Ecological Processes

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Modeling the distribution of *Aloe ankoberensis* and *A. debrana* under different climate change scenarios in North Shewa Zone, Amhara National Regional State, Ethiopia

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Abstract

Background *Aloe ankoberensis* M.G. Gilbert & Sebsebe and *A. debrana* Christian are Ethiopian endemic species currently classified as endangered and least concern, respectively under International Union for Conservation of Nature (IUCN) categories. Recent studies indicate that climate change is anticipated to significantly influence the distribution of plant species. Therefore, this study aimed to model the distribution of *A. ankoberensis* and *A. debrana* under different climate change scenarios in the North Shewa Zone, Amhara National Regional State of Ethiopia. Thirty-six and 397 georeferenced presence points for *A. ankoberensis* and *A. debrana*, respectively, and 12 environmental variables were used to simulate their current and future distributions. The ensemble model approach was used to examine the current and future (2050 and 2070) climatic suitability for both species under three shared socio-economic pathway (SSP) climate scenarios (SSP 2.6, 4.5 and 8.5).

Results The performance of ensemble model was excellent for *A. ankoberensis* with score of area under curve (AUC) 0.96 and true skill statistics (TSS) 0.88, and good for *A. debrana* with score of AUC 0.87 and TSS 0.63. The main variables that affected the species' distributions were mean diurnal range of temperature, annual precipitation, and elevation. According to the model, under the current climate conditions, 98.32%, 1.01%, 0.52%, and 0.15% were not suitable, lowly, moderately, and highly suitable areas, respectively for *A. ankoberensis*, and 63.89%, 23.35%, 12.54%, and 0.21% were not suitable, lowly, moderately and highly suitable areas, respectively for *A. debrana*. Under future climate scenarios, suitable habitats of these species could shrink. In addition, under all climate change scenarios, it is anticipated that highly suitable areas for both species and moderately suitable areas for *A. ankoberensis* will be lost completely in the future unless crucial interventions are done on time.

Conclusions The results indicate that the future may witness a decline in suitable habitat for *A. ankoberensis* and *A. debrana*, which leads to increasing threat of extinction. Therefore, it is crucial to develop a conservation plan and enhance climate change adaptation strategies to mitigate the loss of suitable habitats for these highland and sub-Afroalpine endemic *Aloe* species.

Keywords Biodiversity, Endemic *Aloe*, Environmental variable, Habitat suitability, Species distribution, Species extinction

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Introduction

Climate change has now taken a serious place on the global common agendum. By 2100, the atmospheric CO_2 concentration would have doubled, and the pattern of precipitation would have changed, causing an increase in the global average temperature of 1.4 to 5.8 °C (IPCC 2014). The greenhouse gases (GHGs) like CO_2, CH_4, and N_2O concentrations will rise by 47%, 156%, and 23%, respectively (IPCC 2021). This change is impairing biodiversity and associated ecosystem services (Sintayehu 2018; Shambel et al. 2022). The IPBES-IPCC (2021) report stated that changes in abiotic conditions, the physical environment, atmospheric GHGs concentrations, and species compositions that led to shifts in species ranges are all impacts of climate change. Additionally, it has an impact on the phenology, distribution, architecture, and intraspecific and/or interspecific competitions of plant species (Kumar et al. 2017; Sintayehu 2018). Climate change could also lead to land use and land cover change (LULCC) (IPBES-IPCC 2021). The LULCC contributed to higher emission of carbon, fragmentation of habitats, and deterioration of ecosystem services which had resulted in hampered and threatened biodiversity and other ecosystem resources (Asnake and Amare 2019; Temesgen et al. 2022).

The climate change impacts are resulting in several ecosystem dynamics so that the research arena has initiated diverse modeling approach like species distribution models (SDMs). The SDMs are a modern approach to investigate the potential impacts of climate change on biodiversity under various global change scenarios (Kaky and Gilbert 2017). As global temperatures continue to rise, SDMs are an appropriate tool for identifying threatened species, which are mostly at risk of extinction (Boral and Moctan 2021). In addition, SDMs relate occurrence point of species and spatially explicit environmental data such as precipitation, temperature, elevation, population, soil type, and land use/cover to predict species distributions in space and time (Elith and Leathwick 2009; Borzée et al. 2019). They are often used for the management of threatened species (Hu et al. 2015; Kumar and Stohlgren 2009), management of invasive species (Eckert et al. 2020; Sintayehu et al. 2021), evaluating the impacts of climate change (Banda and Nega 2018; Sintayehu et al. 2020a, b, c), ecological restorations (Riordan et al. 2018), and conservation planning (Meyer 2017). Several algorithms have been used in SDMs (Elith et al. 2011; Barbet-Massin et al. 2012). To reduce uncertainty inherent and to produce better accuracy in species distribution prediction, an ensemble model approach was used (Meller et al. 2014; Breiner et al. 2015).

The genus *Aloe* are among the richest genera of plant species in Ethiopia. There are about 46 species of *Aloe* and three subspecies, of which 67.3% are endemic that makes the country one of the known centers of *Aloe* diversity in the world (Edwards et al. 1997; Sebsebe and Nordal 2010; Sebsebe et al. 2011). *Aloe* species have potential values for medicinal, social, environmental, materials, and food use (Bjorå et al. 2015; Bula and Baressa 2017; Eshetu et al. 2020), of which medicinal uses accounted for the highest percentage in Ethiopia and elsewhere in the world (Steenkamp and Stewart 2007; Bjorå et al. 2015; Zahra et al. 2019; Anteneh et al. 2020;). *Aloe ankoberensis* and *A. debrana* are among the endemic *Aloe* species of Ethiopia (Edwards et al. 1997; Sebsebe and Nordal 2010). Though, *Aloes* are a keystone species of succulent perennial plants with the capacity to withstand drought and high temperatures (Sebsebe and Nordal 2010), the current climate change could have affected the distribution and population of *Aloes* and other endemic species in Ethiopia.

In Ethiopia, studies on historical climate variability reveal that the average annual temperature has risen by 0.6 to 0.8 °C, while there has not been a significant change in average annual precipitation, albeit with a tendency for a decrease in the central part of the country and an increase in other regions (EPCC 2015). Projections indicate that by the end of the twenty-first century, the average annual temperature will rise by 1, 2, and 5 °C under representative concentration pathways (RCP) scenarios (2.6, 4.5, and 8.5), respectively, accompanied by a corresponding 4 to 12% increase in average annual precipitation compared to 1975–2005 (EPCC 2015). *A. ankoberensis* and *A. debrana* are likely affected by these climate changes. In addition, habitat loss due to agriculture and infrastructure expansions, and increasing rate of settlements poses major threats to the stability of *Aloe* species' wild population in their ecosystems (Eshetu et al. 2020). The IUCN conservation status indicated that *A. ankoberensis* was endangered (Weber and Sebsebe 2013a) while *A. debrana* was under least concern categories (Weber and Sebsebe 2013b) and qualify categories with Red List. These data coupled with the recent higher rate of local commercial exploitation may aggravate the wild population status of these *Aloe* species in their natural habitat. Understanding how *A. ankoberensis* and *A. debrana* respond to these threats is crucial for designing sustainable and effective conservation strategies. Therefore, the objectives of this study are to: (1) identify and map current and future suitable areas for *A. ankoberensis* and *A. debrana* under different climate change scenarios, (2) detect the change in suitability area for both species under different climate change scenarios, and (3) assess impacts of climate change on the distribution of *Aloe* species.

Materials and methods

Study area

This study was conducted in North Shewa Zone of Amhara National Regional State, Ethiopia. It is situated within 39° 0′ 0″–40° 0′ 0″ E and 9° 0′ 00″ to 10° 0′ 00″ N and it covers total area of 16,172.52 km^2 (Fig. 1). Unpublished data from North Shewa Zone Agriculture Department Office (NSZADO) indicates that 38.86% of the area is plain, 23.4% rugged topography, 25.89% mountains, and 11.85% valleys (NSZADO 2020). The elevation ranges from 937 m above sea level at Berehet district (referred as Woreda in Ethiopia) (Nigate and Girma 2018) to 3700 m above sea level at Ankobere Woreda (NSZADO 2020). These elevation ranges are characterized by four major traditional agro-ecological zones namely: Kola at lowland (21.96%) Woina-Dega at midland (45.58%), Dega at highland (32.02%), and Wurch at alpine (0.46%) topographies (NSZADO 2020). The area is characterized by bimodal rainfall, long rainy season runs from June to mid-September locally called *Kiremt* (summer) and short rainy season between February and April locally called *Belg* (autumn) (Girma 2017). The mean annual rainfall ranges from 600 to 1250 mm and the mean annual temperatures range from 8.7 to 20 °C. At high altitudes, the wet season is characterized by a combination of rainfall, frequent fog and occasional snow, and the dry season is characterized by frost (Girma 2017). The predominant land use types were 38.54% of cultivated land, 14.13% of shrubland, 8.62% of forest land, 5.49% of grassland, 21.08% of settlement and other infrastructure, and 12.14% of bare land (NSZADO 2020). The study area is part of the Shewa floristic region of Central Ethiopia known to harbor many endemic plant species (Friis et al. 2010).

Study species

A. ankoberensis and *A. debrana* are among the endemic *Alo*e species of Ethiopia. They are found under order: Asparagales, family: Asphodelaceae and genus of *Aloe* Linneus (Edwards et al. 1997; Chase et al. 2016). The specific epithets '*ankoberensis*', refers to the place, *Ankober* and '*debrana*' refers to the locality *Debre Berhan* in Shewa floristic region of Ethiopia where the type collections and their descriptions have been based.

A. ankoberensis is pendant shrub with up to 6 m long stem hanging down cliffs. It has numerous leaves with 2–3 mm long; marginal spines of 7–9 per 10 cm; inflorescence with 1–6 cylindrical racemes of 6–18 cm long; perianth cylindrical and 35–40 mm long, 6–10 mm wide when pressed, bright orange red; pedicels is 6–25 mm before fruit and up to 10–30 mm including fruit and dark brown with pale round spots; and bracts ovate-lanceolate with acute tips (Edwards et al. 1997). It grows in sub-Afroalpine vegetation type, on cliffs or steep rocky

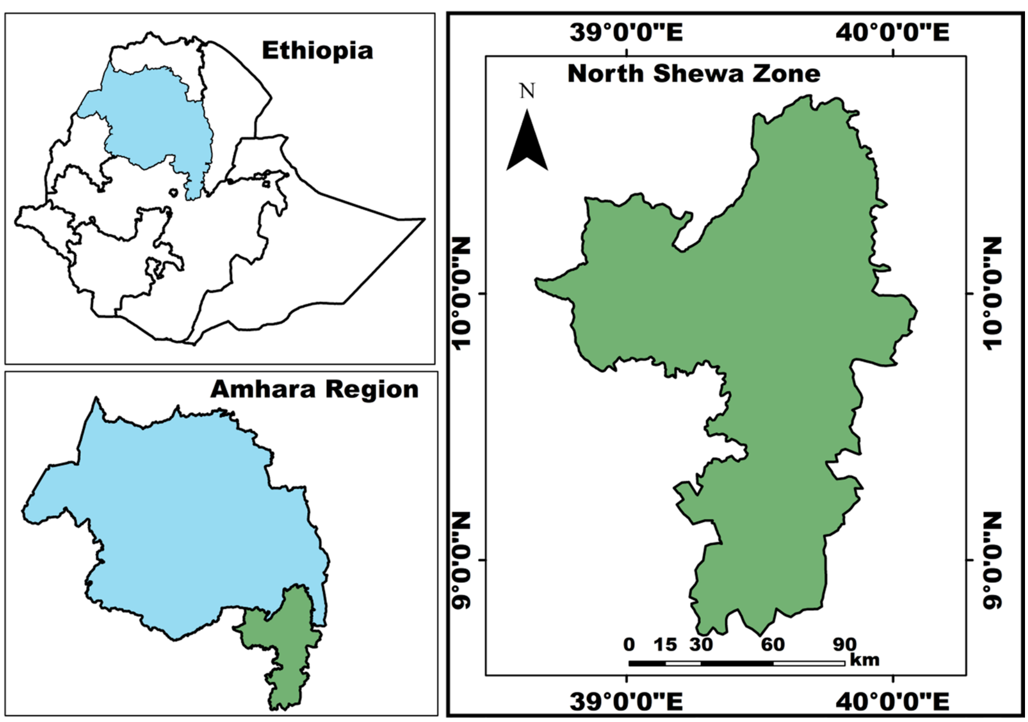

Fig. 1 Location map of the North Shewa Zone covered in this study

slopes (Fig. 2a) and with the elevation range of 3000 up to 3500 m above sea level (Friis et al. 2010; Sebsebe and Nordal 2010). The flowering period is from October to February (Sebsebe and Nordal 2010). *Aloe debrana* is a stemless *Aloe* characterized by suckers from the base to form small groups with very dense rosettes and dull green colored leaves of spreading and recurved. The leaves are (25–60) × (7.5–15) cm long with marginal teeth up to 7–14 per 10 cm with 2–4 mm long red tips. Inflorescence ca. 100 cm long, compoundly branched. perianth cylindrical and (17–30) × (4–6) mm when pressed; the pedicels become 10–15 mm before fruit and grow up to 17 mm long during fruit period; and bracts are ovate-triangular and scarious (Edwards et al. 1997). It is found in dry evergreen Afromontane forest and grassland complex vegetation type specifically in undifferentiated Afromontane forest, gentle slopes (Fig. 2b) and with the elevation range of 2000 up to 2700 m above sea level (Friis et al. 2010; Sebsebe and Nordal 2010). The flowering period is from December to February (Sebsebe and Nordal 2010).

A. ankoberensis is used for antimicrobial activity, prevention of soil erosion, honey bee plants, treatment of malaria, insect repellent, and wound healing (Eshetu et al. 2020; Nigus et al. 2020). *A. debrana* is used for treatment of poultry diseases in chickens, to massage broken bones, used as incense, thickening agent, and protection of a person from evil eyes (Sisay et al. 2013; Tigist et al. 2019; Eshetu et al. 2020). In addition, *A. debrana* leaf mesophyll is used in a thickening agent (Sisay et al. 2013) and for treating sisal fiber for packing Ethiopian export coffee (e.g. www.gseventiplc.com).

Species occurrences data

The occurrences data for both species were obtained from the global databases such as Global Biodiversity Information Facility (www.gbif.org), IUCN (www.iucn.org); herbarium sheets of the National Herbarium at Addis Ababa University, Ethiopia; and field survey using global positioning system (GPS) that were conducted between November 2021 and June 2022. The recorded occurrences data were entered into Microsoft Excel and saved in comma-separated value format. A total of 76 and 665 georeferenced presence points for *A. ankoberensis* and *A. debrana* species, respectively were collected along the transect lines with a systematic sampling techniques targeted the two species. All points were mapped using ArcGIS for visual observation and to check spatial accuracy. To reduce spatial autocorrelation and to achieve good performance results, duplicated occurrence points at a distance of 1 km between each point were removed using "spthin" package (Dagnew et al. 2022). Finally, after removing the duplicated occurrence points 36 presence points of *A. ankoberensis* and 397 presence points of *A. debrana*, were selected to build the model. In addition, 1000 false absence points were generated for both species using random sampling to perform more reliable SDMs (Xu et al. 2021).

Fig. 2 *A. ankoberensis* (**a**) and *A. debrana* (**b**) growth form in their natural habitats

Environmental variables

A total of 23 environmental variables with 19 bioclimatic and 4 non-climatic variables were used in this study to understand their distribution under different climate change scenarios (Additional file 1). The present and future bioclimatic variables for the year 2050s and 2070s as well as elevation data were obtained from Worldclim database (www.worldclim.org) version 2.1 with 30 arc second spatial resolution (Fick and Hijmans 2017). The slope data were derived from elevation data. The current and future scenario prediction LULCC data were obtained from geographical simulation and optimization system (GeoSOS) global database (http://geosimulation.cn/GlobalLUCCproduct.html), and human population density data were obtained from global downscaled population projection grids (https://sedac.ciesin.columbia.edu/data/sets/browse) at a resolution of 30 arc second (accessed on 9th July 2022). For future prediction, the second-generation Euro-Mediterranean Centre on Climate Change Earth System Model (CMCC-ESM2) from the CMIP6 general circulation models (GCMs) was selected for the year 2050 (2041–2060) and 2070 (2061–2080). This climate projection model has been widely applied in SDMs, and provide a good performance for Ethiopian environment (Dagnew et al. 2022). In addition, CMCC-ESM2 shows an equilibrium climate sensitivity of 3.57 °C and a transient climate response of 1.97 °C (Lovato et al. 2022). In this study, three shared socioeconomic pathways (SSP) namely low emission (SSP2.6), intermediate (SSP4.5), and high emission scenarios (SSP8.5) were used. SSP2.6 scenario is the most aggressive among all SSP in terms of GHG emissions reductions; SSP4.5 scenario is GHG emissions are roughly similar to the current emission and global average temperature tends to decrease with human intervention; and SSP8.5 is the worst-case emission scenario in that entails GHG emissions are roughly double from current and global temperature tends to increase (Meinshausen et al. 2020). All environmental variables were kept in raster format (geotiff) with similar cell sizes and reference systems to be appropriate for SDMs.

Selection of environmental variables

Important environmental variables were selected for this study depending on three criteria such as statistically important in predicting presence data for the selected species, biologically relevant for survival of selected species, and no collinearity with other variables (Abdulbasit and Sintayehu 2021). To do this, first Spearman correlation analysis was used to group environmental variables that have a correlation coefficient < 0.8 and biologically relevant for survival of selected species. Second, variance inflation factors (VIF) test was used to distinguish multi-collinearity among environmental variables. A stepwise procedure used to remove environmental variables with Variance Inflation Factor (VIF) larger than 3. Out of these 23 environmental variables, 10 non-correlated environmental variables such as bio2, bio3, bio4, bio7, bio14, bio18, bio19, landcover, population, and slope were selected based on the spearman correlation test and VIF test (Additional file 2). In addition, biologically important variables such as bio12 and elevation were used to map the distribution of both *Aloe* species. The relative variable importance of environmental variables was assessed by running the "getVarimp" function in R software based on correlation-based and area under curve (AUC)-based metrics (Naimi and Araújo 2016).

Species distribution modeling

Many algorithms were used to predict species distribution and their projection, which were classified into three main groups such as profile methods, classical regression and machine learning algorithms (Fick and Hijmans 2017). For this study two regression algorithms: Generalized Linear Models (GLM) and Multivariate Adaptive Regression Splines (MARS), and four machine learning algorithms: Boosted Regression Trees (BRT), Maximum Entropy model (Maxent), Random Forests (RF), and Support Vector Machines (SVM) were used (Dagnew et al. 2022; Xu et al. 2021). These six model algorithms are among the most commonly employed for species distribution modeling, depend on the level of complexity, appropriateness, predictive power, and capability to incorporate presence-only data because of limited access to absence data (West et al. 2016; Nurhussen et al. 2021). The details of the models are described in (Table 1). These algorithms combined into one ensemble models through the 'sdm' package (Naimi and Araújo 2016), by applying a weighted mean approach using true skill statistic (TSS) (Hu et al. 2015).

Model validation and mapping

The species occurrences data were divided into two sets such as a random set of 70% for training data and 30% for evaluating model accuracy (Sintayehu et al. 2021). Bootstrapping replication approach with ten times replication was used using statistical software R version 4.2.2 with packages sdm (Venables and Smith 2022). The performance of the model was assessed based on threshold-independent AUC, threshold-dependent true skill statistics (TSS), sensitivity and specificity. The AUC value range indicates that 0.5–0.7 is weak, 0.7–0.9 good, and greater than 0.9 excellent model performance (Sintayehu et al. 2021). TSS values indicate that less than 0.4 is weak, 0.4–0.75 is good, and greater than 0.75 is an excellent model performance (Sintayehu et al. 2020a, b, c;

Table 1 SDMs used for our modeling and their description

Models	Descriptions
Boosted Regression Trees (BRT)	Works based on a combination of a relatively small number of trees to increase the performance of predictive variables (Elith et al. 2009), has the ability to process several predictors at high predictive accuracy (Gu et al. 2019), constructs the models using stochastic gradient boosting (Friedman 2002)
Generalized Linear Model (GLM)	Is a modern regularization method often performing well (Reineking 2006), uses parametric functions such as linear or higher-degree polynomials to model the relationship between the response and predictors, is a generalization of ordinary least squares regression (Guisan et al. 2002)
Multivariate Adaptive Regression Splines (MARS)	a flexible nonparametric regression model by using piecewise linear basis functions (Elith and Leathwick 2007), combines the species data and uses information on the presence of the species to supplement information for the modeled species, considers interactions between variables locally, and selects predictors using the signal from the species presence data automatically (Choe et al. 2018)
Maximum entropy modeling (MaxEnt)	Performs better with small sample sizes compared with other modeling methods (Perkins and Frey 2022), developed for modeling presence-only species data (Phillips et al. 2006), flexible to fit complex models depending on number of occurrence points and user-defined settings (Elith et al. 2011)
Random Forest (RF)	popular method for SDMs, effective method for predicting species occurrence data (Abdi 2020), not very sensitive to tuning the model parameters (Freeman et al. 2016), avoids over fitting by randomly selecting variables to create a large number of classification trees (Jin et al. 2016)
Support Vector Machine (SVM)	a non-parametric machine-learning technique for regression and classification problems (Ashraf et al. 2017), works by defining linear hyperplanes that best separate different classes in the data (Stecanella 2017), uses nonlinear forms of the predictor variables for increased flexibility (Hastie et al. 2009)

Sintayehu et al. 2021). To select best threshold, maximum sensitivity plus specificity threshold were used from the model. The areas of suitability changes for the current and future prediction (2050 and 2070, which are the current projections global standards) were analyzed under four suitability categories using ArcGIS. These categories include 0.0–0.25 as not suitable, 0.25–0.50 as lowly suitable, 0.50–0.75 moderately suitable, and from 0.75–1.00 highly suitable (Hamid et al. 2018). Change in the percentage of area (percentage lost or gain areas) by the 2050 and 2070 were calculated according to Duan et al. (2016) formula as described below:

$$\mathrm{AC} = \frac{Af - Ac}{Ac} \times 100\%$$

where AC = Percentage of area change; Af = the predicted area of suitable habitat for future and Ac = the predicted area of suitable habitat under current conditions. The overall modeling methods used in this study are presented in Fig. 3.

Results

Performance of species distribution models

The ensemble model exhibited excellent performance for *A. ankoberensis*, achieving a score of AUC value of 0.96 and a score of TSS value of 0.88. For *A. debrana*, the model's performance was good, with a score of AUC value of 0.87 and a score of TSS value of 0.63. The performances of SDMs using different evaluation criteria were illustrated for both *Aloe* species based on the provided training and testing data sets (Table 2). At the individual level, Maxent achieved the highest scores for *Aloe ankoberensis*, while Random Forest (RF) attained the highest score for *Aloe debrana*. Additionally, MARS had the lowest score for *A. ankoberensis* while GLM had the lowest score for *A. debrana*. In general, machine learning algorithms performed better than classic regression algorithms for both species. Moreover, sensitivity and specificity scores for both species were high for all models, indicating precise delineation of both suitable and unsuitable areas, with maximum correctly classified samples (Table 2).

Relative contribution of environmental variables

The key environmental variables crucial for predicting the potential distribution of *A. ankoberensis* and *A. debrana* species were outlined. For *A. ankoberensis*, bio2 exhibited the highest percentage contribution (53.6%), while for *A. debrana*, elevation had the higher percentage contribution (44.4%). Among the environmental variables used, bio2, bio3, bio7, bio12, and elevation were ranked as the top five important variables predicting the potential distribution of both species. On the other hand, landcover and population for *A. ankoberensis*, and bio19 and landcover change for *A. debrana* were found to have lower influence on their distribution (Fig. 4).

The response curve showed that *A. ankoberensis* prefers the mean diurnal range of temperature ranges from 14.5 to 15.5 °C, annual precipitation ranges from 1000 to 1200 mm, temperature annual range ranges from 15 to 19 °C, elevation ranges from 3000 to 3500 m and isothermality ranges from 60 to 73 °C (Fig. 5).

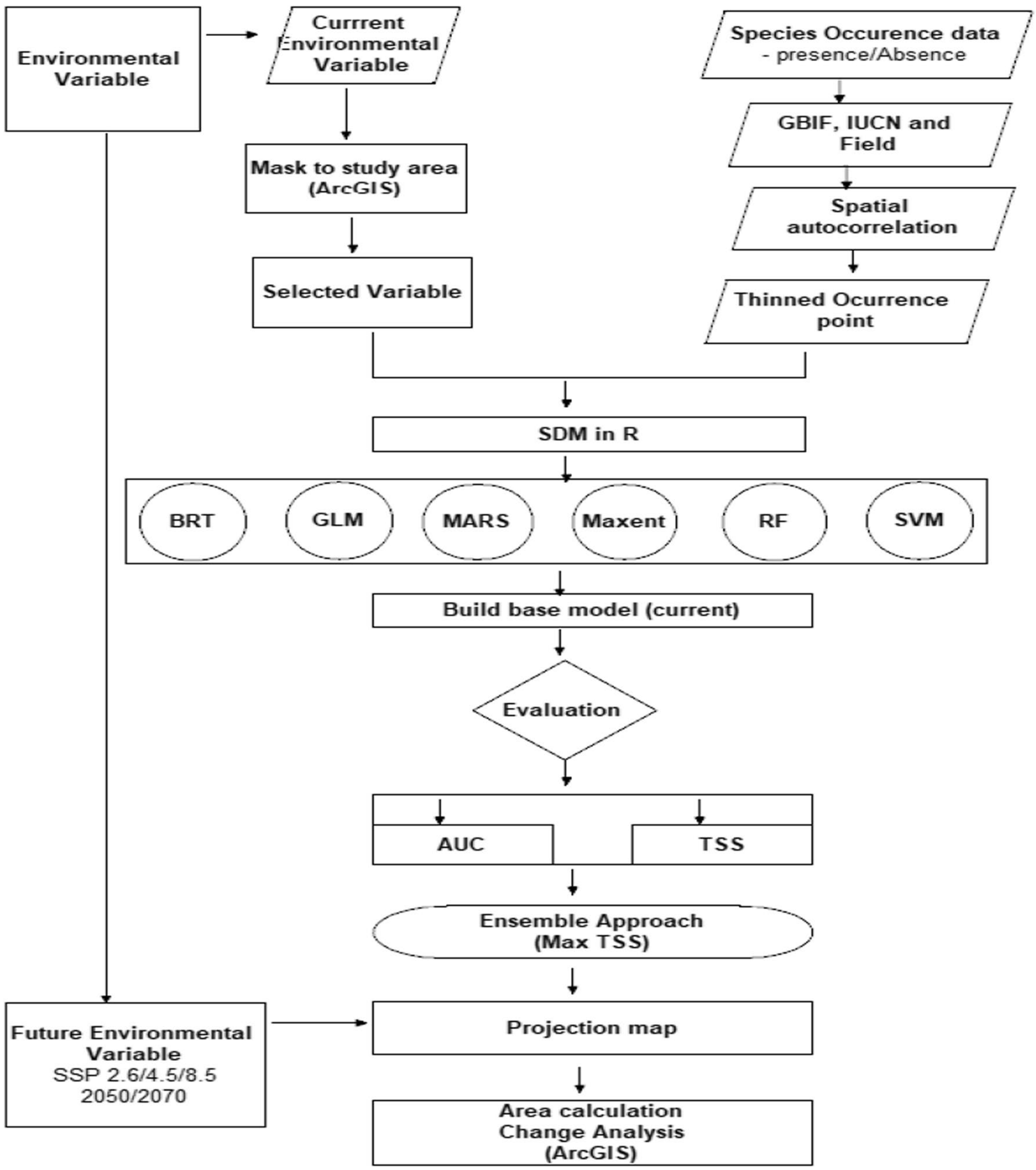

Fig. 3 Schematic representation of modeling procedures

A. debrana prefers elevation ranges from 2000 to 2900 m, annual precipitation from 800 to 1100 mm, mean diurnal range of temperature ranges from 14 to 17 °C, isothermality ranges from 60 to 75 °C, and temperature annual range from 18 to 20 °C (Fig. 6).

Current distribution of *A. ankoberensis* and *A. debrana*

The current area distribution prediction indicated that 98.32% of the North Shewa zone was unsuitable for *Aloe ankoberensis*, leaving only 1.68% classified as suitable area (Table 2). Within the total suitable area for *A. ankoberensis*, the model indicated that 1.01%, 0.52%, and 0.15% were categorized as low, moderate, and high suitability, respectively. For *Aloe debrana*, the prediction of current area distribution indicated that 63.89% was unsuitable, while 36.11% was classified as suitable area (Table 3).

Furthermore, results showed that 0.21% and 12.54% of the study areas were highly and moderately suitable

Table 2 Performance evaluation of each SDM using different statistical parameters

Species	Evaluation criteria	SDMs						
		BRT	GLM	MARS	Maxent	RF	SVM	Ensemble
A. ankoberensis	AUC	0.96	0.97	0.90	0.99	0.97	0.96	0.96
	TSS	0.88	0.89	0.80	0.94	0.91	0.88	0.88
	Sensitivity	0.94	0.96	0.82	0.99	0.95	0.91	0.93
	Specificity	0.94	0.93	0.98	0.95	0.96	0.97	0.95
A. debrana	AUC	0.87	0.81	0.86	0.87	0.95	0.86	0.87
	TSS	0.60	0.52	0.62	0.63	0.79	0.62	0.63
	Sensitivity	0.89	0.93	0.88	0.89	0.91	0.89	0.90
	Specificity	0.72	0.59	0.74	0.74	0.88	0.72	0.73

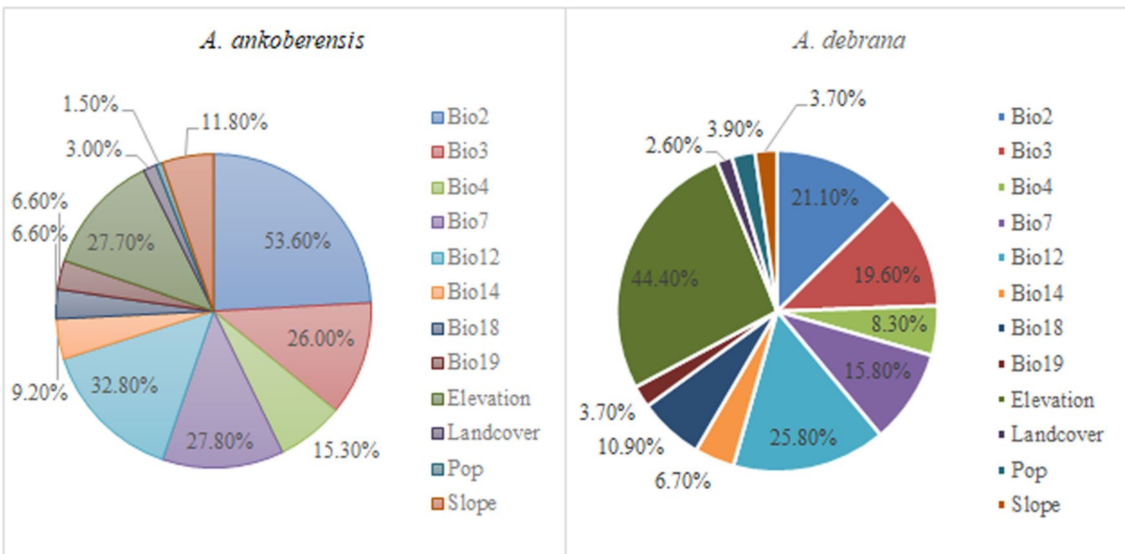

Fig. 4 Relative contribution of environmental variables for ensemble SDMs

areas for *A. debrana*, respectively. Correspondingly, the highly and moderately suitable areas for *A. ankoberensis* lie within Ankober, Asagrt, and Tarma Ber districts (Fig. 7). Highly suitable areas for *A. debrana* were mainly found in Menz Gera Midir. In addition, the vast majority of moderately suitable areas for *A. debrana* were found in Basona Worena, Menz Gera Midir, Menz Mama Midir, and Mojan Wedera Woredas (Fig. 7).

Future distribution of *A. ankoberensis* and *A. debrana*

The future scenario prediction indicated that *A. ankoberensis* will be completely loss its current highly and moderately suitable habitat or niche in the mid of twenty-first century and end of 2070s under all scenarios except SSP 4.5 scenario by 2050s for moderately suitable habitat (Table 3).

The maximum lowly suitable areas found in 2050s and 2070s were 4.45% and 2.14%, respectively. Moreover, the lowly suitable areas will be increased under all scenarios by 2050s, and SSP 4.5 and SSP 8.5 scenarios by 2070s compared with the current distribution. But lowly suitable area will be decreased under SSP 4.5 scenario by 2070s. According to the model prediction, lowly suitable areas for *A. ankoberensis* lie within Antsokiya, Eferatana Gidem, Kewet, Ankober, Angolela Tera, Assagirt and Hagere Mariam districts (locally called woreda) by 2050s under SSP 2.6 scenario. But, in 2050s and 2070s under SSP 4.5 and SSP 8.5 scenarios, the expansion of the lowly suitable area to Antsokiaya, Eferatna Gidem and Harеger Mariam woredas will be predicted to be lost (Fig. 8).

Similarly, *A. debrana* will be completely loss its highly suitable habitat or niche in the mid of twenty-first century and end of 2070s under all scenarios. The moderately suitable area will be 0, 0.68% and 1.89% by 2050, and continuously decrease by 2070 under SSP (2.6, 4.5 and 8.5) scenarios, respectively. The maximum lowly

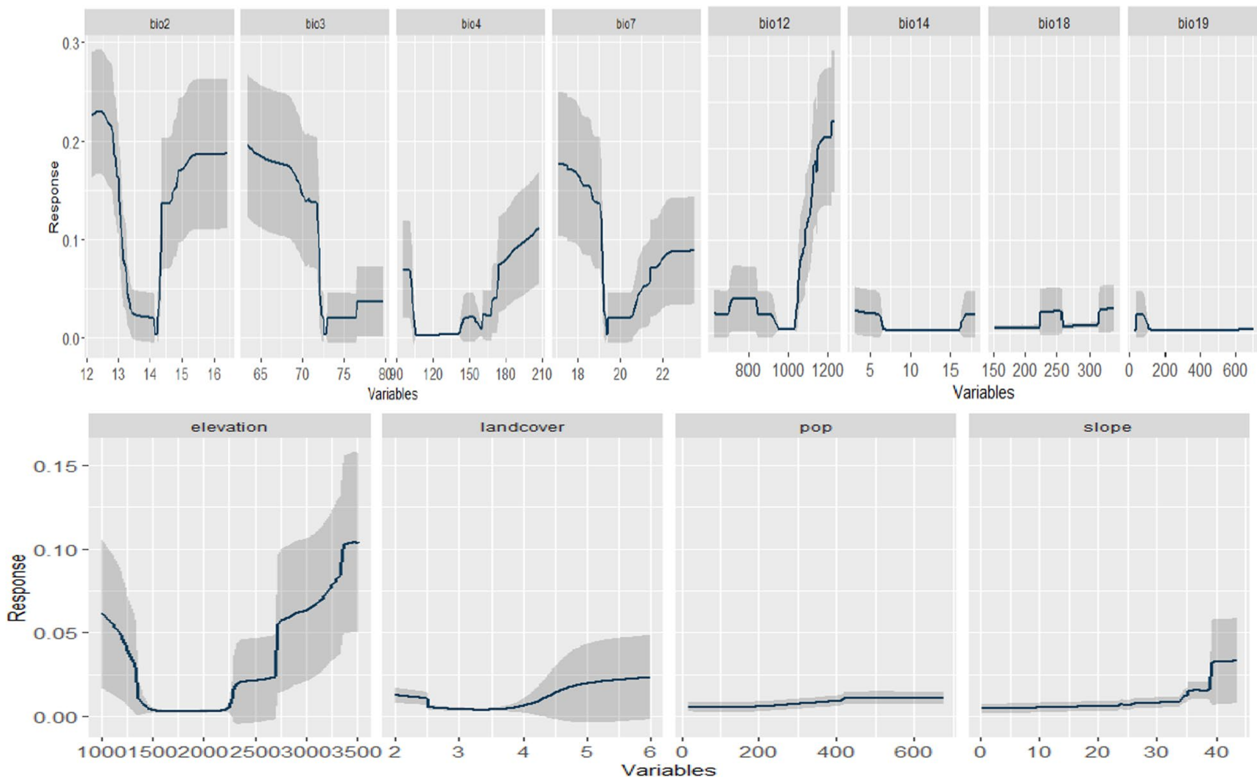

Fig. 5 Response curve for *A. ankoberensis* distribution. The *X*-axis represents the range of values of the environmental variables, and the *Y*-axis gives the probability of occurrence on a scale from 0 to 1

suitable areas found in 2050s and 2070s will be 31.36% and 26.21%, respectively. Moreover, the lowly suitable areas will be expected to decrease under SSP 2.6 and 4.5 scenarios by 2050, and SSP 4.5 and 8.5 scenarios by 2070 compared with the current distribution. According to the model prediction, moderately suitable areas for *A. debrana* lie within Mimo Werremo, Merhabete, Moretna Jiru, Ensaro, and Siya Debrirna Wayu Woredas (Fig. 9). Similarly, lowly suitable area for this species could expand across most parts of the North Shewa zone.

Habitat change analysis in the distribution of *A. ankoberensis* and *A. debrana*

In the case of *A. ankoberensis*, the highly and moderately suitable habitats will be expected to decrease by 100% under SSP 2.6 and SSP 8.5 scenarios, and 98.67% under SSP 4.5 scenario compared to the current distribution. The lowly suitable habitat increased by 343.07% under SSP 2.6 scenario and show decreasing trend for the rest scenarios in 2050s. But, by 2070s, the predicted lowly suitable habitats will be expected to decrease under SSP 2.6 and SSP 4.5 scenarios as compared to predicted lowly suitable habitats of the year 2050s. In addition, by 2070s the non-suitable habitat will be expected to increase by 1.3% while the lowly suitable habitat will decrease by 59%, moderately and highly suitable habitats by 100% under SSP 4.5 scenario. In the case of *A. debrana*, compared to the current distribution, the highly suitable habitat will be lost by 100% under all scenarios in 2050s and 2070s. The area covered by moderately suitable habitat decreased by 100%, 94.63%, and 84.95% under SSP scenarios (2.6, 4.5, and 8.5), respectively by 2050s, and show decreasing trend under all scenarios by 2070s. The lowly suitable habitat for this species will be expected to decrease by 72.45% and 12.67% under SSP 2.6 and 4.5 scenarios respectively by 2050s, while decreased by 12.2%, 29.66% and 28.6% under SSP 2.6, 4.5 and 8.5 scenarios respectively by 2070s (Table 4). In addition, under all scenarios the non-suitable habitats will be expected to increase as compared to the current distribution.

Discussion

Data quality and model performance

The current and future distribution of *A. ankoberensis* and *A. debrana* under different climate change scenarios was done for the first time in this study. This prediction helps in understanding how these endemic species of *Aloe* will respond to future climate conditions. The SDMs are the most important methods for predicting the potential distribution of species by producing

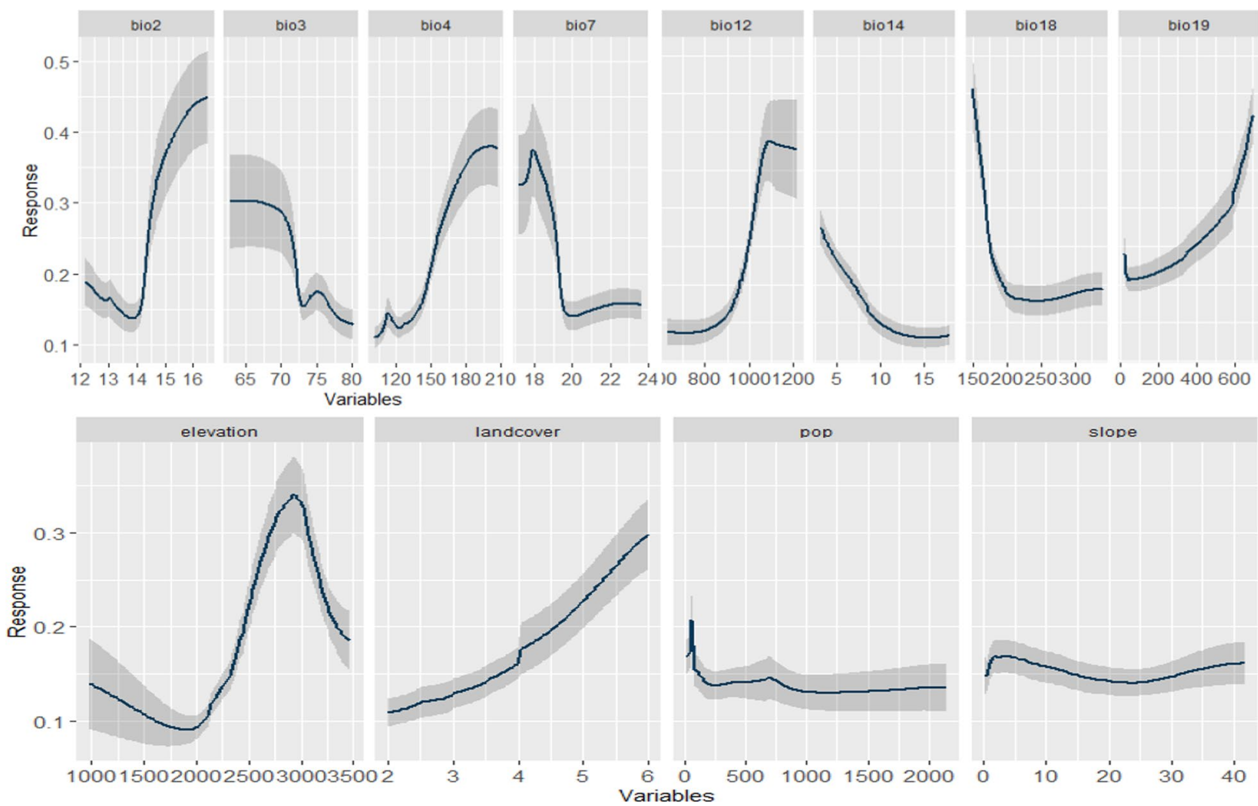

Fig. 6 Response curve for *A. debrana* distribution. The *X*-axis represents the range of values of the environmental variables, and the *Y*-axis gives the probability of occurrence on a scale from 0 to 1

Table 3 Predicted suitable area per species for current and future climate change scenarios

Species	Decades	Scenarios	Total suitable area (km^2) and percent of land							
			Not suitable		Lowly suitable		Moderately suitable		Highly suitable	
			km^2	%	km^2	%	km^2	%	km^2	%
A. ankoberensis	Current	–	15,901.43	98.32	162.57	1.01	83.74	0.52	24.59	0.15
	2050	SSP2.6	15,452.03	95.55	720.31	4.45	0	0	0	0
		SSP4.5	15,790.88	97.64	380.34	2.35	1.12	0.01	0	0
		SSP8.5	15,874.09	98.16	298.25	1.84	0	0	0	0
	2070	SSP2.6	15,884.46	98.22	287.88	1.78	0	0	0	0
		SSP4.5	16,105.68	99.59	66.66	0.41	0	0	0	0
		SSP8.5	15,825.57	97.86	346.77	2.14	0	0	0	0
A. debrana	Current	-	1033.69	63.89	3777.02	23.35	2028.79	12.54	33.84	0.21
	2050	SSP2.6	15,131.92	93.57	1040.42	6.43	0	0	0	0
		SSP4.5	12,765.09	78.93	3298.29	20.39	108.97	0.68	0	0
		SSP8.5	10,794.9	66.75	5072.19	31.36	305.24	1.89	0	0
	2070	SSP2.6	11,882.93	73.48	4239.14	26.21	50.27	0.31	0	0
		SSP4.5	13,515.11	83.57	2656.66	16.43	0.58	0.004	0	0
		SSP8.5	13,475.54	83.32	2696.8	16.68	0	0	0	0

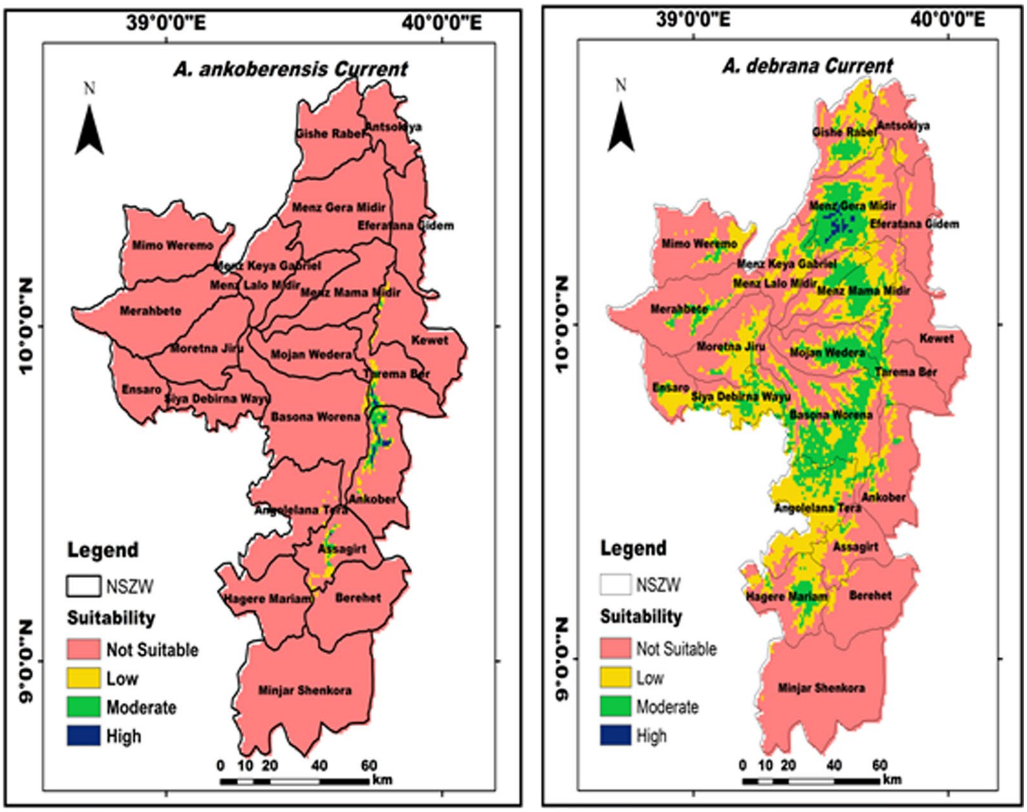

Fig. 7 Current predicted habitat suitability of *A. ankoberensis* and *A. debrana*

habitat suitability maps and developing priority site for conservation (Elith and Leathwick 2007; Kaky and Gilbert 2017; Borzée et al. 2019). Moreover, the SDMs are gaining recognition as a tool for sustainable biodiversity management (Qazi et al. 2022). The model achieved with an excellent degree of accuracy for *A. ankoberensis* with an AUC/TSS score of 0.96/0.88 respectively, and a good degree of accuracy for *A. debrana* with AUC/TSS score of 0.87/0.63 respectively. Congruently, Dagnew et al. (2022) found an AUC/TSS score of 1/0.96 for highland bamboo, and Mkala et al. (2022) found an AUC/TSS score of 0.91/0.82 for *Aloe clasenii* and 0.83/0.64 for *Aloe ballyi*. Moreover, numerous studies showed that performance of RF was higher for predicting species distribution in ensemble model approach (Lee et al. 2021; Nurhussen et al. 2021; Xu et al. 2021; Urziceanu et al. 2022). This model result also revealed that RF has the highest performance with AUC/TSS score of 0.97/0.91 and 0.95/0.79 for *A. ankoberensis* and *A. debrana*, respectively.

In addition, to determine level of threats for the species categorized under Red List, the IUCN started using SDMs (Cassini 2011). Previous studies revealed that the use of largest set of environmental variables will increase the possibility of finding important variables for prediction (Lissovsky et al. 2021). Accordingly, in this study variety of environmental variables were added to improve the accuracy of the model. To get truthful prediction, preparing quality data is a key point. This can be performed by removing auto-correlated occurrence records, correlation test, and reasonable selection of environmental variables (Pattanaik et al. 2022; Tesfamariam et al. 2022).

Current distribution and key environmental variables for *A. ankoberensis* and *A. debrana*

Species distributions are limited by availability of habitat (Wang et al. 2015). To improve the management and conservation of a species, it is vital to look at its potential range given the current climatic conditions. Climate change is the significant factor that affects the distribution of global plants (Tshabalala et al. 2020). According to our results, for *A. ankoberensis*, suitable habitat is currently concentrated in the Ankober, Tarmaber, and Asagrt woredas while for *A. debrana*, it is found mostly in the North Shewa zone showing decreasing and narrowing patterns of habitat ranges compared to historical distribution records of previous studies (Sebsebe and Nordal 2010; Eshetu et al. 2020).

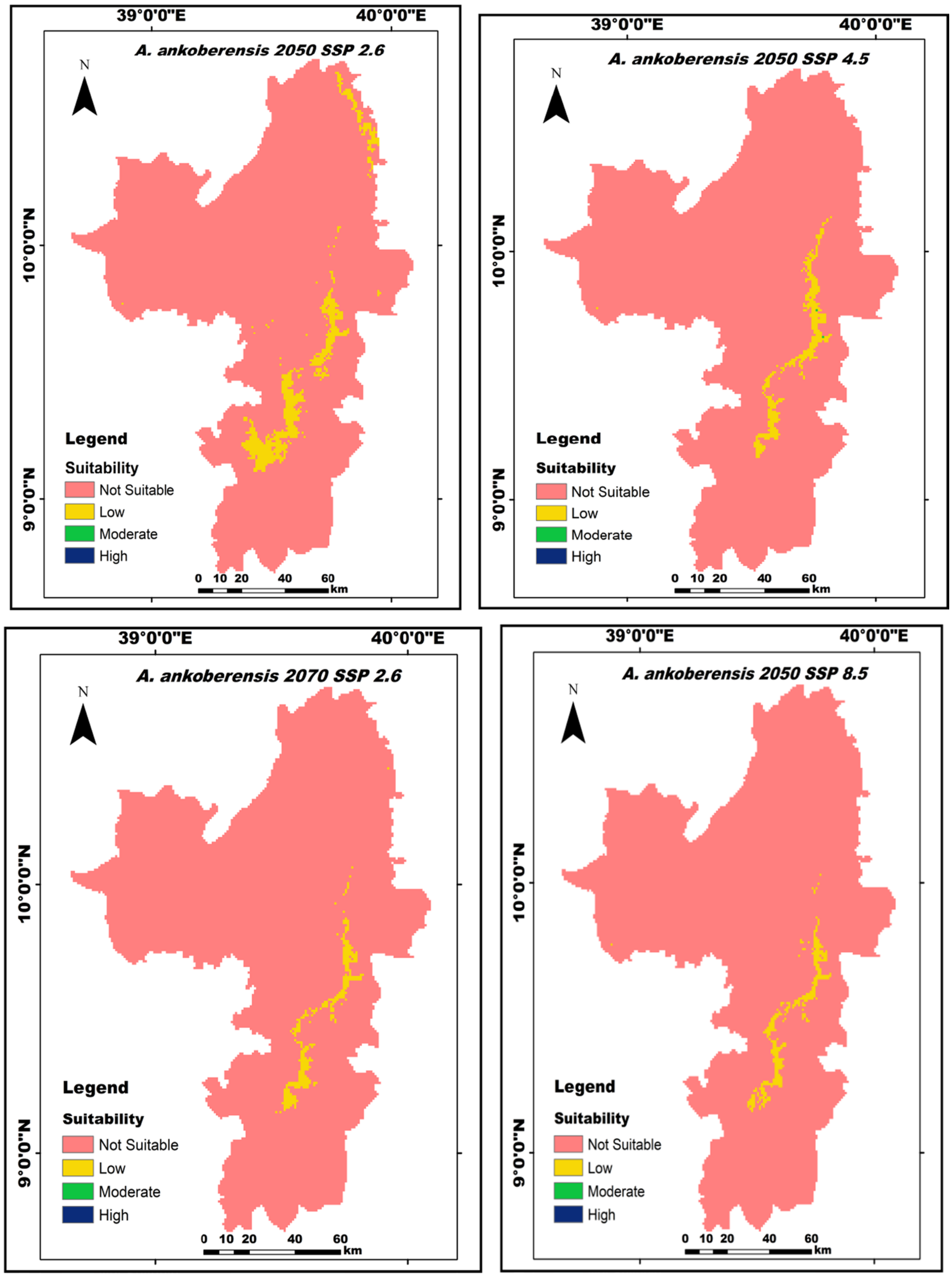

Fig. 8 Future predicted habitat suitability of *A. ankoberensis* under different scenarios

According to Mkala et al. (2022), climate change could have a substantial impact on endemic species in the present and the future, displacing them from their original niche ranges to new ones (Qin et al. 2017). These findings showed that climate change could have a significant impact on the distribution of *A. ankoberensis* and *A. debrana*. Identifying the environmental variables that have a significant effect on species distribution is a key for conservation and restoration of species in their natural habotats (Cao et al. 2016). With this regard this study showed that temperature and precipitation related environmental variables were the most

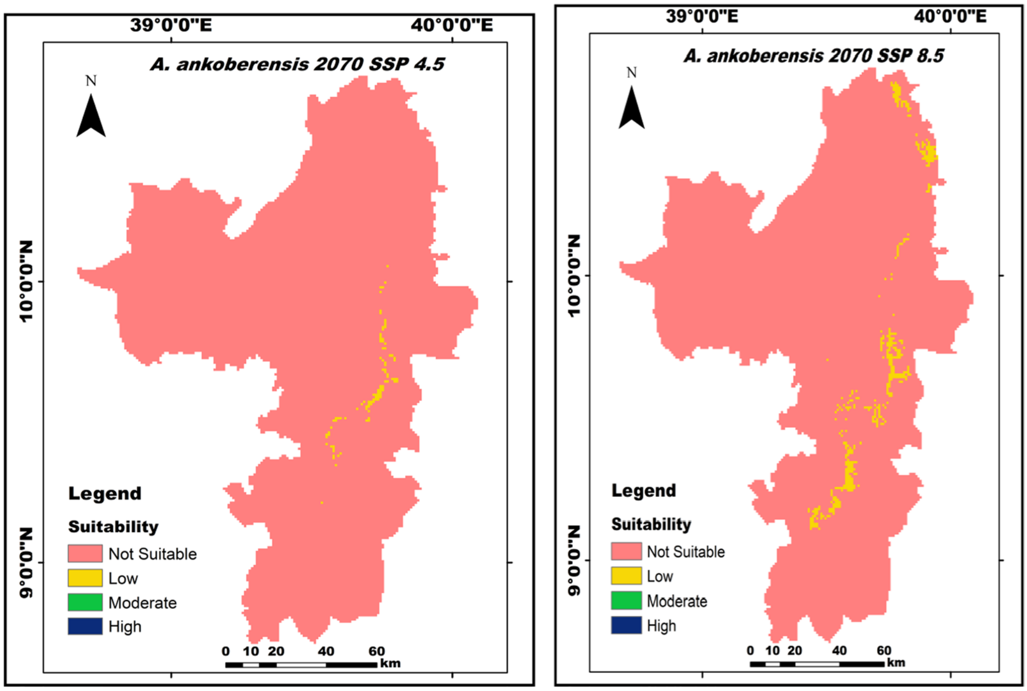

Fig. 8 continued

significant factors for *Aloe* species distribution (Abdulbasit and Sintayehu 2021; Guo et al. 2021).

In addition, elevation is also the most significant factor for distribution of species (Cotrina et al. 2021; Yericho et al. 2022). Similar studies also showed that climate change could have affected species growth and distribution, particularly along elevation gradients (Odeny et al. 2019). Similarly, *A. ankoberensis* was greatly affected by mean diurnal range of temperature and annual precipitation, while *A. debrana* was affected by elevation and annual precipitation. Previous studies by Wilson et al. (2020) reported that precipitation, temperature, water availability, humidity, and wind are significantly limiting species distribution in Africa. Despite the fact that both species are more sensitive to variations in temperature and precipitation, their tolerance to these variables may not be the same as a result of difference in elevations in the natural habitats. According to the findings from this study, *A. ankoberensis* prefers areas with an elevation range of 3000–3500 m above sea level while *A. debrana* prefers areas with an elevation range of 2000–2900 m above sea level. This is in consistence with previous studies on *Aloe* species distribution in Ethiopia (Sebsebe and Nordal 2010). In Ethiopia, though the correlation of rainfall with altitude above about 1800 m is particularly poor due to oreographic effects, metrological data indicated that the range of *A. debrana* areas gets more precipitation than the sub-Afroalpine ecosystem of *A. ankoberensis,* which favores more population distribution and able to withstand the impact of climate change. However, *A. ankoberensis* could be less tolerant to an increased temperature at higher elevation of sub-Afroalpine ecosystem so that affected the population distribution coupled with other factors. Different scholars identified that anthropogenic activities such as urban development programs, excessive logging, mining, conversion of forest areas to farmland, over exploitation and others combined with climate change influence species distribution (Weelden et al. 2021; Zahoor et al. 2021). Moreover, these anthropogenic factors are one of the factors for global warming in the atmosphere which results in diminishing of biodiversity and affects survival of species in their natural habitats. Sintayehu (2018) showed that extreme climate warming's could alter plant growth, as well as increasing their vulnerability within natural habitat. Additionally, other biological factors that affect local adaptations, such as physiological features and phenotypic plasticity, may have a larger impact on species' reactions to climate change than temperature changes alone (Urban et al 2016). As a result, significant level of the natural habitats for these *Aloe* species are currently vulnerable to further habitat loss and fragmentation, in addition to climate change impacts. It has been stated that the main risks to the wild population instability of *Aloe*

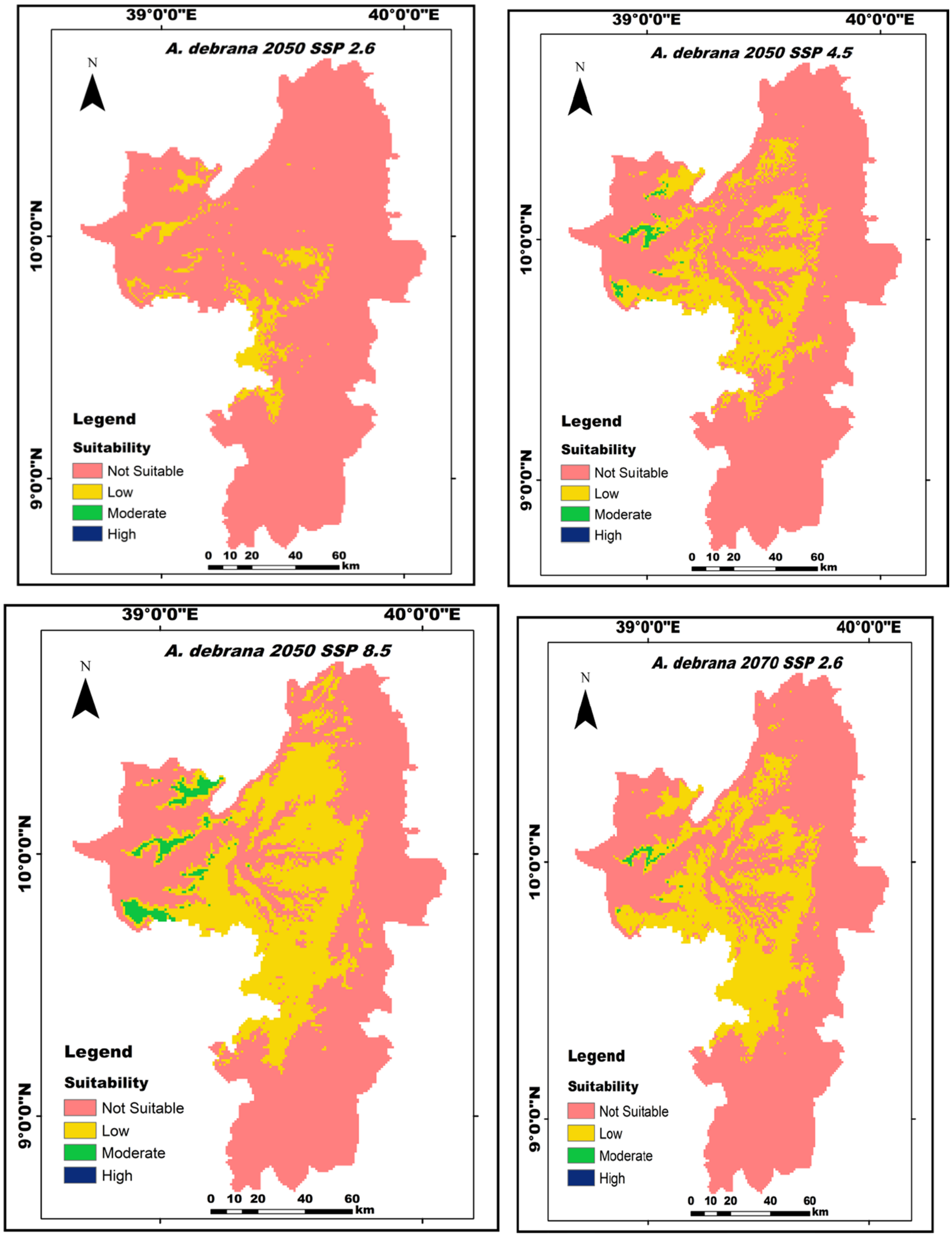

Fig. 9 Future predicted habitat suitability of *A. debrana* under different scenarios

species in the environment are habitat loss brought on by agriculture, infrastructure growth, and an increase in settlement rates (Eshetu et al. 2020). In addition, growth of human population, land use and land cover change and development of tourist industry affect species diversity and distribution pattern (Nugroho et al. 2022). These phenomena in the study areas aggravated decline *Aloe* species population distribution coupled with the climate change.

Future distribution of *A. ankoberensis* and *A. debrana*

Climate change predictions suggest that the ranges of these endemic *Aloe* species will gradually shrink, leading to a reduction in their suitable habitats. Climate change

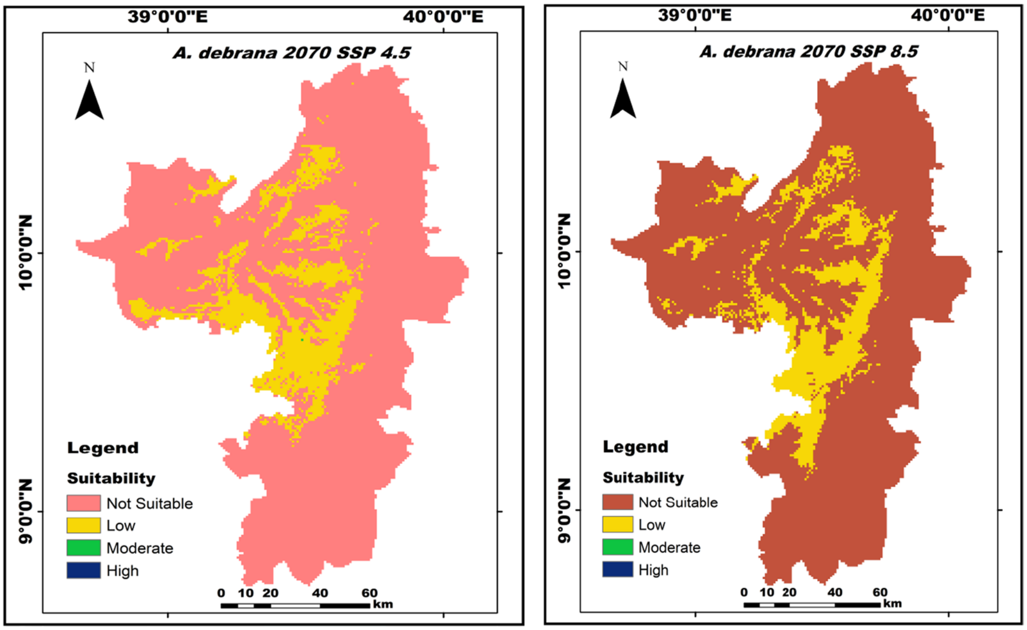

Fig. 9 continued

Table 4 Percentage of area changes (gain or loss) of *A. ankoberensis* and *A. debrana* for future periods (2050 and 2070) under SSP (2.6, 4.5 and 8.5) scenarios

Species	Decades	Scenarios	Change (%) compared with current suitability			
			Not suitable	Lowly suitable	Moderately suitable	High suitable
A. ankoberensis	2050	SSP2.6	– 2.83	343.07	– 100	– 100
		SSP4.5	– 0.70	133.95	– 98.67	– 100
		SSP8.5	– 0.17	83.45	– 100	– 100
	2070	SSP2.6	– 0.11	77.08	– 100	– 100
		SSP4.5	1.30	– 59.00	– 100	– 100
		SSP8.5	– 0.48	113.30	– 100	– 100
A. debrana	2050	SSP2.6	46.45	– 72.45	– 100	– 100
		SSP4.5	23.54	– 12.67	– 94.63	– 100
		SSP8.5	4.47	34.30	– 84.95	– 100
	2070	SSP2.6	15.00	– 12.20	– 97.52	– 100
		SSP4.5	30.80	– 29.66	– 99.97	– 100
		SSP8.5	30.40	– 28.60	– 100	– 100

has already initiated significant large-scale alterations in species distribution, abundance, and genetic diversity (Weiskopf et al. 2020). It is clear that species' geographic distributions may be altered in the future due to climate change (Sales et al. 2020). Previous research demonstrated that some species may experience benefit from climate change, gaining access to more areas that are optimal for growth and reproduction (Sintayehu et al. 2021; Sintayehu et al. 2020a, b, c). However, other species suffer from the negative consequences of climate change (Kaky 2020; Abdulbasit and Sintayehu 2021; Lee et al. 2021; Xu et al. 2021). Endemic species are more affected by climate change than non-endemic species (Manes et al. 2021). This indicates that areas that have high endemic species are more vulnerable to climate change.

According to most predicting models, the temperature in Ethiopia will increase significantly in the future, and its precipitation will also slightly increase. The model predicts that in both the 2050s and 2070s, the highly suitable area for both species will decrease by

100% under all scenarios. Similar to this, in the 2050s, the moderately suitable region for *A. ankoberensis* will shrink by 100% under all scenarios other than SSP 4.5. According to SSP scenarios (2.6, 4.5, and 8.5), the moderately suitable area for *A. debrana* will drop by 100%, 94.63%, and 84.95% in the 2050s and by 97.52%, 99.97%, and 100% in the 2070s, respectively. This is likely due to a decline in area available and its suitability as global temperature increase. Similarly in the future climate change could have negative impact by reducing the geographical range of species (Jamwal et al. 2021). Given the possible effects of climate change and habitat fragmentation on unstable and isolated populations, the long-term viability of threatened and endangered plant species is becoming increasingly crucial (Wang et al. 2015). This cumulative impact of all climate extreme events will accelerate the total alteration of the ecosystem and its structure. For different reason, the conservation and expansion of these endemic species habitat need to pay attention. First, they have been recognized for their economic potential in Ethiopia particularly for livelihood security, economic development and enhancing biodiversity conservation on marginal lands (Mukonyi et al. 2007). Second, they are considered as a keystone species that alters ecosystem (Sebsebe and Nordal 2010). Third, they have potential values for medicinal, social, environmental, materials, and food use (Anteneh et al. 2020; Eshetu et al. 2020). Fourth, these endemic species are found in restricted range, peculiar features of the limited number of *Aloe* species on the Afromontane and sub-Afroalpine ecosystems, and their habitats are susceptible to habitat fragmentation.

The model predicted that annual precipitation increases from 1000–1200 mm for *A. ankoberensis* and from 800 to 1100 mm for *A. debrana* that could result in challenges on the suitable habitats of the species. However, the future precipitation prediction in Ethiopia indicated an erratic rainfall pattern (IPCC 2021). This erratic rainfall can cause imbalances in the soil moisture, vegetation, and microclimate of the environment (Bates et al. 2008) and extreme rainfall can accelerate soil erosion. Furthermore, the incidence of disease outbreaks accumulated each year due to climate change (Jeon et al. 2020). These factors could pose significant threats to the survival of both *A. ankoberensis* and *A. debrana*. Consequently, the future suitable area for both *A. ankoberensis* and *A. debrana* would become lost. In addition, the prediction showed that *A. ankoberensis* and *A. debrana* will change their distribution in response to future climatic changes. Because of the rise in global average temperature, the species could shift to high-elevation areas (Faticov et al. 2021). The current and future challenges posed on these endemic species could be an indicator for the great challenge faced on the peculiar habitats like sub-Afroalpine and Afroalpine ecosystems of the country.

Conclusion

This study investigated the potential distribution and environmental niche of *A. ankoberensis* and *A. debrana* in the North Shewa zone, employing an ensemble model approach across current, 2050s, and 2070s time periods under three climate scenarios SSP (2.6, 4.5, and 8.5). Such investigation is vital for future monitoring activities and proper design of conservation strategies and management plans of endemic and rare species that become under threat due to climate and land use and land cover changes. The findings underscored that the suitable habitat for the narrowly endemic *A. ankoberensis* and endemic *A. debrana* is projected to diminish under future climate change scenarios, potentially exacerbating their conservation status beyond the categories listed in IUCN reports. The limited number of presence points for *A. ankoberensis* suggest a significant decline in the population of this sub-Afroalpine and narrowly endemic *Aloe* species. Furthermore, the existing and forthcoming challenges confronting these endemic species serve as indicators of the substantial threats faced by peculiar habitats such as sub-Afroalpine and Afroalpine ecosystems in the country. In summary, the findings suggest an urgent call for developing species conservation plans, designing appropriate conservation strategies, and strengthening adaptation measures to tackle the compounded factors contributing to habitat loss. These efforts are vital to ensure the survival of these endemic, narrowly endemic, and rare species within their natural habitats.

Abbreviations

AUC	Area under curve
BRT	Boosted regression trees
CMCC- ESM2	Second-generation Euro-Mediterranean Centre on climate change earth system model
GCMs	General circulation models
GHGs	Greenhouse gases
GLM	Generalized linear models
IPBES	Intergovernmental science-policy platform on biodiversity and ecosystem services
IPCC	Intergovernmental Panel for Climate Change
IUCN	International Union for Conservation of Nature
LULCC	Land use and land cover change
MARS	Multivariate adaptive regression splines
Maxent	Maximum entropy
RF	Random forests
SDMs	Species distribution models
SSP	Shared socio-economic pathway scenarios
SVM	Support vector machines
TSS	True skill statistics
VIF	Variance inflation factors

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13717-024-00511-x.

Additional file 1: Table S1. List of environmental variables used for modeling the distribution of the species.

Additional file 2: Table S2. Correlation matrix among environmental variables.

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Author contributions

HA and AB initiated the work; HA collected the data, AB and SWD supervised the study; HA, AB and SWD analyzed data, wrote and revised the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets analyzed during this study are included in this manuscript as supplementary information files.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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