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Response of plant species to impact of climate change in Hugumbrda Grat-Kahsu forest, Tigray, Ethiopia: Implications for domestication and climate change mitigation

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ABSTRACT

This study aimed to predict distribution and Total Carbon Stock (TCS) dynamics of *Acacia abyssinica, Carissa edulis*, and *Juniperus procera* in the Hugumbrda Grat-Kahsu National Forest in current (1970–2000) and future climate scenarios (2021–2100). Bioclimatic, soil, and elevation data were used for modeling using Maxent, with model accuracy evaluated using Area Under the Curve (AUC), Kappa test and True Skill Statistic (TSS). Significant differences were observed in distribution of species between current and future periods under Shared Socioeconomic Pathways (SSPs) of SSP2-4.5 and SSP5-8.5 scenarios. The main contributing predictors of the species distribution were temperature seasonality, altitude, and precipitation of the warmest quarter. All species were projected to shift to higher altitudes in the future. *Acacia abyssinica*'s current potential distribution (42.9 %) could expand to 77.1–99.2 % (SSP2-4.5) and 63.8–72.9 % (SSP5-8.5). *Carissa edulis* could extend from 54.2 % to 89.5–100 % (SSP2-4.5) and 77.1–87.9 % (SSP5-8.5). *Juniperus procera*'s might increase from 63.8 % to 91.8-99.7 % (SSP2-4.5) and 78–88.1 % (SSP5-8.5). The projected future climate is expected to result in an expansion of new suitable areas for all three species. The TCS estimates per km^2 were 169 (*Acacia abyssinica*), 46 (*Carissa edulis*), and 1381 ton (*Juniperus procera*). In SSP2-4.5, *Acacia abyssinica*'s TCS could rise from 25,688 to 59,319 tons, *Carissa edulis* from 8,832 to 16,284 tons, and *Juniperus procera* from 312,106 to 487,493 tons. In SSP5-8.5, projections indicated 43,602 tons (*Acacia abyssinica*), 14,306 tons (*Carissa edulis*), and 430,872 tons (*Juniperus procera*). The study concludes by recommending the strategic planting of these species in both current and future suitable areas to enhance ecosystem services and ensure their sustained existence in the face of changing climates.

1. Introduction

Climate change has effects on biodiversity at all levels, ranging from individual organisms to entire biomes (Parmesan et al., 2011). It results in the loss of habitats, alterations in geographic landscapes, and impacts on the survival of various species. It contributes to accelerating upward shifts of species to high elevations (Wolf et al., 2016). In addition, climate change causes both expansions and contractions of forest coverage (Lucier et al., 2009).

Ethiopia, a biodiverse country in Africa, boasts approximately 6,000 species of plants, including 600 endemics (Kelbessa and Demissew, 2014; Demissew et al., 2021). Much of the biodiversity finds its concentration in the Ethiopian Highlands (Fashing et al., 2022). However, the diverse ecosystems and biodiversity are facing threats from climate change (Fashing et al., 2022).

The effects of climate warming are causing geographic shifts among species in Ethiopia (Semu et al., 2021). It is crucial to study where different species might shift as the climate changes, in order to minimize

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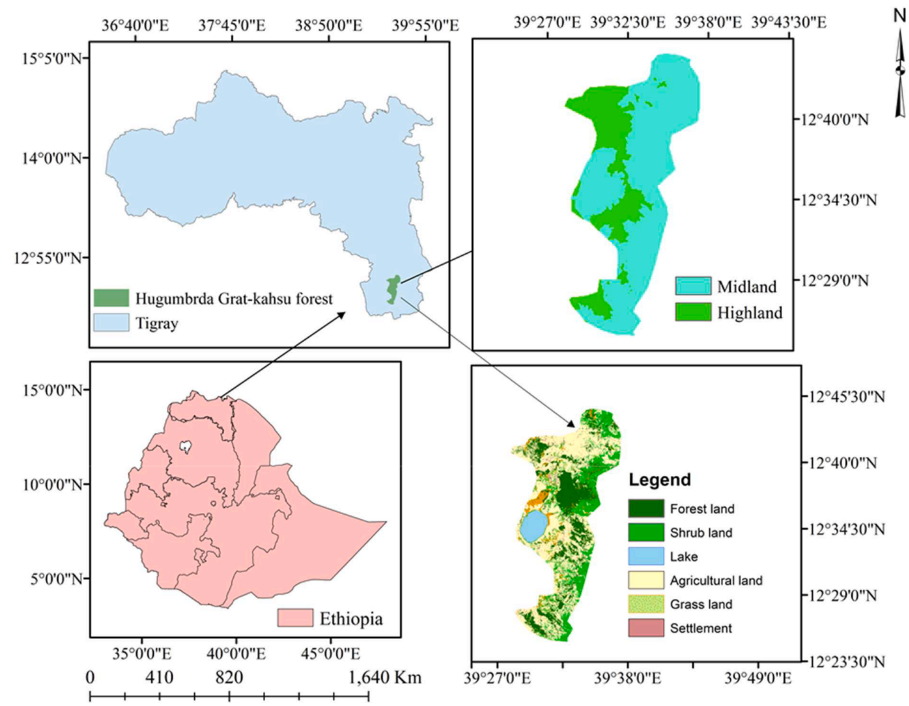

Fig. 1. Map of the study area, where the study forest is denoted by a green-colored area. The map also includes elevation classes and land use/land type classes of present within the forest.

the associated impacts. Researchers (e.g., Abrha et al., 2018; Beaumont et al., 2011) are actively working on understanding the diverse impacts of climate change on the geographic shift of various plant and animal species.

Global climate models (GCMs) from various phases of the Coupled Model Intercomparison Project have been central to climate change studies (Su et al., 2021). The Collaborative Framework for Comparing Coupled Models, known as the Coupled Model Intercomparison Project (CMIP), was established in 1995 by the Working Group on Coupled Modeling (WGCM) under the World Climate Research Programme (WCRP). Its primary objective is to advance the understanding of historical, current, and future climate changes by comparing how models respond to various standardized forcings and scenarios. CMIP has evolved into a crucial resource for the Intergovernmental Panel on Climate Change (IPCC) and various international and national climate assessments (Meehl et al., 2000; Eyring et al., 2016).

GCM-based predictions play a crucial role in developing early warning systems (Parmesan et al., 2011; Pereira et al., 2010) for sustainable forest management as forests provide ecosystem services. The Intergovernmental Panel on Climate Change (IPCC) through the Coupled Model Intercomparison Project (CMIP) adopts different greenhouse gas concentration trajectory in climate change projection studies. Over the past years, the Representative Concentration Pathways (RCPs, van Vuuren et al. 2011) adopted in the fifth assessment report (AR5) of the IPCC have been applied for species distribution modeling and predicting climate trends. The recent IPCC's sixth Assessment Report (AR6), Coupled Model Intercomparison Project Phase 6 (CMIP6) climate model datasets have been utilized. CMIP6 model includes a set of new emission scenarios driven by shared socioeconomic pathways (SSPs, Riahi et al. 2017), which are important for predicting species distribution (Zhou et al., 2021). This study used the SSPs sourced data from average of ensemble GCMs within the framework of CMIP6.

Forests play an important role in the ecosystem (Brashears et al., 2004). For instance, they function as significant carbon reservoirs, storing substantial quantities of carbon within their biomass and soil (Pan et al., 2011). Plants, including trees, absorb atmospheric carbon dioxide and sequester it in both Above Ground Biomass (ABG) and Belowground Biomass (BGB) (Izaurralde et al., 2012). This leads to the need to determine the amount of carbon that various types of plants can store. As a result, this study is conducted to modeling the distribution and carbon storage dynamics of *Acacia abyssinica, Carissa edulis*, and *Juniperus procera* under climate change within the Hugumbrda Grat-Kahsu national forest. These particular species were chosen due to their elevated importance value index within the forest ecosystem.

Acacia abyssinica belongs to the family Fabaceae (Leguminoseae) and the sub-family Mimosodeae. It is primarily found in afromontane areas and is extensively used for soil and landscape conservation and restoration due to its ability to improve degraded soils (Negash, 1993). It is a leguminous tree capable of nitrogen fixation, thereby enhancing soil fertility (Degefu et al., 2011; Negash, 1993). *Juniperus procera*, commonly known as the African pencil cedar, belongs to the family Cupressaceae. It is predominantly found in mountainous areas (Friis, 1992; Negash, 1993). This species serves various purposes such as pencil production, construction, furniture, joinery, and ecological restoration (Friis, 1992; Negash, 1993; Orwa et al., 2009). *Carissa edulis*, classified in the family Apocynaceae, is a shrub species that bears edible fruits. Moreover, it is employed for soil and water conservation, ecological functions, and fuelwood. Different chemical compounds have been extracted from this species (Al-Youssef et al., 2014). However, studies on the distribution of species and their carbon stock potential under climate change are not well-studied, especially in the context of the latest emission scenarios (SSP).

Hence, this research was designed to achieve four primary objectives. Firstly, it aimed to model the impact of climate change on the distribution of three specific species. Secondly, it aimed to detect current and future suitable and unsuitable areas for the selected species. Thirdly, the research aimed to investigate the carbon dynamics and responses of these selected species to climate change. Lastly, the study identified and analyzed the environmental variables that play a significant role in shaping the distribution patterns of the studied species.

Table 1
Environmental variables used as predictors.

Code	Bioclimatic variables	Code	Bioclimatic variables
Bio01	Annual Mean Temperature	Bio13	Precipitation of Wettest Month
Bio02	Mean Diurnal Range	Bio14	Precipitation of Driest Month
Bio03	Isothermality	Bio15	Precipitation Seasonality
Bio04	Temperature Seasonality	Bio16	Precipitation of Wettest Quarter
Bio05	Max Temperature of Warmest Month	Bio17	Precipitation of Driest Quarter
Bio06	Min Temperature of Coldest Month	Bio18	Precipitation of Warmest Quarter
Bio07	Temperature Annual Range	Bio19	Precipitation of Coldest Quarter
Bio08	Mean Temperature of Wettest Quarter	Altitude	Elevation
Bio09	Mean Temperature of Driest Quarter	Silt	Percent silt
Bio10	Mean Temperature of Warmest Quarter	Sand	Percent sand
Bio11	Mean Temperature of Coldest Quarter	Clay	Percent clay
Bio12	Annual Precipitation		

2. Methodology

2.1. Study area description

Hugumbrda Grat-Khassu National Forest is located in the southern zone of Tigray, about 160 km south of Mekelle, the capital of the Tigray region of Ethiopia. The forest founds in the OFla, Raya Alamata, Raya Azebo, and Endamohoni districts of the Tigray region. Its geographical coordinates range between latitude 12°25′11.564"N and 12°44′29.025"N and longitude 39°28′11.262"E and 39°37′28.411"E. The forest covers an elevation range of 1501 to 3683 m above sea level (m.a.s.l.) and is classified as a dry evergreen Afromontane Forest. It includes both midland and highland altitudinal classes (Fig. 1). The area is characterized by rough and hilly landscape. The predominant soil types are Vertisol, leptosoil, and cambosols. The annual average rainfall in the forest varies from 653 to 818.6 mm, while mean maximum temperatures range from 21.4 to 30 °C. The average minimum temperature in the forest ranges between 9.4 and 14.8 °C (Abrha et al., 2023). Lake Hashenge, a highland lake with no outlet, is found within the forest. It is about 5 km in length and 4 km in width, reaching a maximum depth of 25 m (Tsegay, 2017).

The forest area is composed of plantation forests, natural forests, bushes, shrubs, agricultural fields, and settlement areas (Kidane et al., 2018). The land use types found in the forest area include forest land, grassland, lake, settlement, and agricultural land (Fig. 1). The total population within and around the forest amounts to 26,889 households, with 5,496 households located entirely within the forest area and the remaining 21,393 households residing in the surrounding areas (Woldemichael et al., 2010). The local farming practices mainly involve mixed farming systems. Key food crops cultivated include *Zea mays, Sorghum bicolor, Triticum durum, Eragrostis tef, Hordeum vulgare, Pisum sativum*, and *Cicer arietinum*. Additionally, valuable tree crops like *Mangifera indica, Persea americana, Carica papaya*, and *Malus domestica* are grown. The main livestock species raised are cattle, sheep, goats, donkeys, horses, mules, and camels (Gebru et al., 2019).

2.2. Input data sets

The study used various input datasets from satellite images and ground-based experimental designs for forest measurements. Those data sets were used for predicting the distribution of three woody plant species under current and projected climate conditions using the Maximum Entropy Model (Maxent 3.4.4). Future climate data from ensemble General Circulation Models (GCMs) for different time periods were used for an ensemble approach to reduce model uncertainty. This study includes current climate data from WorldClim version 2.1 ranging from 1970 to 2000 and future data from CMIP6 from 2021 to 2100.

Elevation data was sourced from the WorldClim database, and soil data from SoilGrid was also used due to their influence on species distribution. The soil data considered were silt, clay, and sand percentages at a depth of 15–30 cm. The study employed an experimental design involving 188 plots to collect occurrence data and species structure.

2.2.1. Climate data

Maximum Entropy Model (Maxent 3.4.4), an ecological niche model was used to predict the distribution of three woody plant species under both current and projected climate conditions. The future climate data were acquired from four General Circulation Models (GCMs) for distinct periods: 2021-2040, 2041-2060, 2061-2080, and 2081-2100. The study used an ensemble of climate models, including the Australian Community Climate and Earth System Simulator-Coupled Model 2 (ACCESS-CM2), Hadley Global Environment Model 3-Global Coupled 31-Low Resolution (HadGEM3-GC31-LL), Model for Interdisciplinary Research On Climate 6 (MIROC6), and Max Planck Institute Earth System Model 1-2-High Resolution (MPI-ESM1-2-HR) GCMs. These models were selected for ensemble due to their good performance in Ethiopian research studies: ACCESS-CM2 and MPI-ESM1-2-HR (Gebresellase et al., 2022), HadGEM3-GC31-LL, MPI-ESM1-2-HR, MIROC6 (Berhanu et al., 2023), and MPI-ESM1-2-HR (Rettie et al., 2023). Ethiopia, like other of African countries, lacks its own calibrated General Circulation Model (GCM). As a result, an ensemble of various models was applied in the study.

The ensemble of these four GCMs was employed to address the uncertainty and limitations of a single global climate model in accurately projecting future climate trends (Bağçaci et al., 2021). The multi-model ensemble approach has developed as the most important method to mitigate model uncertainty, as stated by numerous studies (Wu et al., 2018; Feng et al., 2010). Arithmetic mean has been widely applied to ensemble multiple models. In the case of arithmetic averaging, ArcGIS was used, integrating the GCMs with equal weighting (Her et al., 2019; Ferro et al., 2013). The utilization of an ensemble of models in the modeling process supports to produce more accurate predictions (Wu et al., 2018).

The current climate data has been extracted from WorldClim version 2.1. Within the framework of the WorldClim version 2.1 dataset, the climate data has been structured to encompass the temporal range spanning from 1970 to 2000, in addition the future is from 2021 to 2100 (Fick and Hijmans, 2017). Both current and future datasets were at a resolution of 30 s (~1 km^2) accessed from worldclim. The future climate data were sourced from the CMIP6, demonstrating both qualitative and quantitative enhancements compared to earlier CMIP phases like CMIP5. These improvements encompass a better representation of physical processes, simulated fields, and a higher spatial resolution (Gebresellase et al., 2022). Moreover, when contrasted with CMIP5, CMIP6 shows better perform better (Zhang et al., 2023). CMIP6 shows improvements in resolution, leading to more significant findings (Di Luca et al., 2020; Srivastava et al., 2020).

The five "families" of SSP-based scenarios used in CMIP6 can be categorized along two broad axes: challenges to mitigation and challenges to adaptation. SSP1 (Sustainability) has low challenges to both mitigation and adaptation. In this scenario, policies focus on human well-being, clean energy technologies, and the preservation of the natural environment. In contrast, SSP3 (Regional Rivalry) is characterized by high challenges to both mitigation and adaptation. In this scenario, nationalism drives policy, and the focus is placed on regional and local issues rather than global ones. SSP4 (Inequality) is defined by high challenges to adaptation and low challenges to mitigation, while SSP5 (Fossil-fueled Development) is characterized by high challenges to

Table 2
An error matrix used to evaluate the predictive accuracy of presence–absence models absence; d, number of cells for which absence was correctly predicted by the model.

		Validation test data	
		Presence	Absence
Model	Presence	Number of cells for which presence was correctly predicted by the model (a)	Number of cells for which the species was not found but the model predicted presence (b)
	Absence	Number of cells for which the species was found but the model predicted absence (c)	Number of cells for which absence was correctly predicted by the model (d)

mitigation and low challenges to adaptation.

SSP2 (Middle of the Road) represents moderate challenges to both mitigation and adaptation (Meinshausen et al., 2020; O'Neill et al., 2020). To examine the trend, two SSPs were selected: SSP2-4.5 and SSP5-8.5. These two SSPs were selected to simulate the distribution of the three species under future climate conditions. They were chosen because they represent both a moderate and an extreme emission scenario, as well as various mitigation and adaptation strategies. This choice was made to examine both a "Middle of the Road" and a "Fossil-fueled development" scenario, capturing the two extremes when compared to the current adaptation and mitigation activities.

2.2.2. *Elevation*

While climate data has as a significant contribution in species distribution modeling (Van der Putten et al., 2010), it is known that elevation can also have influence on species distribution (Sekercioglu and Schneider, 2008). Studies (e.g., Luoto and Heikkinen 2008; Virkkala et al. 2010) recommend that the accuracy of predicted species ranges can remarkably improve with the inclusion of elevation data. Consequently, elevation data was integrated. Altitude data with the same resolution as the climate data were sourced from the WorldClim database and applied (Table 1).

2.2.3. *Soil data*

MaxEnt can incorporate topographic, climatic, soil, and other variables. The inclusion of soil data is important, as the absence of soils in models can lead to an overestimation of future habitat suitability for many plant species (Zuquim et al., 2020). The impacts of climate change on forest structure and distribution can vary along soil properties across a landscape (Levine et al., 2016). Soils may support species establishment through factors like nutrient availability (Tuomisto et al., 2016), water retention properties (Schietti et al., 2014), root growth and others. If soils are unsuitable for a species, the area falls outside its niche tolerance and the probability of occurrence reduces, regardless of climatic conditions. Consequently, relying solely on climate-based ecological niche models is conceptually weak (Velazco et al., 2017) and their spatial predictions may lack reliability. The inclusion of soil variables has an impact on the size and shape of predicted suitable areas, particularly in future models (Zuquim et al., 2020). As a result, this study was run using climate data, elevation and soil data.

The ISRIC (International Soil Reference Information Centre) World Soil Information released a Global Soil Information system known as "SoilGrids," which was employed to obtain soil attributes such as the percentage of silt, clay, and sand at a depth of 15–30 cm (Table 2). The soil map had an initial resolution of 250 m and was subsequently resampled to 1km to achieve a consistent cell size with the worldclim data. Soil texture was chosen because it influences soil biophysical properties, such as soil porosity, bulk density, and hydraulic conductivity (Upadhyay and Raghubanshi, 2020). Soil texture strongly affects soil functions and water and nutrient availability (Khalil et al., 2015). Many scientists consider soil texture the most important soil property, as it can impact soil-water relationships, gas exchange, and plant nutrition (Ritchey et al., 2015), as well as soil biophysical properties (Martín et al., 2018). Therefore, using the percentages of soil texture is essential for determining soil suitability.

2.2.4. *Experimental design*

A total of 188 plots were established to collect occurrence points and structure of the species. These plots were arranged with a horizontal interval of 250 m between transects and a vertical distance of 100 m between plots using systematic sampling. Systematic sampling is a widely employed technique in forest inventory applications, providing advantages in terms of precision and ease of implementation (McRoberts et al., 2016). It is positioned at regular intervals, with a fixed set of non-overlapping samples (Kershaw et al., 2016). The study involved placing linear transects within the forest area. These transects were systematically arranged, extending horizontally from east to west, thus offering comprehensive coverage across the forest's width. Additionally, ground plots were established at regular intervals, running vertically from south to north of the study area. This intentional spatial arrangement was designed to ensure an inclusive and representative sampling strategy.

The Diameters of woody plant species were measured using both diameter tape and caliper at a height of 1.3 m above ground level, as well as the diameter at stump height at 30 cm. Heights were measured employing meter tape and clinometers. Trees exceeding 1 meter in length were subjected to measurement. Furthermore, the tree occurrence data, as well as tree height and diameter, were collected using circular plots with a radius of 11.28 m, which corresponds to an area of 400 m^2 (Fig. 2).

Within the 37 transects of 188 plots, a total of 6,813 trees belonging to 42 woody species were recorded. Among the 42 species, three species,

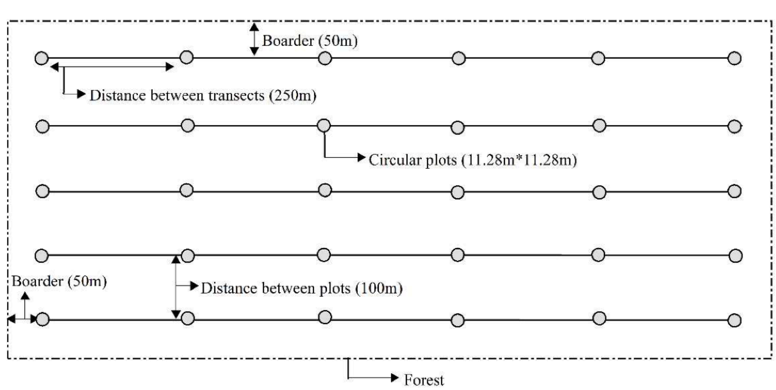

Fig. 2. Experimental design (The vertical distance between transects covers 250 meters from lower to higher, and the horizontal separation between plots is 100 meters on either side).

Table 3
Overlaying maps and classification of potential area changes.

Situation	Potential area			
	Future	Current	Result after subtracting	Future suitability class
High impact areas	0	1	-1	Unsuitable
Outside of realized niche	0	0	0	
Low impact areas	1	1	0	Suitable
New suitable areas	1	0	1	

namely *Acacia abyssinica, Carissa edulis*, and *Juniperus procera*, were chosen for this study due to their high importance values, with 600, 872, and 1,449 occurrences, respectively. The occurrence of the species were recorded using Geographic Positioning System (GPS). Those species had a high Importance Value Index (IVI) in the forest, with IVI values of 26.41, 28.78, and 76.85 for the three species, respectively.

2.3. Data analysis

2.3.1. Model selection

The Maxent model was chosen for the analysis due to its robustness in correlating environmental variables with species presence records, as described by Elith et al. (2011). This model is particularly effective when dealing with presence-only records (Elith et al., 2006; Phillips and Dudık, 2008). It is a machine-learning approach that utilizes presence data and environmental variables to generate estimated species distributions (Phillips et al., 2004). It has demonstrated excellent predictive performance compared to other structured decision-making models (Pearson and Dawson, 2003; Elith et al., 2006).

Maxent proves resilient to predictor collinearity during model training, and the exclusion of highly correlated predictor variables has minimal impact on model performance (Feng et al., 2019). It possesses the ability to manage model complexity by reducing the emphasis on redundant variables; the algorithm effectively handles collinearity issues (Elith et al., 2011; Phillips and Dudík, 2008; Shcheglovitova and Anderson, 2013). Maxent achieves a balance between model fit and complexity through regularization (Elith et al., 2011), which means that the level of collinearity among predictors is not expected to have a substantial impact on Maxent.

2.3.2. Model calibration and validation

Model validation in this study involved dividing the occurrence points into two sections: 80% of the observed species data (training data) was used to calibrate the model, while the remaining 20 % (test data) served for model validation. Model prediction performance was evaluated using the area under the Receiver Operating Characteristic (ROC) curve of Area Under the Curve (AUC), True Skill Statistic (TSS), and Kappa statistic (Duan et al., 2014).

The AUC metric is a widely used for assessing model accuracy and selection criteria (Braunisch et al., 2013; VanDerWal et al., 2009). The model accuracy was assessed using a threshold value for the AUC, which ranges from 0.5 to 1.0, serving as an indicator of level of model accuracy (Mbatudde et al., 2012). According to Thuiller et al. (2008), AUC thresholds are categorized as follows: AUC $\geq$ 0.9 (very good), 0.8 $<$ AUC $<$ 0.9 (good), 0.7 $<$ AUC $<$ 0.8 (satisfactory), 0.6 $<$ AUC $<$ 0.7 (unsatisfactory), and 0.5 $<$ AUC $<$ 0.6 (invalid). These thresholds assist in determining the accuracy and reliability of the model predictions.

The True Skill Statistic (TSS) is another measure gaining acceptance for model evaluation (Konowalik and Nosol, 2021). Models generating presence-absence predictions are typically assessed by comparing predictions with a set of validation sites and constructing a confusion matrix, recording true positive (a), false positive (b), false negative (c), and true negative (d) cases predicted by the model (Table 2). The TSS accounts for both omission and commission errors, as well as success resulting from random guessing, and ranges from -1 to +1, where +1 indicates perfect agreement, and values of zero or less indicate performance no better than random (Allouche et al., 2006).

The Kappa statistic, another widely used measure, evaluates the performance of models generating presence-absence predictions. The Kappa statistic for agreement is derived from the optimal threshold that maximizes the information in the mixed matrix to gauge model performance (Eq. 6). Evaluation criteria for the Kappa statistic are as follows: excellent (0.85–1.0), very good (0.7–0.85), good (0.55–0.7), fair (0.4–0.55), and fail (<0.4) (Duan et al., 2014). Generally, AUC, kappa, and TSS, based on sensitivity and specificity calculated from presence and absence records, are commonly used metrics for model performance (Allouche et al., 2006; Shabani et al., 2018). Therefore, this study also employed these three crucial parameters to evaluate model performance. AUC was calculated by MaxEnt as the default measure, whereas Kappa and TSS were manually computed using Eqs, 1–6.

$$n = a + b + c + d \tag{1}$$

$$Overall\ accuracy = \frac{a + d}{n} \tag{2}$$

$$Sensitivity = \frac{a}{a + c} \tag{3}$$

$$Specificity = \frac{d}{b + d} \tag{4}$$

$$TSS = sensitivity\ +\ specificity\ -- 1 \tag{5}$$

$$Kappa\ statistic = \frac{\left(\frac{a+d}{n}\right) - \frac{(a+b)(a+c)+(c+d)(d+b)}{n^2}}{1 - \frac{(a+b)(a+c)+(c+d)(d+b)}{n^2}} \tag{6}$$

2.3.3. Environmental variables contribution

All variables were run 20 times in the Maxent model to evaluate the individual contribution of environmental variables to species distribution. This analysis aimed to estimate the importance of each variable in explaining the species distribution. The percent contribution table provides understandings into the relative importance of each variable in explaining the species distribution. It quantifies the unique information that each variable contributes to the model. This analysis allows for the identification of key environmental variables that influence the ecological distribution of the species.

2.3.4. Species suitability

The Maxent technique generates continuous raster outputs representing habitat suitability, with values ranging between 0 and 1. To classify the maps, the 10th percentile value was applied to obtain and predict presence and absence projected maps. In this study, the maps produced by the model were classified based on a current suitable area using Diva GIS 7.5 and ArcGIS 10.1. ArcGIS 10.1 were used to classify the image and to extract suitability thresholds in point. Diva GIS were used for classification aimed to identify areas with high impact, areas outside the realized niche, low-impact areas, and new suitable areas. The classified maps based on suitability thresholds resulted in four distinct categories, each providing valuable insights into the potential impact of climate change on species distribution. The high-impact zone (Loss) represents areas that are currently suitable for species presence but are projected to become unsuitable in the future, indicating potential loss of habitat suitability. The zone outside the realized niche (Neutral) comprises areas that are currently unsuitable and will remain unsuitable for species presence in the future.

On the other hand, the low-impact zone (Neutral) includes areas that are currently suitable and will continue to be suitable for species presence in the future. This suggests that these areas may serve as stable

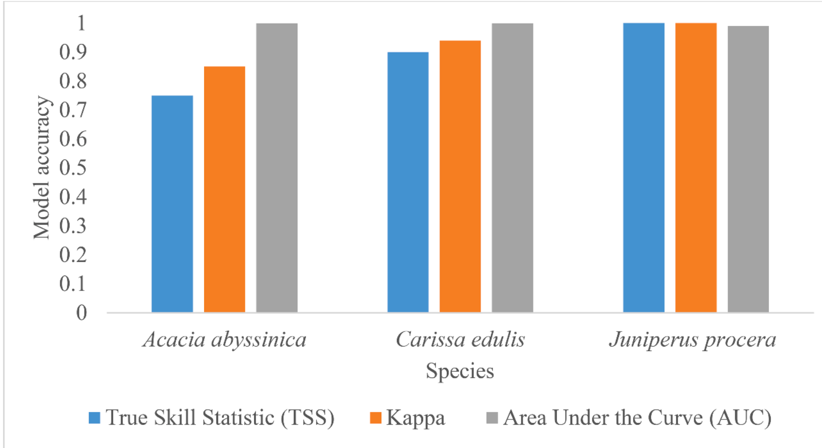

Fig. 3. Model accuracy assessment (All values for TSS (True Skill Statistic), Kappa, and AUC (Area Under the Curve) exceed 0.7).

habitats that can support the persistence of species despite changing climatic conditions. Lastly, the new suitable zone (Gain) identifies areas that are currently unsuitable but are predicted to become suitable for species presence in the future. The four classifications were computed from each binary raster, which has two values: presence (1) and absence (0) (Table 3). By considering these zones, we gain a comprehensive understanding of the potential consequences of climate change on species distributions and develop targeted strategies for domestication and management efforts.

2.3.5. *Carbon stock estimation and modeling*

Allometric equations were employed to estimate carbon stocks without the need for tree cutting, particularly in areas where protected tree species are present, as observed in the study area. These equations utilize measurements such as tree diameter at breast height (DBH), density, or a combination of DBH, height, and density to establish allometric relationships for estimating tree carbon stock. Therefore, an existing allometric equation was utilized to estimate carbon stocks, aiming to prevent deforestation and obey with regulations set by the relevant authorities, which prohibit tree cutting. Once the Above-Ground Biomass (AGB) was obtained, BGB, encompassing all live root biomass, was estimated at 20–26 % of the AGB (Handavu et al., 2021). In this study, a value of 25 % of the AGB was used to estimate the BGB. Total Biomass (TB) is the summation of AGB and BGB. For TCS estimation, 50 % of the TB was taken into consideration (Brown, 1986). Other studies have also found that the carbon stock of tropical dry forests makes up approximately 50 % of the biomass (Solomon et al., 2017; Ekoungoulou et al., 2014).

The TCS potential of *Carissa edulis* was computed using a tailored allometric equation by Chave et al. (2014) for tropical dryland environments (Eq. 7). For *Juniperus procera* and *Acacia abyssinica*, specific models developed in Ethiopia were used, attributed to Gereslassie et al., 2019 (eqn 8), and Solomon et al., 2017 (Eq. 9), respectively.

$$AGB = 0.0673 * \left(WD * DBH^2 * H\right)^{0.976} \tag{7}$$

$$\mathrm{AGB} = 0.348 DBH^{0.57}\mathrm{H}^{0.032} \tag{8}$$

$$AGB = 0.55 * DBH^{1.89} + 0.74 * H^{2.15} \tag{9}$$

- Where: AGB = above ground biomass (in kg dry matter)
- WD = wood density (0.6 g/cm^3), which is average of wood density for all species.
- DBH = diameter at breast height (in cm)
- H = total height of the tree (in m)

In order to analyze the future impact of climate change, the TCS of trees was used as the current amount by assuming that both current and future suitable areas may produce the same size of carbon, which is Business As Usual (BAU) scenarios. This scenario was based on the principle that the future suitable area for these species would support a similar number TCS as their current suitable area. The TCS was multiplied by the projected suitable area to project the future TCS. This approach mirrors how the current TCS is derived by multiplying the current TCS by the current suitable area in square kilometers. Similar studies have been undertaken by Goswami et al. (2014), Wang et al. (2022) and Pechanec et al.(2018).

2.3.6. *Statistical analysis*

To compare the potential distribution in both current and future raster maps, which were obtained from MaxEnt output, points were extracted using ArcGIS. These extracted points were then converted to Excel format to ensure compatibility for statistical analysis using SPSS version 20 software. The transition from the current state to the future was analyzed in time slices based on the SSP2-4.5 and SSP5-8.5 scenarios, using the nonparametric statistical method. Furthermore, the magnitude of suitability was also compared using the same statistical approach.

3. Result and discussion

3.1. *Model accuracy*

The model result showed excellent performance in accurately describing the distribution of *Acacia abyssinica, Carissa edulis*, and *Juniperus procera*, with mean training and test AUC values of 0.99. All runs for the three species produced AUC values exceeding 0.9, indicating high accuracy. In addition, TSS values for all three species exceeded 0.75, and the Kappa values were each greater than 0.85 (Fig. 3). Therefore, the model performance was excellent, and the results of the model are acceptable.

3.2. *Suitability thresholds*

The suitability thresholds for each specie were determined. The *Juniperus procera* had a threshold of "suitable 0.37 < P < 1 and unsuitable 0 < P < 0.37," *Carissa edulis* had a threshold of "suitable 0.46 < P < 1 and unsuitable 0 < P < 0.46," and *Acacia abyssinica* had a threshold of "suitable 0.42 < P < 1 and unsuitable 0 < P < 0.42." All of these suitability thresholds were found to be statistically significant for species distribution classification at $p < 0.05$, based on the 10th percentile training presence. The suitability percentage and the impact of the area

Table 4
Magnitude of distribution thresholds in different time slices and SSP.

Period	*Acacia abyssinica*		*Carissa edulis*		*Juniperus procera*	
	Maximum	Mean	Maximum	Mean	Maximum	Mean
Current	0.76	0.35	0.80	0.45	0.78	0.43
2021-2040SSP2-4.5	0.98	0.70	0.98	0.85	0.98	0.83
2021-2040SSP5-8.5	0.95	0.52	0.98	0.71	0.98	0.69
2041-2060SSP2-4.5	0.98	0.93	0.98	0.97	0.98	0.97
2041-2060SSP5-8.5	0.97	0.62	0.98	0.80	0.98	0.79
2061-2080SSP2-4.5	0.97	0.69	0.98	0.80	0.98	0.80
2061-2080SSP5-8.5	0.98	0.64	0.98	0.79	0.98	0.79
2081-2100SSP2-4.5	0.98	0.80	0.98	0.91	0.98	0.91
2081-2100SSP5-8.5	0.98	0.67	0.98	0.72	0.98	0.75

on habitat suitability were assessed based on the total area of the study area, which is 369 km^2.

Furthermore, a significant difference ($p < 0.05$) was observed between the suitability values of current and future time slices under the two SSPs (Table 4). The mean suitability value of SSP2-4.5 showed a higher magnitude compared to the current value. The average suitability value of SSP5-8.5 indicates a notably higher magnitude for the future, exceeding the current suitability thresholds.

3.3. Contribution of variables

Temperature seasonality, altitude and precipitation of warmest quarter are top three predictors, each making good contributions on the species distribution. The soil texture have contribution on the species distribution (Fig. 4). These findings highlight the contribution of topography, soil and climate variables in shaping the distribution patterns of the studied species.

For *Acacia abyssinica*, the environmental variable with the highest gain when used in isolation is bio18, indicating that it contains the most useful information on its own. On the other hand, altitude has the most significant impact on reducing the gain when omitted, suggesting it provides unique information not present in the other variables. Similarly, for *Carissa edulis*, the environmental variable with the highest gain in isolation is also bio18, indicating that it contains the most useful information on its own. In addition, bio16 shows the greatest reduction in gain, indicating that it contributes distinct information not found in the other variables. In the case of *Juniperus procera* distribution, the

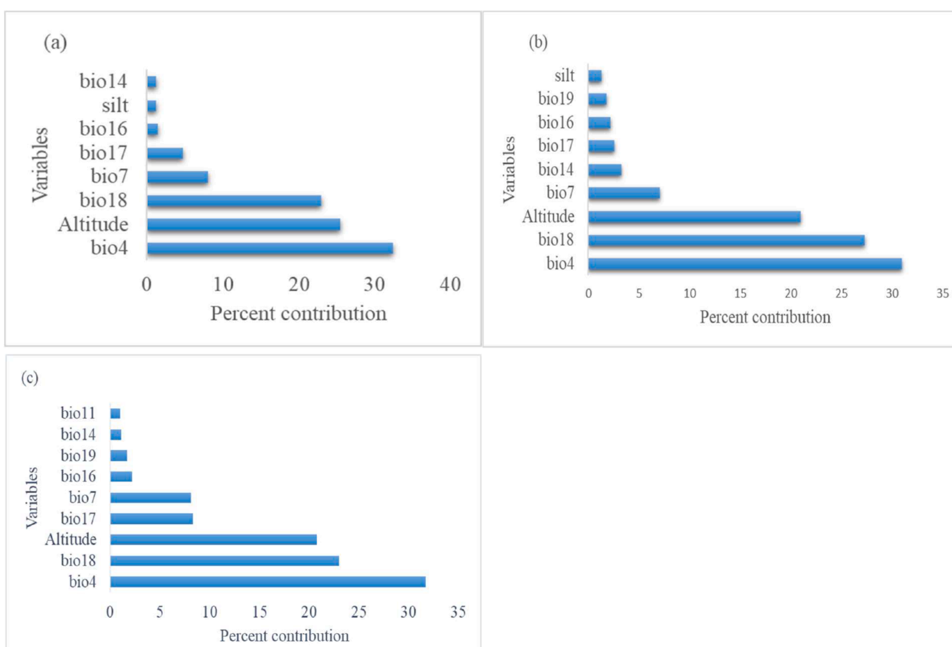

Fig. 4. Contribution of environmental variables on (a) *Acacia abyssinica*, (b) *Carissa edulis*, and (c) *Juniperus procera* distribution (Bio4 makes the most significant contribution).

Table 5
Distribution of the species in SSP2-4.5 (in % and in km^2) relative to the total area of the study, which is 369 km^2.

Period	Potential distribution %(km^2)			New suitable area %(km^2)		
	Acacia abyssinica	*Carissa edulis*	*Juniperus procera*	*Acacia abyssinica*	*Carissa edulis*	*Juniperus procera*
Current	42.9(158)	54.2(200)	63.8(235)			
2021-2040	78.8(291)	94.1(347)	94.9(350)	46(170)	44.9(166)	46.3(171)
2041-2060	99.2(366)	100(369)	99.7(368)	68.9(254)	52(192)	55.6(205)
2061-2080	79.7(294)	89.5(330)	91.8(339)	46.3(171)	41(151)	42.4(156)
2081-2100	77.1(284)	97.7(361)	98.6(364)	54(199)	49.4(182)	52.3(193)

Table 6
Distribution of the species in SSP5-8.5 (in % and in km2) relative to the total area of the study, which is 369 km^2.

Period	Potential distribution (%)			New suitable area (%)		
	Acacia abyssinica	*Carissa edulis*	*Juniperus procera*	*Acacia abyssinica*	*Carissa edulis*	*Juniperus procera*
Current	42.9(158)	54.2(200)	63.8(235)			
2021-2040	63.8(235)	77.1(284)	78(288)	29.7(110)	28(103)	29.4(108)
2041-2060	72.9(269)	87.9(324)	88.1(325)	39.3(145)	37.9(140)	39(144)
2061-2080	70.9(262)	86.4(319)	88.1(325)	40.1(148)	36.2(134)	37.9(140)
2081-2100	64.4(238)	77.1(284)	81.4(300)	40.7(150)	27.4(101)	33.3(123)

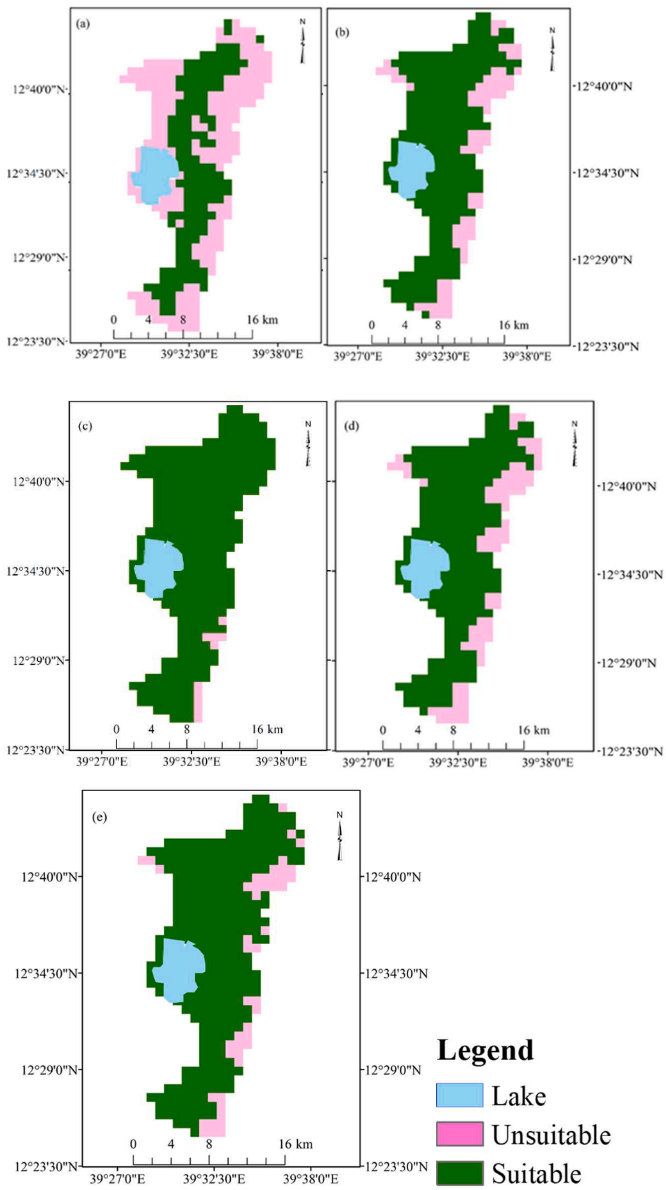

Fig. 5. *Acacia abyssinica* distribution (a) Current (b) 2021-2040 SSP2-4.5 (c) 2041-2060 SSP2-4.5 (d) 2061-2080 SSP2-4.5 and (e) 2081-2100 SSP2-4.5.

environmental variable with the highest isolated gain remains bio18, signifying its standalone significance. Furthermore, altitude stands out as the variable that leads to the most substantial reduction in gain upon omission, indicating that it carries unique information absent from the other variables. Hence, similar with other studies, it is important to note that in addition to climate, elevation has an influence on species distribution as well (Sekercioglu and Schneider, 2008) and soil also plays a role in species distribution (Schietti et al., 2014).

3.4. Species distribution

All three species, *Juniperus procera, Acacia abyssinica*, and *Carissa edulis*, were found at different altitudes, identified in both midland and highland areas of the study. In the case of *Juniperus procera*, it would reach up to 3660 m.a.s.l, the maximum altitude of the study area under current and future both SSPs. The observed geographical expansion is a response to the adaptation to a more suitable climate at higher altitudes. This is notable, particularly considering that these species are primarily found in mid-elevation, and the presence of a larger area of high elevation contributes to their distribution in these regions.

Due to climate change impacts, different species are showing shifts in their altitudinal distributions and elevation ranges (Wilson et al., 2005). Research suggests that most non-native plant species in mountains are initially introduced at low elevations and then spread upwards to fill their climatic niche (Alexander et al., 2011). This leads to the prediction that, over time and under stable climatic conditions, upward range shifts will be most pronounced for non-native species initially found at low elevations. Global warming could contribute to accelerating upward shifts, even at high elevations (Wolf et al., 2016). The study area, being mountainous with different climate conditions (Abrha et al., 2023), is suitable for lowland and midland species. These species are predominantly found at mid-elevations rather than high elevations. In response to rising temperatures, species may shift their ranges towards higher elevations in search of suitable climatic conditions to which they are adapted (Couet et al., 2022).

Habitat availability disproportionately amplifies climate change risks for lowland species compared to mountainous ones (Hülber et al., 2020). While some studies have found instances of species migrating up in elevation to stay within their suitable climate, the situation is complex and varies depending on the species, model resolution, and climate forcing (Maxwell et al., 2020). The current study species are primarily located in the midland, and the highland represents a significant opportunity for their future suitable area.

The current distribution of *Acacia abyssinica* accounts for 42.9 % of an area of 369 km^2 and is projected to expand to a range of 77.1–99.2 % from the 369 km^2 in SSP2-4.5 for the period 2021–2100, with a potential new suitable area ranging from 46 % to 68.9 %. *Carissa edulis* presently covers 54.2 % of its potential distribution from the 369 km^2, with a projected expansion to 89.5–100 % in SSP2-4.5 from 2021–2100, and the possibility of a new suitable area ranging from 41 % to 52 %. *Juniperus procera*'s current distribution is at 63.8 %, and there is potential for expansion to 91.8–99.7 % in SSP2-4.5 from 2021-2100. The future projection indicates a new suitable area ranging from 42.4 % to 55.6 % from the 369 km^2 in SSP2-4.5 for the period of 2021–2100 (Table 5).

The distribution range of *Acacia abyssinica* in SSP5-8.5 for the period 2021–2100 might extend from 63.8 % to 72.9 % from the total area of 369 km^2. Furthermore, there is the possibility of a new suitable area covering 29.7 % to 40.7 % from the total area of 369 km^2. In the case of *Carissa edulis*, its potential distribution in SSP5-8.5 from 2021–2100 may expand to a range of 77.1 % to 87.9 %, with the potential for new suitable areas ranging from 27.4 % to 37.9 %. Similarly, for *Juniperus procera*, its distribution could potentially expand to a range of 78 % to 88.1 %. Its new suitable area might occur, potentially ranging from 29.4 % to 39 % from the total area of 369 km^2 in SSP5-8.5 for the period

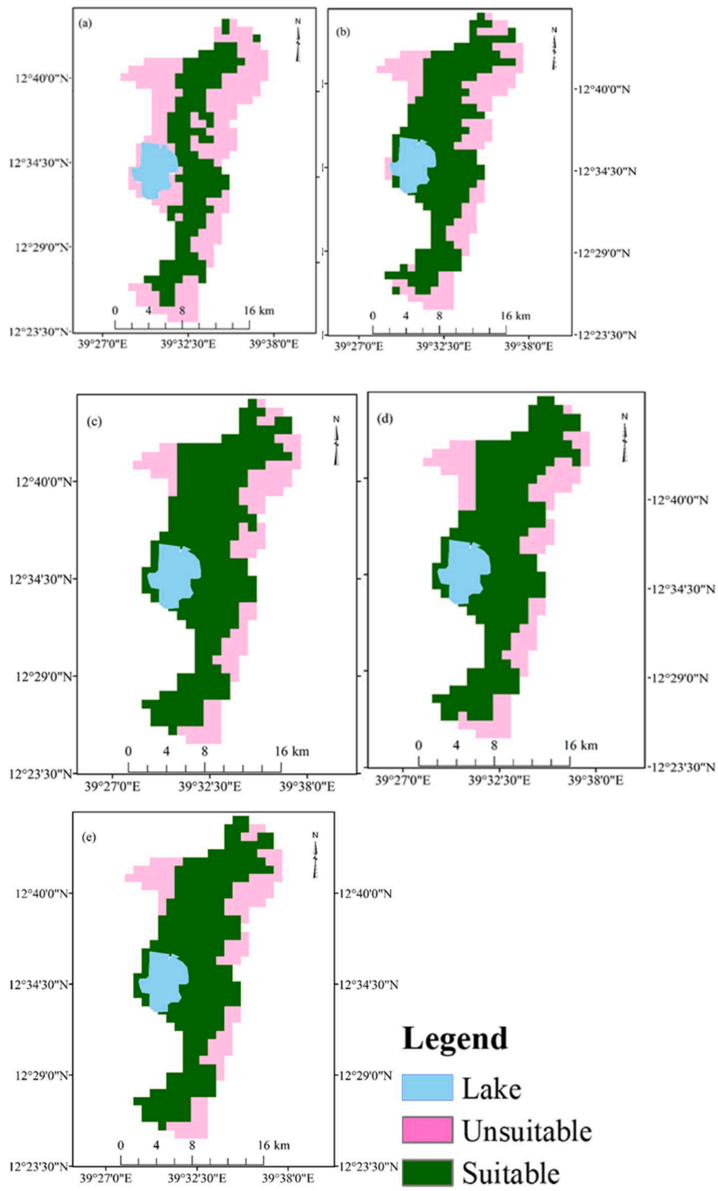

Fig. 6. *Acacia abyssinica* distribution (a) Current (b) 2021-2040 SSP5-8.5 (c) 2041-2060 SSP5-8.5 (d) 2061-2080 SSP5-8.5 and (e) 2081-2100 SSP5-8.5.

2021-2100 (Table 6).

The model prediction maps shown that considerable changes in the projected distribution of *Juniperus procera, Acacia abyssinica*, and *Carissa edulis* in the future, as compared to their current distribution. Our findings emphasize a significance increase ($p < 0.05$) in the distribution of these species under future climatic conditions, especially in the scenario of SSP2-4.5 when compared with the current (Figs. 5–10 and Table 5).

The "high impact" and "low impact" areas shown minimal change, while the "new suitable area" and "area outside of realized niche" have more changes when compared with current situation. Among the three species, *Juniperus procera* demonstrates a more suitable area in the current, SSP2-4.5, and SSP5-8.5 scenarios, maintaining elevation stability at 3660 m.a.s.l. In comparison, *Carissa edulis* showcases a more suitable range than *Acacia abyssinica* across the current, SSP2-4.5, and SSP5-8.5 conditions, projecting an elevation range from 2928 m.a.s.l (current) to 3568 m.a.s.l (future). Meanwhile, *Acacia abyssinica* distribution elevation rises from 2959 m.a.s.l in the current to 3576 m.a.s.l in the future and might contain more new suitable areas compared to the other species. This shows the altitudinal expansion of the species in order to adapt the impact of climate change.

In line with our study, climate is pushing species to their ecological limits, resulting in significant shifts in their geographical ranges. Under the influence of climate change, species are adapting by shifting and resizing their ranges, primarily migrating towards higher elevations to locate suitable habitats (Scheffers et al., 2016). Additionally, highland areas have the potential to play a crucial role in protecting biodiversity in the face of climate change. This is because they act as thermal buffers, mitigating the effects of warming and creating cooler microclimates (Hoffmann and Beierkuhnlein, 2019). This suggests that, due to climate change, lowland and midland species may be capable of shifting their geographic ranges to higher elevations, enabling them to find more suitable habitats. Conversely, species in highland areas are currently more vulnerable to the effects of climate change. Additionally, species from lower elevations are on the rise in mountain areas, resulting in more homogeneous vegetation and increasing risks for mountain-top species (Adler et al., 2022).

Different evidences supports the consistent trend of numerous species altering their distribution ranges to higher elevations, a phenomenon observed in studies by Ramalho et al. in 2020 and Charney et al.

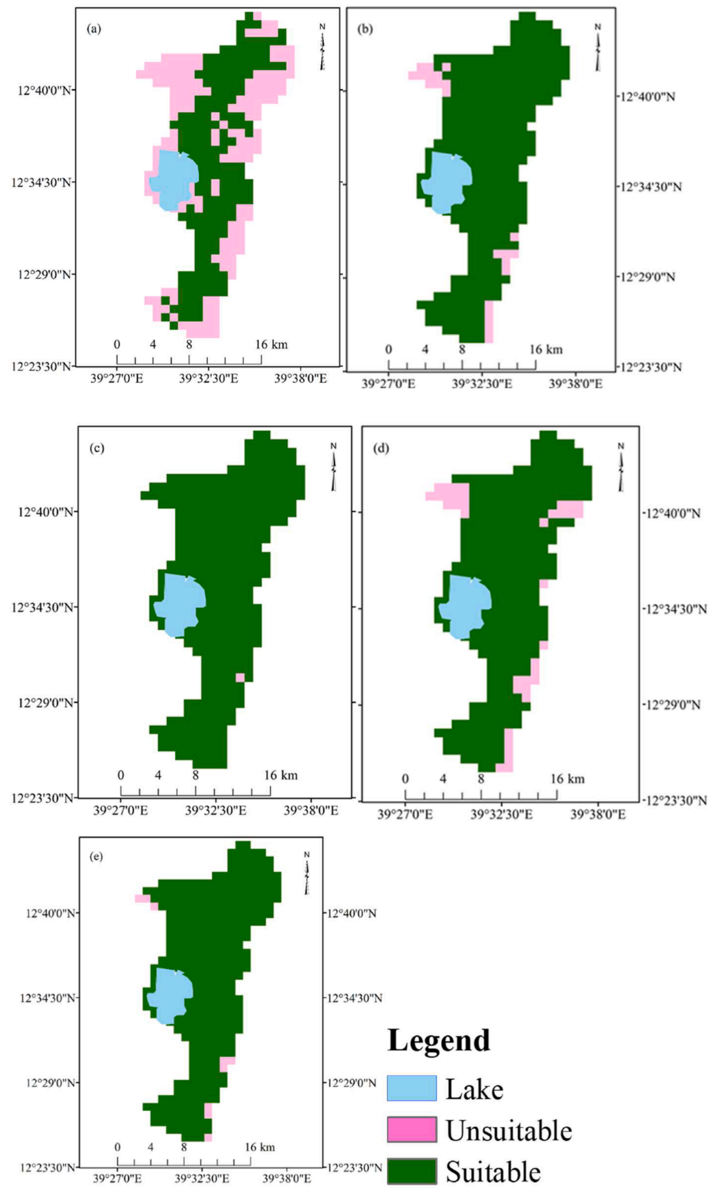

Fig. 7. *Carissa edulis* distribution (a) Current (b) 2021-2040 SSP2-4.5 (c) 2041-2060 SSP2-4.5 (d) 2061-2080 SSP2-4.5 and (e) 2081-2100 SSP2-4.5.

(2021). This trend indicates a broad response to climate change, with species gravitating towards higher habitats. The phenomenon of elevation shifts has been acknowledged as a direct response to climate warming, as noted by Chen et al. in 2021 and Mamantov et al. (2021). This implies that higher elevations could increasingly become favorable zones for species distribution in the future. Within our study area, both midland and highland areas show diverse climate trends projected for the future (Abrha et al., 2023). Consequently, these fortunate species possess potential habitats in both midland and highland zones, suggesting a promising future. The area may remain suitable for species survival until 2100; however, comprehensive investigation beyond that timeframe is warranted to establish the area's long-term suitability.

3.5. Carbon stock estimation and modeling

The average total carbon stock per single tree was estimated to be 25.66 kg for *Acacia abyssinica*, 4.53 kg for *Carissa edulis*, and 94.59 kg for *Juniperus procera*. Based on these values, the total carbon stock potential per hectare was calculated to be 1.69 tons for *Acacia abyssinica*, 0.46 tons for *Carissa edulis*, and 13.81 tons for *Juniperus procera*, or equivalently 169 tons, 46 tons, and 1381 tons per square kilometer.

Considering the results obtained from Maxent simulations of potential suitable areas, the carbon stock trends for each species, considering different time periods and climate scenarios (SSP2-4.5 and SSP5-8.5), reveal a similar pattern of increase. The carbon stock of *Acacia abyssinica* might rises from 25,688 tons to 59,319 tons when comparing the current and future periods, respectively. It is projected to add an additional 41,236 tons of carbon stock in the newly suitable areas in the future. *Carissa edulis* is also predicted to experience an increase from 8,832 tons to 16,284 tons, with an additional carbon stock of 8,464 tons from the newly suitable areas. Similarly, *Juniperus procera's* carbon stock is expected to grow from 312,106 tons to 487,493 tons when comparing the current and future periods. Additionally, a substantial 272,057 tons of carbon stock is projected to accumulate from the newly suitable areas in the future under the SSP2-4.5 scenario (Table 7).

Under the SSP5-8.5 scenario, similar to SSP2-4.5, the carbon stock of *Acacia abyssinica* is projected to increase to 43,602 tons. Moreover, taking into account the areas that will become suitable in the future, it is estimated that a cumulative carbon stock of around 24,336 tons could be accumulated. Comparing the carbon stock of the current suitable area

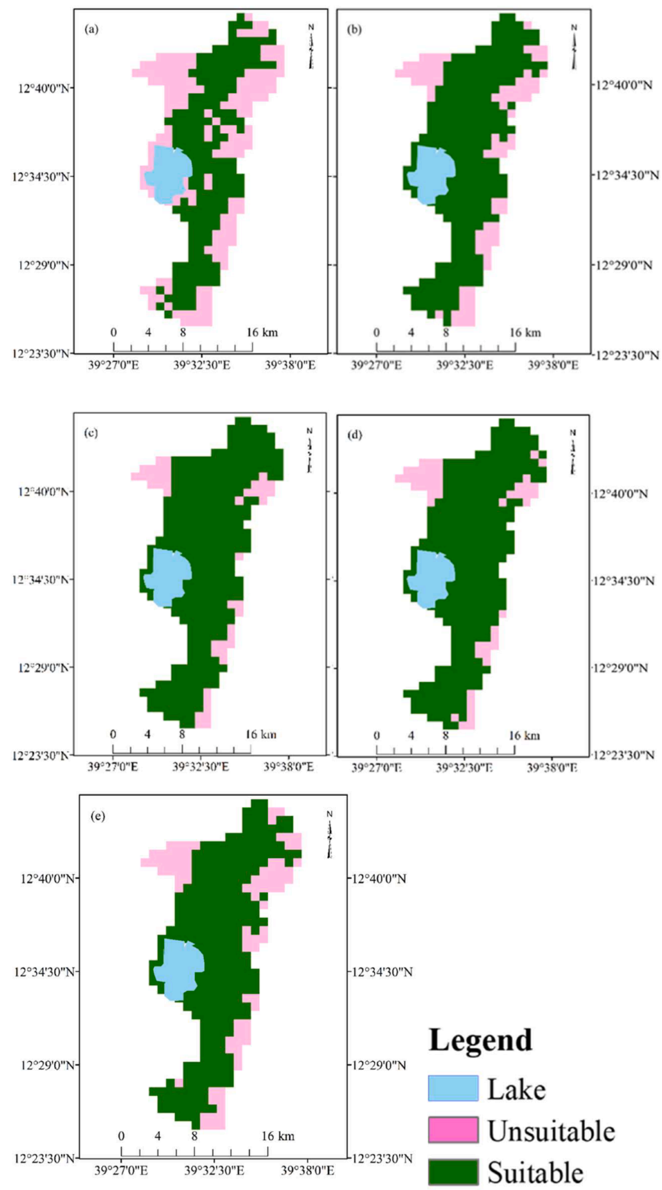

Fig. 8. *Carissa edulis* distribution (a) Current (b) 2021-2040 SSP5-8.5 (c) 2041-2060 SSP5-8.5 (d) 2061-2080 SSP5-8.5 and (e) 2081-2100 SSP5-8.5.

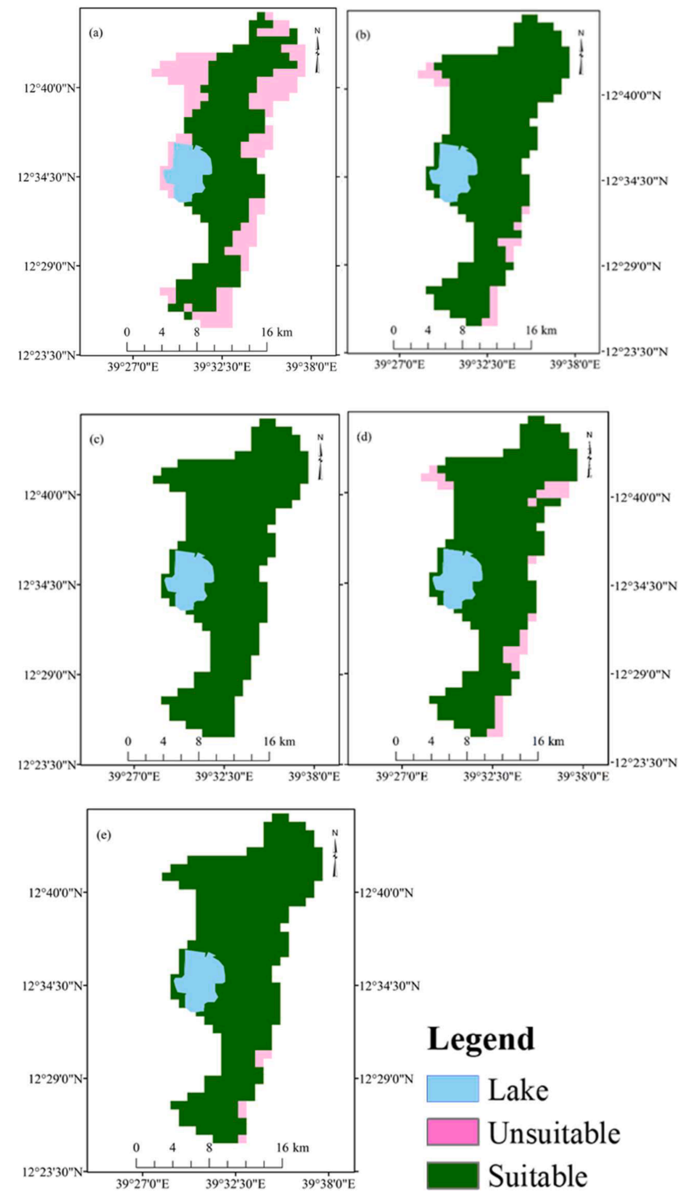

Fig. 9. Juniperus *procera* distribution (a) Current (b) 2021-2040 SSP2-4.5 (c) 2041-2060 SSP2-4.5 (d) 2061-2080 SSP2-4.5 and (e) 2081-2100 SSP2-4.5.

and the future new suitable area, they are nearly identical at 25,688 tons and 24,336 tons respectively. This emphasizes the significant potential of the future suitable area for Acacia abyssinica. Similarly, for *Carissa edulis*, the carbon stock is anticipated to rise to 14,306 tons in the future, with an additional 6,164 tons of carbon stock from the new suitable areas. The carbon stock of *Juniperus procera* is also expected to increase to 430,872 tons in the future, with the new suitable areas contributing an additional 190,578 tons of carbon stock in the future (Table 8).

In comparison, the carbon stock is projected to be higher in the future under both climate scenarios for all three species. This highlights the need for human-assisted plantation of these species within their current and potential suitable areas in order to enhance the ecosystem services of the species. The optimal scenario for suitable area and potential carbon stock is projected to be between 2041 and 2060 under the SSP2-4.5 climate scenario. The overall carbon stock of *Juniperus procera* surpasses that of both *Carissa edulis* and *Acacia abyssinica*. Similarly, the carbon stock associated with *Acacia abyssinica* is greater than that of *Carissa edulis*.

The results align with previous findings where the highest carbon stocks (67.4 %) were observed in *Juniperus procera*, with a combined AGB and BGB of 35.3 tons per hectare in Kibate Forest near Wonchi Crater Lake, located in the Central Highland of Ethiopia (Meragiaw et al., 2021). This highlights that, on average, *Juniperus procera* stands out for its significant CO_2 sequestration capacity per tree as this study. Similarly, the AGB of *Juniperus procera* was estimated at 26.77 ± 2.6 kg per tree, while that of *Acacia abyssinica* was calculated as 17.68 ± 3.32 kg per tree in Tigray, Ethiopia (Solomon et al., 2017). Moreover, the aboveground carbon stock of *Carissa spinarum* was reported as 0.15 tons per hectare, while *Juniperus procera* showed a higher value of 78.68 tons per hectare in Chilimo-Gaji Forest, Ethiopia (Siraj, 2019). Additionally, estimates indicated that the AGB of *Acacia abyssinica* amounted to 25.4 tons per hectare in a managed exclosure in Tigray, Ethiopia (Giday et al., 2013). These findings illustrate the diverse carbon sequestration capacities of different species, with *Juniperus procera* being a more significant contributor to carbon capture and storage.

Carbon stock modeling serves a crucial role in predicting the impact of climate change on carbon storage within different ecosystems (Pechanec et al., 2018). This predictive capability is essential for

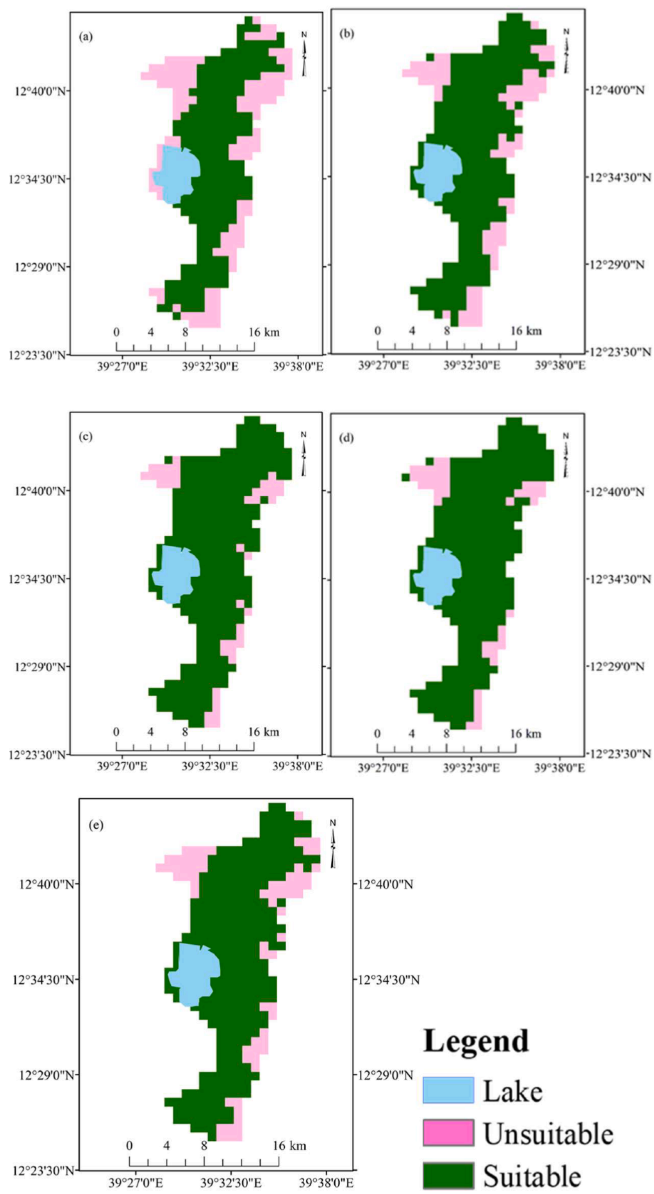

Fig. 10. *Juniperus procera* distribution at (a) Current (b) 2021-2040 SSP5-8.5 (c) 2041-2060 SSP5-8.5 (d) 2061-2080 SSP5-8.5 and (e) 2081-2100 SSP5-8.5.

developing adaptation strategies aimed at mitigating climate change effects. Tree carbon stock modeling is integral to the formulation of climate change mitigation plans. By projecting potential future carbon stocks, these models assist policymakers and land managers in identifying areas with high carbon sequestration potential, guiding the implementation of practices like afforestation and reforestation to enhance carbon storage (Ma et al., 2021). This modeling approach also enables the estimation of carbon stock potential across diverse species. This knowledge aids in understanding tree species with substantial carbon storage capacity that can effectively contribute to climate change mitigation efforts (Kaul et al., 2010).

3.6. Implications of the study

The model's accuracy is evident through its excellent performance, indicated by high AUC, TSS, and Kappa values. This high precision enables reliable predictions of species distribution, underscoring the model's effectiveness in projecting the ecological distribution of the selected tree species. The study underscores the significance of various environmental variables in influencing the distribution patterns of the studied species. Identifying these contributing variables is essential for evaluating their impact on species survival and distribution. Gaining an understanding of the relative importance of these variables provides valuable insights into the ecological requirements of the species and their responses to environmental factors. This study holds significant implications for understanding the potential effects of climate change on tree species distribution and carbon storage. By modeling the distribution and carbon stock of *Acacia abyssinica, Carissa edulis*, and *Juniperus procera* under climate change, the research provides insights into how these species might react to forthcoming climate change. This knowledge is instrumental in shaping conservation and management strategies aimed at mitigating the adverse impacts of climate change on these ecologically crucial species.

The observed shifts in latitudinal, altitudinal distributions, and elevation ranges due to climate impacts emphasize the need for conservation efforts to adapt to these changes. Implementing a conservation strategy is important for ensuring the survival of species across diverse geographic areas. This strategy contains in situ and ex-situ conservation, as well as human-assisted migration techniques. As trees are immobile and unable to migrate on their own, human-assisted plantation becomes a critical strategy for conserving tree species in the face of climate change. Planting trees in their predicted future suitable habitats allows for the proactive adaptation of ecosystems to changing climate conditions. Actively involving local communities in conservation efforts and raising public awareness and education about biodiversity conservation are crucial measures for effective conservation. The implementation of human-assisted migration involves a careful scientific assessment, identifying suitable habitats and considering species adaptability and potential ecological impacts. Collaboration among conservation experts, government agencies, organizations, and local communities is essential. Communities provide valuable knowledge, governments offer permits and regulations, and organizations contribute funding. The timing of migration efforts depends on species and environmental conditions, with ongoing monitoring and adaptive management ensuring success. The migration of species should align with time slices that have a climate suitable for each respective species. Incentives, such as financial support and positive recognition, further motivate stakeholders.

In addition, the model prediction of new suitable areas for these species in the future have significant importance. Identifying these newly suitable zones is essential for planning future species plantations and enhancing ecosystem services. This collaborative, multidisciplinary approach, guided by a long-term conservation strategy, aims to urgently address the critical need for biodiversity conservation under changing climate. Understanding the carbon stock potential of these species is

Table 7
Carbon stock potential under changing climate in SSP2-4.5.

Period	Carbon stock from the suitable areas (ton)			The carbon stock could potentially increase in the new suitable areas (ton)		
	Acacia abyssinica	*Carissa edulis*	*Juniperus procera*	*Acacia abyssinica*	*Carissa edulis*	*Juniperus procera*
Current	25688	8832	312106			
2021–2040	47151	15318	464016	27547	7314	226484
2041–2060	59319	16284	487493	41236	8464	272057
2061–2080	47658	14582	448825	27716	6670	207150
2081–2100	46137	15916	481969	32279	8050	255485

Table 8
Carbon stock potential under changing climate in SSP5-8.5.

Period	Carbon stock from the suitable areas (ton)			The carbon stock could potentially increase in the new suitable areas (ton)		
	Acacia abyssinica	*Carissa edulis*	*Juniperus procera*	*Acacia abyssinica*	*Carissa edulis*	*Juniperus procera*
Current	25688	8832	312106			
2021–2040	38194	12558	381156	17745	4554	143624
2041–2060	43602	14306	430872	23491	6164	190578
2061–2080	42419	14076	430872	23998	5888	185054
2081–2100	38532	12558	397728	24336	4462	162958

vital to assess their capacity for mitigating climate change effects. This knowledge is also important for monitoring changes in carbon sequestration, aligning with initiatives like Clean Development Mechanisms (CDM), Reducing Emissions from Deforestation and Forest Degradation (REDD+), and other organizations promoting plantation and financial incentives. The community stands to potentially benefit from carbon credit programs. In light of these findings, it becomes evident that addressing the potential impacts of climate change on species distribution is of highest importance. Developing effective conservation strategies to mitigate these effects is crucial for conserving these species and maintaining balanced ecosystems.

3.7. Limitations and challenges

The study used developed allometric equations to estimate the amount of carbon that the plants could store. This was done due to the war and complete siege for more than two years in Tigray region, which made it challenging to obtain permission to cut down trees and create new equations, as the offices were closed. As a result, the study used allometric equations that had already been created by other researchers and published in peer-reviewed journals.

4. Conclusion and future works

The results of the model work were accurate for modeling species distribution. A significant difference ($p < 0.05$) might exist in the suitability of the environment for these species current compared to the future, using two different pathways (SSP2-4.5 and SSP5-8.5) that predict future conditions. Interestingly, the average suitability value for SSP2-4.5 was higher than the current value. Remarkably, the average suitability value for SSP5-8.5 pointed to even higher values in the future, greater than that of the current thresholds. Areas with either high impact or low impact did not seem to change significantly. It is important to point out that areas outside the realized niche experienced only minor shifts, while new suitable areas shown more noticeable increments.

Juniperus procera shown a larger distribution in both current and future scenarios compared to the other species, and it is predicted to maintain its elevation in future scenarios. Similarly, *Carissa edulis* appears to possess a more suitable range than *Acacia abyssinica* across present, SSP2-4.5, and SSP5-8.5 scenarios, with the potential to expand to higher altitudes (3568 m.a.s.l.) in the future. In addition, Acacia abyssinica is projected to occupy elevations up to 3576 m.a.s.l. in the future. Furthermore, *Acacia abyssinica* shows a greater area of newly suitable areas compared to the other species.

The study shown that *Juniperus procera* stores more carbon than *Carissa edulis* and *Acacia abyssinica*. Similarly, *Acacia abyssinica* stores more carbon than *Carissa edulis*. These species are predicted to store more carbon in the future, even under changing climate conditions, when compared to their current suitable areas.

Hence, future studies should consider incorporating additional predictor variables such as water access, disturbance, habitat fragmentation and competition and species interactions to better understand the impact of climate change on species distribution. Further investigation into the additional ecosystem services provided by trees is important. All species present in the forest should model using additional species distribution models, such as statistical and process-based models, to determine their future suitable areas. This proactive approach aims to prevent extinction and identify new suitable habitats for the species (Gonçalves et al., 2021; Morera et al., 2021). Furthermore, it is more useful to assess the carbon stocks of all species. In general, this study recommends developing management strategies based on the projected species distributions and carbon storage capacities.

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CRediT authorship contribution statement

Haftu Abrha: Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Soro Dodiomon:** Writing – review & editing, Supervision, Formal analysis. **Victor Ongoma:** Writing – review & editing, Supervision, Formal analysis. **Haftom Hagos:** Formal analysis, Conceptualization. **Emiru Birhane:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Girmay Gebresamuel:** Writing – review & editing, Formal analysis. **Ashenafi Manaye:** Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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