the biomod2 package (Thuiller et al., 2009, 2020), which include: the Generalized Linear Model (GLM) (McCullagh and Nelder, 1989), the Generalized Additive Models (GAM) (Hastie and Tibshirani, 1990), Generalized Boosted Models (GBM) (Ridgeway, 1999), Classification Tree Analysis (CTA) (Breiman et al., 1984), Flexible Discriminant Analysis (FDA) (Hastie et al., 1994), Artificial Neural Networks (ANN) (Ripley, 1996), Maximum Entropy (MAXENT) (Phillips et al., 2006), Random Forest (RF) (Breiman, 2001), and Surface Response Envelope (SRE) (Busby, 1991). As the different algorithms used for distribution modeling require both presence and absence data types, it is impossible to obtain the actual absence data throughout the study region. Therefore, in this study, we randomly generated an equal number of pseudo-absences to that of presence points within the study area, as recommended by Barbet-Massin et al. (2012) and Guisan et al. (2017). We built the models using 80% of the data (training set) and evaluated the model performance with the rest of the 20% of the data (evaluation set). We generated each of the models three times. We preferred two evaluation metrics to evaluate the accuracy of the models: the area under the curve (AUC) of receiver operating characteristics (ROC) and true skills statistics (TSS) (Allouche et al., 2006; Rather et al., 2022; Wani et al., 2022a). We built the final ensemble models for each climate scenario and time period based on both the committee averaging and weighted mean separately; finally, for creating the final ensemble models, only those models with a TSS score of $\geq$0.8 were used.

TABLE 1 Bioclimatic variables selected for modeling the distribution of *Olea europaea* subsp. *cuspidata* in the present study.

Description of bioclimatic variables	Units	Temporal scale
Annual mean temperature (BIO-1)	Degree Celsius	Annual
Mean diurnal range (BIO-2)	Degree Celsius	Variation
Isothermality (BIO-3)	Dimensionless	Variation
Max temperature of warmest month (BIO-5)	Degree Celsius	Month
Min temperature of coldest month (BIO-6)	Degree Celsius	Month
Mean temperature of wettest quarter (BIO-8)	Degree Celsius	Quarter
Mean temperature of driest quarter (BIO-9)	Degree Celsius	Quarter
Annual mean precipitation (BIO-12)	Millimeter	Annual
Precipitation of driest month (BIO-14)	Millimeter	Month
Precipitation of coldest quarter (BIO-19)	Millimeter	Quarter

Variable importance

To assess the relative impact of each climate condition in determining the distribution of selected plant species, we employed the permutation approach (Elith et al., 2005).

Predictions are made from a particular algorithm after changing only one target variable, while the rest of the variables are maintained statically in this method. The variable relevance estimations are obtained as the difference between the original forecast and the permuted variable prediction divided by one minus the correlation score (1-correlation score) (Ahmad et al., 2019a). As a result, high values indicate that the predictor variable is more important in the model, while a value of 0 indicates that the variable is not important in the model.

Species range change

In order to visualize and measure the range change of the target plant species under future climatic conditions, we used the same biomod range size function as that implemented in the biomod2 package (Guisan et al., 2017). This function provides a summary statistic on species range change, and the prediction map shows the gain or loss of suitable conditions for the studied plant species, according to Guisan et al. (2017). Interestingly, detailed information on four absolute metrics related to "species loss" (i.e., loss of suitable habitat by the studied species under future climate change), "species absence" (i.e., amount of area not occupied by the studied species under current and future climatic scenarios), "stable" (i.e., the amount of area occupied by the studied species both under current and future climatic scenarios) and "gain" (i.e., a gain of suitable habitat by the studied species under future climate change) can be obtained (Guisan et al., 2017). Lastly, from the above four absolute metrics, three additional relative metrics can be calculated, including "percentage loss" (i.e., percentage of currently suitable areas predicted to be lost and is calculated as [loss/(loss + stable)]; "percentage gain" (i.e., percentage of new habitats predicted to be suitable when compared with the species' current distribution size and is calculated as [gain/(loss + stable)]; and "range change," i.e., the overall output of predictions and is calculated as (percentage gain-percentage loss) (Kumari et al., 2022; Wani et al., 2022b).

Results

Model evaluation

The final ensemble models developed had an AUC of 0.991 and a TSS of 0.913 in terms of committee averaging. Similarly, the ensemble models developed had an AUC of 0.992 and a TSS of 0.908 in terms of weighted mean. Both of these scores indicate that our final model had predicted the distribution of the *Olea europaea* subsp. *cuspidata* with higher accuracy. When evaluated against the individual algorithms, the predictive accuracy was again excellent but varied, with RF, GBM, GLM, and GLM performing fairly well, followed by FDA, CTA, and Maxent. Phillips, when compared to the rest of the algorithms, the SRE and ANN had the lowest accuracy (Figure 1).

Variable importance

The performance of the selected bioclimatic variables varied significantly among the different algorithms (Table 2). In particular, the most significant variables governing the distribution of *Olea europaea* subsp. *cuspidata* were BIO-01 (annual mean temperature) with importance scores ranging from 0.13 (in the case of RF) to 0.86 (in the case of GLM) (mean score = 0.46), followed by BIO-05 (max temperature of warmest month) with importance scores ranging from 0.02 (for GBM) to 0.43 (for GLM) (mean score = 0.20) and BIO-03 (Isothermality) with importance scores ranging from 0.08 (for GAM) to 0.31 (for MAXENT.Phillips) (mean score = 0.17). The rest of the variables had diverse responses over different algorithms, therefore their influence on governing *Olea europaea* subsp. *cuspidata* potential distribution was extremely variable (Table 2).

Current distribution

The final ensemble model reveals that under current climatic conditions, the areas having highly suitable and optimal climatic conditions for the growth of *Olea europaea* subsp. *cuspidata* are majority parts of Mexico, the southeastern part of the United States in North America; coastal parts of Columbia, Ecuador, and Peru, major parts of Chile, central, eastern and southern parts of Argentina, majority of Uruguay, and southern and eastern parts of Brazil in South America; coastal parts of western Sahara, Morocco, Libya and Egypt, majority of Ethiopia, Kenya, almost entire of Zimbabwe, Namibia, Botswana, Madagascar, and South Africa in Africa; western coastal parts of Portugal, Spain, France, United Kingdom, Italy, and Turkey in Europe; coastal parts of Yemen and Saudi Arabia, the southeastern part of Pakistan, North Western Himalayan states of Jammu and Kashmir, Himachal Pradesh, Uttarakhand, and Arunachal Pradesh, Bhutan and Nepal, Northwestern part of Myanmar, the northern part of Thailand, the southern part of China in Asia; Central, southern, eastern, western and southern western parts of Australia and major parts of New Zealand in Australasia (Figure 2).

Future potential distribution

The predictions of the future ensemble models showed that there will be a decrease in the habitat suitability for *Olea europaea* Subsp. *cuspidata* under all the future climatic

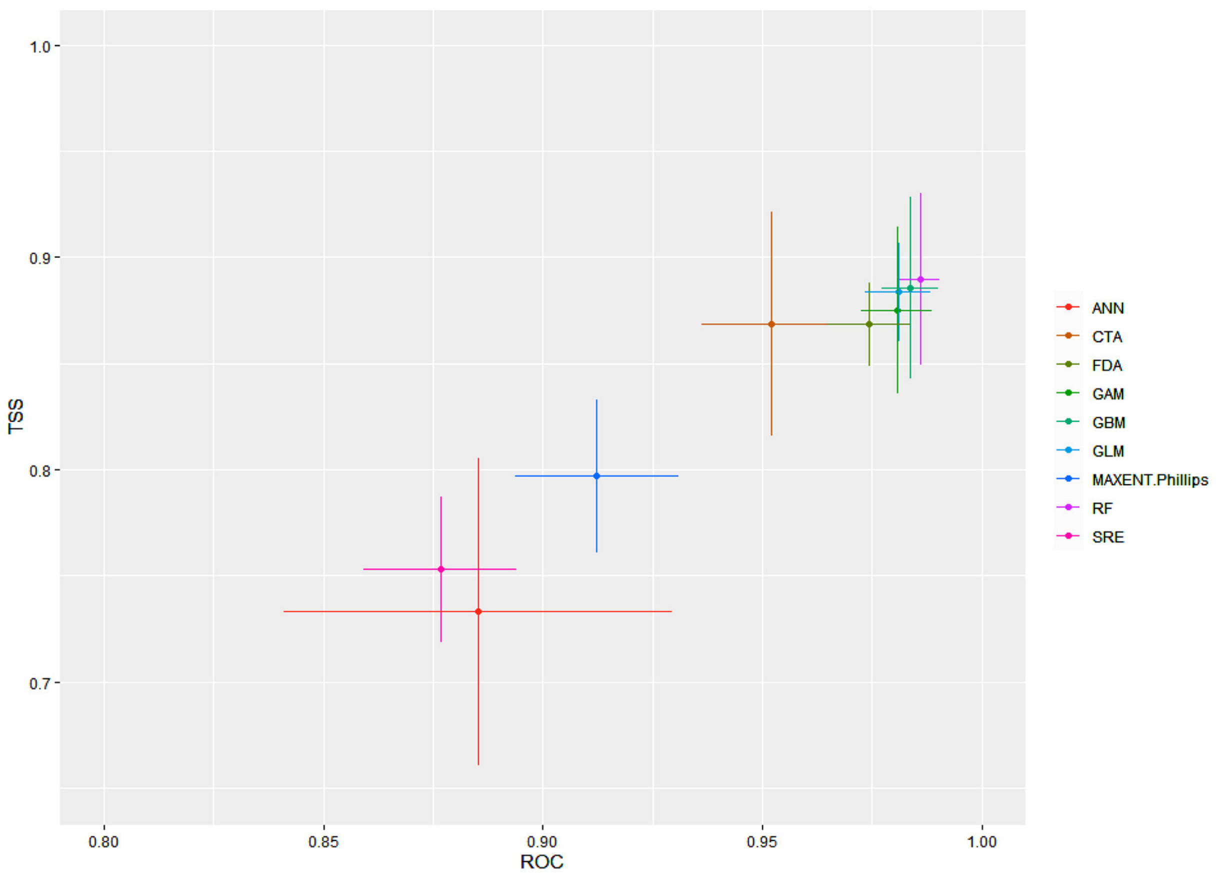

FIGURE 1
For *Olea europaea* subsp. *cuspidata*, mean model evaluation scores by algorithms according to two separate evaluation metrics, ROC (AUC) and TSS.

TABLE 2 The relevance scores of the selected bioclimatic variables, both overall and by the algorithm.

	GLM	GBM	GAM	CTA	ANN	SRE	FDA	RF	MAXENT. Phillips	Mean
bio_01	0.86	0.21	0.68	0.69	0.41	0.35	0.59	0.13	0.19	0.46
bio_02	0.13	0.00	0.08	0.02	0.23	0.13	0.00	0.00	0.02	0.07
bio_03	0.13	0.15	0.08	0.28	0.14	0.25	0.11	0.13	0.31	0.17
bio_05	0.43	0.02	0.40	0.10	0.25	0.23	0.08	0.05	0.22	0.20
bio_06	0.14	0.00	0.10	0.00	0.65	0.30	0.02	0.04	0.06	0.15
bio_08	0.03	0.00	0.05	0.01	0.11	0.20	0.00	0.02	0.11	0.06
bio_09	0.12	0.01	0.09	0.12	0.34	0.33	0.04	0.04	0.05	0.13
bio_12	0.10	0.02	0.08	0.08	0.26	0.18	0.06	0.03	0.16	0.11
bio_14	0.02	0.00	0.02	0.02	0.08	0.12	0.01	0.01	0.14	0.05
bio_19	0.16	0.01	0.08	0.01	0.25	0.14	0.02	0.01	0.06	0.08

scenarios. However, some of the currently suitable areas will consistently remain suitable in future climates also, such as the central part of Mexico, southern and central parts of the United States in North America; coastal parts of Columbia, Ecuador, and Peru, and major parts of Chile, central, eastern and southern parts of Argentina, southern and eastern parts of Brazil in South America; certain parts of Ethiopia, Kenya and Tanzania, eastern Madagascar and Southern parts of Namibia and South Africa in Africa; major parts of Spain, France, United Kingdom, Italy Germany,

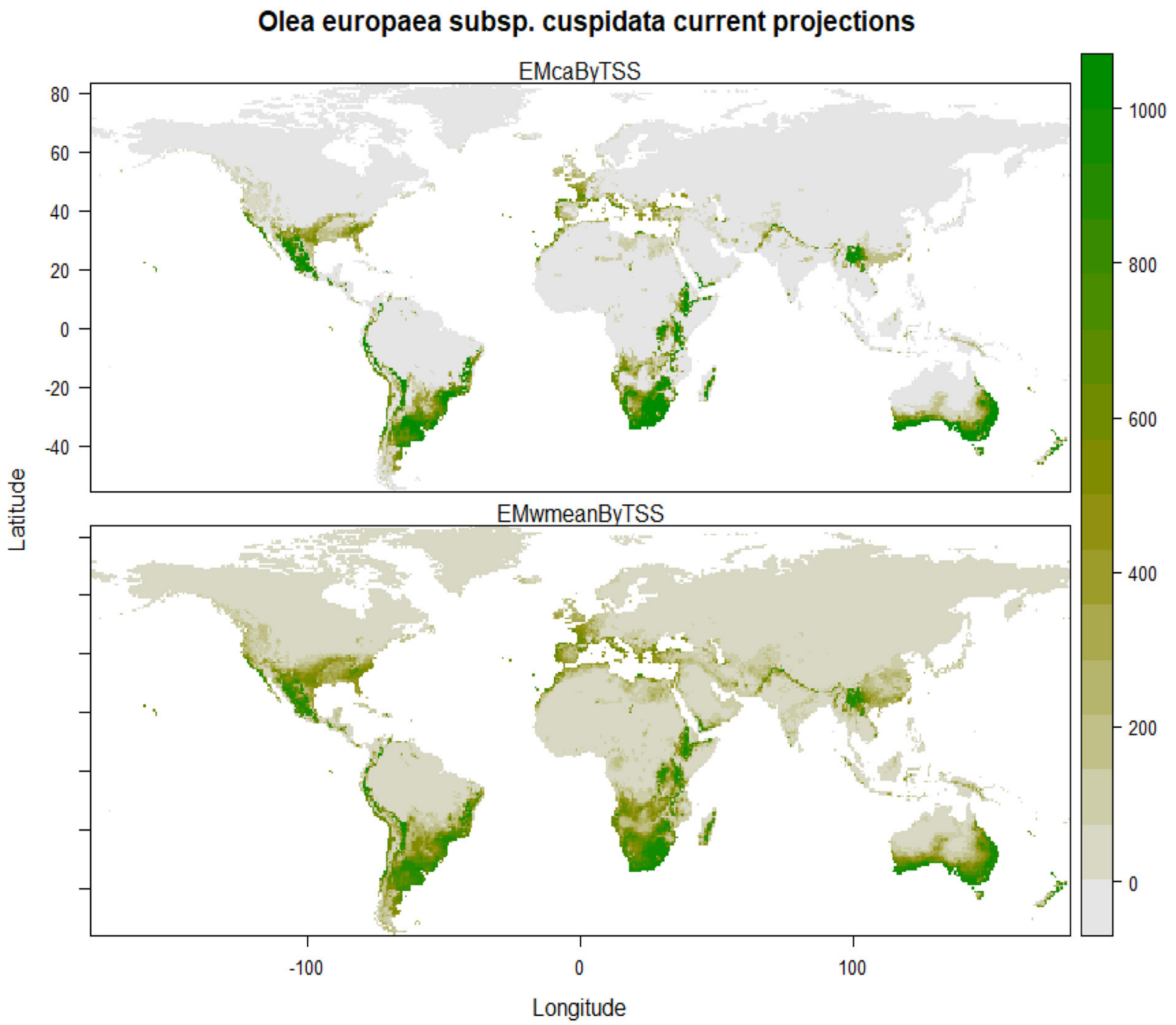

FIGURE 2
Plot showing the geographic projections using the committee average (above) and weighted mean (below) ensemble models for *Olea europaea* subsp. *cuspidata* under current climatic conditions.

and Turkey in Europe; North Eastern Himalayan states of Jammu and Kashmir, Himachal Pradesh, Uttarakhand, and Arunachal Pradesh, Bhutan and Nepal, Northwestern part of Myanmar, the northern part of Thailand in Asia; southern parts of Australia and entire of New Zealand in Australasia (Figure 3).

Species range change

The results of the range change analysis once again indicated that *Olea europaea* subsp. *cuspidata* will undergo significant range changes under future climatic conditions and ranges from −40.52 and −42.11% under RCP4.5 2050 for committee averaging and weighted mean, respectively, to −56.16 and −60.80% under RCP8.5 2070 for committee averaging and weighted mean, respectively (Table 3). This range change will be governed mostly by habitat loss in future climatic scenarios. More specifically, there will be a reduction in suitable areas for *Olea europaea* Subsp. *cuspidata* by about 50.05 and 49.99% (under RCP4.5 2050), 54.20 and 55.04% (RCP4.5 2070), 55.90 and 56.52% (RCP8.5 2050), and 69.17 and 71.11% (under RCP8.5 for the year 2070) for committee averaging and weighted mean, respectively, when compared to current habitat suitability (Table 3). The areas that are likely to become unsuitable in the future include the majority parts of Mexico and the southeastern part of the United States in North America; Northern

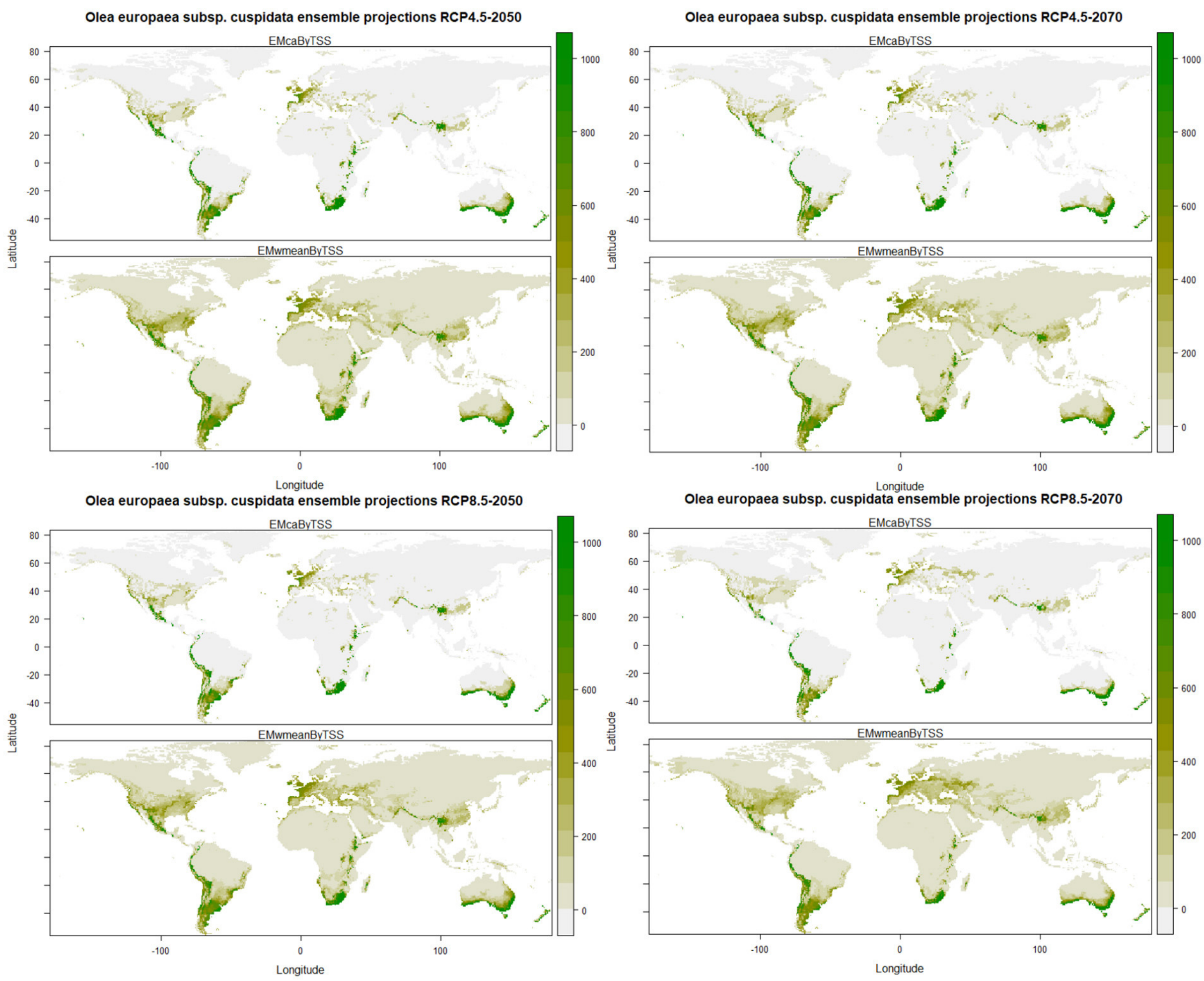

FIGURE 3
Plots of the predicted habitat suitability for *Olea europaea* subsp. *cuspidata* under future climate change scenarios.

Chile, east and central parts of Argentina, certain parts of southern and eastern Brazil in South America; coastal parts of Ecuador and Columbia, central parts of Ethiopia, Kenya and Tanzania, parts of Madagascar and central parts of Namibia and South Africa in Africa; coastal parts of Spain, France, Italy and Greece in Europe; coastal parts of Yemen and Saudi Arabia, the southeastern part of Pakistan and southern part of China in Asia; southwestern and eastern parts of Australia (Figure 4). In contrast, some of the currently unsuitable areas become increasingly suitable for future climate with a range expansion of 9.53 and 7.88% (under RCP4.5 2050), 10.61 and 8.58% (RCP4.5 2070), 11.65 and 9.63% (RCP8.5 2050), and 13.01 and 10.31% (under RCP8.5 2070) for committee averaging and weighted mean, respectively, when compared to current habitat suitability for (Table 3). These expanding suitability areas include a certain portion of the southern United States, most of the parts of Chile, some parts of Indian Himalayan states, North Eastern Himalayan states of Jammu and Kashmir, Uttarakhand, Sikkim, and Arunachal Pradesh, as well as certain parts of Bhutan and Nepal and southern China (Figure 4).

Discussion

This study employed two evaluation metrics to assess the predictive performance of our model run: threshold-independent Area under the Curve (AUC) and threshold-dependent True Skill Statistics (TSS). These criteria are frequently used in ecology to evaluate habitat modeling performance (Allouche et al., 2006). The AUC is extensively

TABLE 3 Summary of the range change statistics in terms of pixels for the *Olea europaea* subsp. *cuspidata* under climate change scenarios compared to current climatic conditions.

Scenario	Ensemble type	Loss	Absent	Stable	Gain	Loss (%)	Gain (%)	Range change (%)
RCP4.5 2050	Committee averaging	356,499	8,087,753	355,798	67,883	50.05	9.53	−40.52
RCP4.5 2070	Committee averaging	386,078	8,080,091	326,219	75,545	54.20	10.61	−43.60
RCP8.5 2050	Committee averaging	398,162	8,072,658	314,135	82,978	55.90	11.65	−44.25
RCP8.5 2070	Committee averaging	492,706	8,062,965	219,591	92,671	69.17	13.01	−56.16
RCP4.5 2050	Weighted mean	271,335	8,282,368	271,478	42,752	49.99	7.88	−42.11
RCP4.5 2070	Weighted mean	298,740	8,278,568	244,073	46,552	55.04	8.58	−46.46
RCP8.5 2050	Weighted mean	306,776	8,272,834	236,037	52,286	56.52	9.63	−46.88
RCP8.5 2070	Weighted mean	385,985	8,269,150	156,828	55,970	71.11	10.31	−60.80

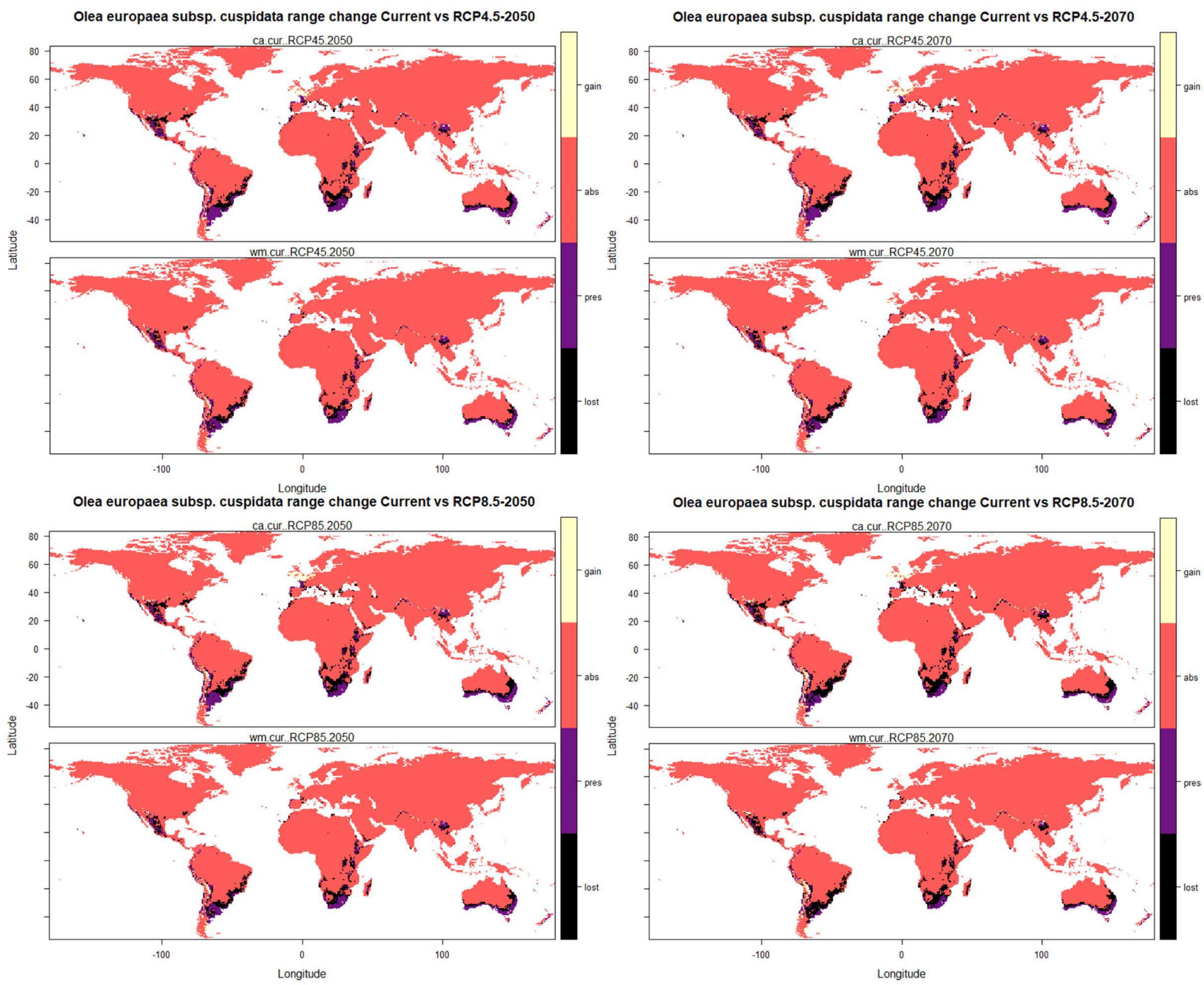

FIGURE 4
Plots of the predicted range changes for *Olea europaea* subsp. *cuspidata* between current and future climatic conditions.

used to evaluate the accuracy of habitat suitability models, while TSS normalizes total accuracy (Allouche et al., 2006; Becerra-López et al., 2017). The threshold-independent AUC and threshold-dependent TSS performance scores for *Olea europaea* subsp. *cuspidata* were 0.991 and 0.913 for committee averaging and 0.992 and 0.908 for weighted mean, respectively. The consistent results obtained prove the model's improved performance.

Environmental conditions influence the distribution of a plant species. This impact is because climate variables such as temperature and precipitation impact species' physiological and reproductive capabilities (Sharma and Raghubanshi, 2006). Several critical biological processes of a species are synchronized by these climate-based characteristics, including dispersion ability, home range size (Bradley and Mustard, 2006), and the ability to survive under unfavorable conditions (Morris et al., 2019). However, this does not hold true for all cases, as other edaphic and topographic factors and interactions among the biotic and abiotic environments significantly impact the species distribution (Norberg et al., 2019). However, when the modeling is performed over large-scale areas such as the whole globe or continents, climatic conditions are reported as the sole determinants for evaluating the degree of distribution of the organisms (Waltari et al., 2014). Earlier SDM studies conducted on *Olea europaea* subsp. *cuspidata* in Asia have reported a loss of suitable habitat, particularly in low elevations, and a shifting distribution toward high altitudes (Ashraf et al., 2016, 2017). The other two wild olive subspecies, *O. europaea* subsp. *europaea* var. *sylvestris*, are predicted to increase habitat suitability, while *O. europaea* subsp. *maroccana* shows substantial contraction in future climate (Kassout et al., 2022). This suggests that plant species behave differently in future climate projections, even at the subspecies level.

The species' distribution range reflects its adaptation to the Mediterranean-type climate of the world. Such a climate is considered one of the most vulnerable zones to global warming (Almeida et al., 2022; Kassout et al., 2022). The current distribution range is stretched across many regions of all the continents, especially prominent parts of the southern hemisphere. During the last few decades, 90 percent of the net global ocean heat gain was concentrated in the southern hemisphere (Rathore et al., 2018). Several meteorological alterations have been observed in the southern hemisphere during the past several decades (Solman and Orlanski, 2016). Certain precipitation-related variables influencing this plant species' distribution have been identified (Deblauwe et al., 2016; Amiri et al., 2020). The distribution of this plant in coastal parts of Western Sahara, Morocco, Libya, and Egypt, the majority of Ethiopia, Kenya, and almost the entire country of Zimbabwe, Namibia, Botswana, Madagascar, and South Africa in Africa reflects its adaptability in the relatively low precipitation-dominated area. These findings are consistent with model-based predictions made by several other researchers, who identified temperature and precipitation-derived variables as the primary determinants of plant distribution (Woodward et al., 2004; Priyanka and Joshi, 2013; Manzoor et al., 2018; Panda and Behera, 2018; Thapa et al., 2018; Xu et al., 2021).

The study is a pioneering but crucial step in looking into the impact of climate change on the current distribution and the possible range of suitable habitats of *Olea europaea* subsp. *cuspidata* on a global scale. The study's findings show that temperature-related bioclimatic variables play a vital role in this species' distribution (Figures 2, 3), with BIO-1 (Annual Mean Temperature) being the most important explanatory variable, followed by BIO-5 (Max Temperature of Warmest Month) and BIO-3 (Annual Mean Temperature) (Isothermality). These variables are expected to alter significantly under the RCP8.5 scenario, causing substantial portions of the current distribution area to become unsuitable by 2050. This study predicts more range contraction under RCP8.5 by 2070, a comparatively more extreme scenario. On the other hand, rainfall patterns in many regions of the world are expected to result in a more widespread variable and extended dry spells. According to a recent climate precipitation trend analysis for the previous few decades, the total amount of annual precipitation is escalating along with increasing trends in consecutive dry days (CDD) (Mudelsee, 2018; Parey, 2019; Dad et al., 2021). Under the predicted importance of rainfall patterns for *Olea europaea* subsp. *cuspidata*, future extreme climate events may put additional stress on already established populations and restrict its spread to places that would be unsuitable under current climatic conditions (Kelly and Goulden, 2008).

Future climate change is expected to impair total habitat suitability for this species, with more than a quarter of suitable habitat predicted to be lost by 2070 under RCP8.5. In fact, our findings are consistent with other reports that have found a decline in the worldwide and regional species distribution as a result of climate change (Rabasa et al., 2013; Panda and Behera, 2018; Moraira et al., 2020; Zu et al., 2021). In a recent study investigating the future predictions for the spread of invasive species under the influence of climate change in South Africa, Bezeng et al. (2017) discovered a range reduction for more than 80 species. Our predicted model for the future distribution of this species corresponds with the results of Ghafoor et al. (2021), which experimentally established the reduced seed germination and vegetative growth in *Olea europaea* subsp. *cuspidate*, and predicted that climate change will significantly influence olive ecophysiology, leading to species composition changes and shifting distribution (Brito et al., 2019). In the southeast of Australia, where the species is predicted to lose its habitat substantially, vegetation type has been demonstrated to have a substantial impact on fire response to warmer temperatures, with wetter, coastal temperate forests being more likely to experience increased fire frequency (Bradstock et al., 2014). Similar observations were recorded about the distribution pattern of 292 naturalized alien species in Australia, which has been observed to be affected under future climate change scenarios (Duursma et al., 2013). Several cases of vegetation and disturbance regimes, local plant extinctions, phenological changes in reproduction, and altered biotic interactions have been observed in Australia, posing a threat to communities and endangered species (Hoffmann et al., 2018). Another most affected region in terms of habitat loss is *Olea europaea* subsp. *cuspidata* is predicted to be in sub-Saharan Africa. According to projections, countries like South Africa, Namibia, and Botswana will face temperatures greater than the global average by 2050 (Davis-Reddy and Vincent, 2017). In addition, rainfall in Southern Africa is anticipated to drop by nearly 10% by 2050 (IPCC, 2014). Our results agree with several other studies which have found that climate change has affected the habitat suitability of several other plant species (Bradley et al., 2009; Taylor et al., 2012; Wan et al., 2016; Manzoor et al., 2018). The availability of moisture and the low temperatures associated with these regions may promote future distribution feasible in the context of climate change (Chen et al., 2011; Fei et al., 2017; Panda and Behera, 2018; Rathore et al., 2018). While projected climate change may negatively shift the distribution of *Olea europaea* subsp. *cuspidate,* due to increased precipitation and temperature, moisture availability, and low temperatures associated with higher latitudes, it may also facilitate its distribution under future climate conditions. Since the majority of *Olea europaea* subsp. *cuspidata* habitat loss is predicted in the mid-latitudes of both hemispheres; the region's surface temperature changes (Tamarin-Brodsky et al., 2020) explain the warming patterns and climatic-dependent factors.

A considerable reduction of the suitable habitats for *Olea europaea* subsp. *cuspidata* will occur under future climatic conditions. As a global trend, the lower the latitude, the more areas will be lost (Sheldon, 2019); the majority of the lost areas are on the American, African, and Australian subcontinents, indicating that many mainland areas will be subjected to more severe climatic changes than coastal areas. The areas predicted for future distribution suitability currently receive less precipitation than those with current distribution. Future climatic projections foresee the emergence of new suitable areas, mostly found at higher latitudes in both the northern and southern hemispheres (Figure 4). Under the model output, such projected latitudinal migration, with *Olea europaea* subsp. *cuspidata* shifting poleward, follows one of the most common and well-documented consequences of climate change on species distribution (VanDerWal et al., 2012; Telwala et al., 2013; Rathore et al., 2018). Considering the species diverse distribution patterns and relatively wide temperature and precipitation habitat ranges (Figure 3), future estimates suggest that the plant will be severely affected by the ongoing global climate change. Other widespread plant species have exhibited probable future range contractions (Kelly and Goulden, 2008; Parmesan and Hanley, 2015; Madani et al., 2018) due to increased temperatures leading to severe heat stress (Tollefson, 2020).

Conclusion

The present work is the first attempt to assess global range shifts not only for a wild olive species but also for a Lamiales species in a climate change scenario. Ecophysiological features of *Olea europaea* subsp. *cuspidata* may be linked to the shrinkage of potential areas in the year 2070 compared to the present. The extraction and comparison of climatic values of gained and lost areas in relation to present and future distribution ranges revealed that *Olea europaea* subsp. *cuspidata* would tend to be displaced to locations with currently low precipitation values. As previously stated, the species appears to be unable to endure significant temperature fluctuations (Bio-1, Bio-3, and Bio-5). As a result, climatically appropriate areas for *Olea europaea* subsp. *cuspidata* are predicted to be drastically reduced by 2070, as a portion of the current potential ranges will become unsuitable due to excessive temperature changes. This is in line with worldwide trend changes, which have been anticipated to include a large increase in extreme periods of lengthy dry cycles (IPCC, 2013; Tollefson, 2020). Finally, we investigated where most suitable habitats will be lost or gained in the future due to climate change. With this ensemble modeling approach, firstly, we can predict the main current locations of *Olea europaea* subsp. *cuspidata* will still appear as suitable. Secondly, it is estimated that several diverse geographical locations where the species has not been documented will be potential colonization sites for the species in the future. Considering the ecological and economical importance, the areas predicted to be suitable for the *O. europaea* subsp. *cuspidata* may be used for the plantation of this species, while the deforested land should be restored for human welfare.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SK wrote and analyzed the manuscript. SV supervised, visualized, reviewed, and edited the manuscript. Both authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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