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Distribution of Selected Species of Dry Afromontane Forest in Relation to Climate Change in Ethiopia

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Abstract

DAF encompasses *nearly 50% of the Ethiopian forest resources with high biodiversity values. Dry Afromontane Forest (DAF) is under serious threats from deforestation, harvest of wood products, fire, encroaching agriculture, over grazing and climate changes related factors. This study aimed to investigate the distribution of key selected DAF species in relation to climate change. We used modern MaxEnt species distribution software to assess the current distribution of these two species (Celtis Africana, and Juniperus procera) and to predict their future distribution under different climate change scenario. We gathered species occurrence data from the Ethiopian National Herbarium (ETH) for the selected species, Global Biodiversity Information Facility (GBIF) and Google earth for herbarium collections that lack geographical location data. Moreover, bioclimatic variable data were collected from the website http://www.worldclim.org. We used MaxEnt model to predict current and future distributions of the species and to identify the most important factor(s) that determine the distribution of the species. Our results indicate a future highly suitable habitat of Celtis africana shift from central and south western areas of DAF to small parts of central region. Moreover, a highly suitable habitat of juniperus procera shift can occur from northern, central and mostly around eastern parts of DAF. This shift in distribution is primarily a factor of climate change. This study highlights the urgent need of species based conservation measures to avert the loss of species and avoid its cascading effects on biodiversity and sustainable human development.*

Key words; *Celtis Africana*, *Juniperus procera*, Dry Afromontane Forest, species Distribution, Climate change.

Acronyms

AAU ……Addis Ababa University

DAF ...……Dry Afromontane

ETH ……Ethiopian National Herbarium

FRA ……Forest Resources Assessment

GBIF ……Global Biodiversity Information Facility

SDM ……Species Distribution Model

MaxEnt ……Maximum entropy modeling

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1. Introduction

Ethiopia, with a total area of 1.1 million m2, is a country located in the Horn of Africa, between Latitudes 3 ° and 15 ° Northern in the Northeastern part of the Sub-Saharan Sea. These are the physical structures that contribute to the country's ecological diversity, ranging from 116 meters below sea level in the Dallol depression to 4620 meters above sea level at Ras-Dashen. The country's geological and tectonic conditions are inextricably linked to the evolution of the East African Rift system and Ethiopia's Magma Dome. Physical conditions and altitude changes have resulted in a wide range of climates, soils, and vegetations. Abay or Blue Nile in other countrie, Baro Akobo, Tekeze, Mereb, Denakil, Ghibe-Omo, the Genale Dawa Lakes, Awash, Shebele-Ogaden are all the main waterways in Ethiopia (Sileshi Bekele, 2001).

These various physiographic characteristics have contributed to the formation of various ecosystems, which are distinguished by differences in species diversity, plant types, soil types, and climate. As a result, Ethiopia has a diverse range of fauna and plants (Tewolde Berhan Gebre Egziabher, 1991). According to the National Forest Inventory report, the land has 15.4 percent forest cover (2018). Forest trees and shrubs are Ethiopia's primary energy and domestic wood suppliers. During the previous decade, the country exported wooden goods and furniture, bamboo, khat (Catha Edulis leaves), forest coffee, natural gum and resin, and charcoal. Ethiopia is home to the biodiversity hotspots of eastern Africa and the Horn of Africa, with over 6,000 higher plant species. In Ethiopia, forest trees and shrubs are the primary sources of energy and domestic wood products. (Kelbessa and Demissew 2014).

The highlands contain Afro-Montane vegetation, the majority of which is dry Afromontane forests, and cover more than half of the country's surface area (Tamrat 1993, 1994; Yalden 1983). Ethiopia's dry Afromontane forests have been given a variety of names, including high mountain tropical coniferous forest (Logan 1946), dry mountain evergreen forest (Pichi-Sermolli 1957), Juniperus-Podocarpus forest (von Breitenbach 1961), dry mountain forest (Hamilton, A.C. 1981), up.forest (anonymous 1988), and undifferentiated forest (Friis 1992). Juniperus Podocarpus forests or Podocarpus forests with broad leaf species characterize Afromontane dry forests. They can be found in both the northwestern and south-eastern highlands, especially on the Shewa, Welo, Sidamo, Bale, and Harerge plateaus, at elevations ranging from 1500 to 2700 meters. The average annual temperature ranges from 14 to 20 °C,

while the annual rainfall ranges from 700 to 1100 mm, with July receiving the most precipitation (Friis 1992). Friis (1992) provides information on dry afromontane and other Ethiopian forest types.

1.1 Statement of the problem

The changing climate is affecting species distributions via changes in growth, reproduction, and mortality, with increasing likelihood of more marked changes in the coming decades. Climate changes can act to directly influence species distributions (e.g., drought, floods, wind) as well as indirectly (e.g., temperature and weather related changes in patterns of wildfire, insects, disease outbreaks, deforestation, encroaching agriculture, and overgrazing). Those are all putting a strain on the Dry Afromontane Forests, those factors lead to climate change. Climate change would be expected to shift plant distribution as a species expand in newly favorable areas and decline in increasingly hostile locations. There has been scarcity of research conducted in Ethiopia on the distribution of selected species of Dry Afromontane Forest in relation to climate change using species distribution modeling, which is why this research was required. Two species were selected for this study: *Celtis Africana*, and *Juniperus procera.* These Two species are dominant canopy trees of dry Afromontane forests.

1.2 Research question

- What will be the future distribution of *Juniperus procera* and *Celtis africana* species under climate change?
- What are the most important bioclimatic factors that affect the distribution of selected species of Dry Afromontane forest?

1.3 Objective

1.3.1 General objective

The general objective of this research is to investigate the distribution of some selected species of Dry Afromontane Forest Biome in relation to climate change scenario.

1.3.2 Specific objective

- To investigate current distribution of selected species (*Juniperus procera* and *Celtis africana*).
- To predict future distribution of selected species under climate change.

2. Literature Review

2.1 Impacts of climate change on biodiversity

The relationship between climate change and biodiversity has long been recognized. Although the climate has always changed with ecosystems and species coming and going throughout Earth's history, rapid climate change affects ecosystems' and species' ability to adapt, contributing to biodiversity loss. Shortly after World War II, humanity entered a period of nearly exponential population growth, increasing from around 3 billion to 7.2 billion people today. Biodiversity loss is a factor that closely follows that trend (J.M. 2008).

Climate change, according to another researcher, is a pervasive and growing global threat to biodiversity and ecosystems (Daz *et al*., 2019). Climate change affects individual species and how they interact with other organisms and their habitats, altering the structure and function of ecosystems as well as the goods and services that natural systems provide to society (Daz *et al*., 2019). Understanding the magnitude and direction of ecological responses enables human communities to better anticipate and adapt to these changes. Periodic assessments of current and future climate change impacts on ecosystems are critical for developing and updating natural resource management plans, as well as evaluating adaptation actions (West *et al.*, 2009).

Global average temperatures have risen by 0.7oC over the last century and are expected to rise further. Temperatures are expected to rise by 1.1–6.4oC by the end of the twenty-first century compared to the 1980–1999 baselines, according to the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2013). Global average precipitation has increased by 2% in the last 100 years and is expected to rise further in the future (IPCC 2013). Africa is the world's most vulnerable continent to climate change. Over the twentieth century, the continent warmed by 0.7°C, and warming is expected to continue, with increases ranging from 0.2°C per decade (low scenario) to more than 0.5°C per decade (high scenario) (Hulme et al. 2001; IPCC 2001).

Climate is inextricably linked to biodiversity and biodiversity-based ecosystem services. Climate change posed significant threats to biodiversity in Africa during the twentieth century, and the consequences are expected to worsen as climate change continues, and possibly accelerates. Climate change is expected to have an impact on all levels of biodiversity, from genes to species to biomes. Climate change-induced biodiversity loss has the potential to alter

the structures and functions of African ecological systems. As a result, the provision of biodiversity-based ecosystem services, as well as the well-being of people who rely on them, is changing.

Climate prediction models have predicted continued warming and more frequent extreme weather events across the region in recent years. Weather-related disturbances, such as El Nio, will place a premium on biodiversity and biodiversity-based ecosystem services on which people rely. As biodiversity underlies all goods and services provided by ecosystems that are crucial for human survival and well-being, (Dejene W. Sintayehu, 2018).

African biodiversity is notable, with many endangered and threatened mammals and plants. However, species abundance and diversity are declining, and threats to species diversity are increasing. Climate change is one of the region's most serious biodiversity and environmental threats (Lepetz *et al*. 2009; Guo, Desmet, and Powrie 2017; Sonwa *et al.* 2017; Matata and Adan 2018). Climate change is recognized as one of the most serious threats to biodiversity by the United Nations Framework Convention on Climate Change and the CBD.

According to a study published in Nature (Thomas et al. 2004), climate change could lead to the extinction of more than a million terrestrial species over the next 50 years. The most vulnerable are rare species, fragmented ecosystems, and areas already under stress from pollution and deforestation. In Africa, fire is a major cause of biodiversity loss. As global warming continues, these fires are likely to become more intense and widespread, potentially causing significant ecosystem changes that would have an impact on biodiversity through species loss or changes in species composition (Bellard *et al.* 2012; Foden *et al.* 2013).

Similarly, the broad conclusions of the review outputs revealed that climate change's direct and indirect effects have posed potential major threats to biodiversity in Africa. Direct effects include those caused by rising temperatures and rising CO2 levels as a result of global climate change (Adler, Leiker, and Levine 2009; Andrew *et al*. 2010; Dawson *et al*. 2011). These direct effects have a number of potentially significant indirect effects, such as changes in hydrologic cycles (evaporation and precipitation) and an increase in the magnitude and extent of extreme weather events, as well as frequent fires that destroy the ecosystem. These changes can have a wide range of effects on biodiversity, including shifting habitat ranges and species distribution, changes in abundance, changes in migration patterns, and changes in the frequency and severity of pest and disease outbreaks.

Another important way that climate change affects African biodiversity is by reducing the amount and availability of suitable habitats and by eradicating species that are critical for the species in question (Lovett, Midgely, and Barnard 2005; Hély *et al.* 2006; Doak and Morris 2010; Dawson *et al*. 2011). A species loss in an ecosystem affects not only the species that is lost, but also the interactions with other species and the general ecological functions that are expected from these interactions. Despite widespread recognition that biodiversity is one of the most vulnerable to climate change, Africa is one of the least studied regions in terms of biodiversity dynamics and climate variability (Getahun and Shefine 2015; Sonwa *et al.* 2017; Matata and Adan 2018). Understanding how climate change affects African biodiversity is critical for examining status or trends, responses, and identifying biodiversity that is sensitive to the climate change system, as well as providing valuable insights to avoid or mitigate climate-induced effects.

2.1.1Biodiversity loss

Globally, biodiversity is being lost and is becoming increasingly threatened as a result of a variety of anthropogenic actions (Jetz, Wilcove, and Dobson 2007; Bellard *et al.* 2012; Fardila *et al*. 2017; Barlow et al. 2018). “Biodiversity loss” is defined by the Convention on Biological Diversity (CBD) as “the long-term or permanent qualitative or quantitative reduction in components of biodiversity and their potential to provide goods and services, to be measured at global, regional, and national levels” (CBD COP VII/30). According to fossil records, it takes an average of one million years for a vertebrate species to become extinct (Lawton and May 1995). As a result, no more than one in a million species should become extinct. However, the current observed extinction rate for vertebrate species is 2.6 percent per 10,000 per year (Pimm and Raven 2006; Whiteside and Ward 2011).

The most significant notable drivers of current biodiversity loss are habitat modification, overexploitation, climate change, invasive alien species, and extinction chains, collectively known as the "evil five biodiversity threats" (Brook *et al*. 2008; Guo et al. 2017; Sonwa *et al*. 2017). As stated in the IPCC (2013) report, global warming and precipitation are expected to increase, and changing climate is predicted to be one of the worst drivers of biodiversity loss over the next 50–100 years, exacerbating the effects of previous threats. Only a few studies, however, have directly quantified climate-induced biodiversity extinctions. Even if it is difficult to distinguish climate change impacts from other anthropogenic stressors for a variety of species, predictions may provide insights into the multiple components of climate

change and their relative distribution threats to global biodiversity (IUCN 2014; Trull, Böhm, and Carr 2018). Predictions of climate-induced extinction rates are uncertain, and expert opinions differ on the magnitude of loss due to uncertainty about the number of species on the planet (He and Hubbell 2011; Mora *et al*. 2011).

2.1.2. Response of biodiversity to climate change

The broad conclusion of the literature results shows that many species have shifted their geographic ranges, generally poleward, toward higher elevations in response to rapid changes in temperature and precipitation regimes (Nye *et al.*,2010; Burrows, Schoeman, and Buckley *et al*., 2011; Chen *et al*., 2011; Doney, Ruckelshaus, and Duffy *et al*,. 2012). Groffman *et al.*, (2014) discovered that plants and animals in terrestrial environments moved toward higher elevations at a rate of 0.011 km per decade and to higher latitudes at a rate of 16.9 km per decade. The geographical distributions of east African species and ecosystems have shifted dramatically as a result of climate change. In order for species to adapt to changing climate, current rates of migration must be much higher than rates during postglacial periods (Malcolm *et al.*, 2002; Hély *et al.*, 2006; Doak and Morris 2010).

Because of their relatively narrow dietary, thermal, and habitat niche breadths, ecological specialists are particularly vulnerable and react strongly to changing resources (Altermatt 2010; Lawton et al. 2010). For example, studies have shown that a reduction in the range of the rare and critically endangered Ethiopian wolf (*C. simensis)* as a result of climate change is likely to increase the risk of local extinction. Gottelli and Sillero-Zubiri (1992) discovered *C. simensis* at 2500 m above sea level in Gojjam and northwestern Showa in the early twentieth century. Today, the species' distribution is shifting toward higher elevations, with the species known to occur above 3000 m above sea level, which extends up to 3700 m above sea level and is largely restricted to the highest peaks (Gottelli and Sillero-Zubiri 1992).

2.1.3. Demographic responses

The loss of natural habitats and the shifting of habitat ranges to more suitable ones as a result of climate change could have a significant impact on the size of species populations (Erasmus *et al.*, 2002; Walther 2010). In response to rapid changes in temperature and precipitation regimes, of some specie’s has already shifted there geographical range toward higher elevations. These shifts are likely to result in new species assemblages (Williams and Jackson 2007), novel interspecific interactions, and, in the worst-case scenario, some extinction

(Channel and Lomolino 2000; Butchart, Walpole, and Collen *et al.*, 2010; Barnosky *et al.*, 2011). As a result, the shift in some species distribution is a likely indicator of a rapid decline in its population size. Furthermore, if climate change restricts a species' range to just a few key sites and an extreme weather event occurs, the species' population decline and extinction may be accelerated in the future.

In general, biodiversity is essential to ecosystem structure and function, and it underpins the wide range of goods and services derived from natural ecosystems (Chapin *et al.*, 2000; Walther et al. 2002; Millennium Ecosystem Assessment (MA) 2005; Naeem *et al.*, 2009; Leadley *et al.*, 2010, Mace, Gittleman, and Purvis 2003). As a result of ecosystem service, at least 40% of the world's economy, and 80% of the economy of less-developed countries, is derived directly from biological resources (Travis 2003). The decline or loss of any aspect of biodiversity to the point where it no longer contributes to ecosystem servicing can have dramatic consequences for the importance of ecosystem services on which people rely.

2.2 Types of vegetation in Ethiopia

Previously, Ethiopian vegetation was classified into nine vegetation types, including Eritrean coastal vegetation (Zerihun Woldu, 1999; Sebsebe Demissew and Friis, 2009). Ethiopia's vegetation potential has recently been systematically revised to include 12 vegetation types and 12 subtypes (Friis *et al.*, 2010).

The classification was mainly based on altitude and climatic variables. The types of vegetation are (1) Desert and semi-desert scrubland (DSS), (2) Acacia-Comiphora woodland and bushland (ACB), (3) Wooded grassland of the western Gambela region (WGG), (4) Combretum-Terminalia woodland and wooded grassland (CTW), (5) Dry evergreen Afromontane forest and grassland complex (DAF), (6) Moist evergreen Afromontane forest (MAF), (7) Transitional rainforest (TRF), (8) Ericaceous belt (EB), (9) Afroalpine belt (AA), (10) Riverine vegetation (RV), (11) Fresh water lakes, lakeshores, marshes, swamps and flood plains vegetation (FLV), and (12) Salt-water lakes, lakeshores, salt marshes and pan vegetation (SLV). Five of the vegetation types, namely ACB, DAF, MAF, FLV and SLV have at least two subtypes while the other seven vegetation types have no subtypes.

Friis et al. provide descriptions of each vegetation type and subtype (2010). The forest plots in the study area were classified as DAF by (Friis *et al.*,2010). However, there is speculation

that the MAF could extend to northwest Ethiopia, particularly west of Gojam, which includes the study area's forests (Friis, 1992).

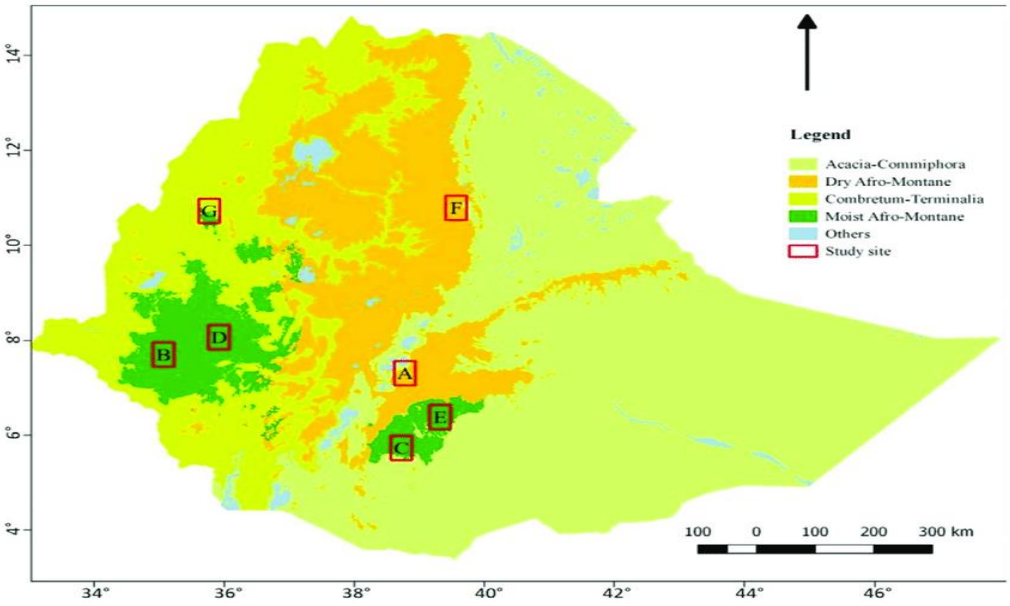


Figure 1: Biomes of Ethiopia (taken from EFCCC)

Table 1 Vegetation types of Ethiopia

Adopted vegetation classes	Vegetation types as classified in the Friis, *et. al*., 2010
Acacia-Commiphora vegetation	*Acacia-Commiphora* woodland and bushland (ACB); Acacia wooded grassland (ACB/RV); Desert and semi-desert scrubland (DSS)
Combretum-Terminalia vegetation	*Combretum-Terminalia* woodland and wooded grassland (CTW); Wooded grassland of the Western Gambela region (WGG)
Dry Afromontane Forest (DAF)	Dry evergreen Afromontane Forest and Grassland complex (DAF) Afro-Alpine vegetation (AA); and Ericaceous Belt (EB);
Moist Afromontane	Moist Evergreen Afromontane Forest (MAF);

Forest (MAF)	Transitional Rain Forest (TRF)
Others	Salt Pans, Saline/brackish and Intermittent wetlands and Salt-lake Shore Vegetation (SLV/SSS); Salt Lake open water vegetation (SLV/OW); Freshwater marshes and swamps, Floodplains and Lake Shore vegetation (FLV/MFS); Freshwater lakes - open water vegetation (FLV/OW)

2.3 Dry evergreen Afromontane forest (DAF)

The Afromontane dry forests account for the majority of Ethiopia's existing natural vegetation (Gidey.K 2013). According to the EFCCC, dry Afromontane includes dry evergreen Afro-montane forest and grassland complex (DAF), Afro-alpine vegetation (AA), and Ericaceous belt (EB). The Ethiopian highlands cover more than half of the land area covered by Afromontane vegetation, the majority of which is dry evergreen Afromontane forest (Yalden, 1983; NBSAP, 2005). The DAF is a complex succession system that includes vast grasslands rich in legumes, shrubs, and small and large trees, as well as a closed forest (Zerihun Woldu, 1999; Sebsebe Demissew & Friis, 2009).

The DBH and height structure of the trees vary greatly between the DAF's different forests, depending on the location and state of the disturbance. The DBH of mature trees in undisturbed forests is typically 270 cm, while their height can reach 45 m. (Haile 10 Yineger et al., 2008; Haileab Zegeye *et al.*, 2011; Desalegn Tadele *et al.*, 2013). *Prunus africana, Juniperus procera, Schefflera abyssinica, Albizia schimperiana, Ekebergia capensis, Celtis africana, Hagenia abyssinica, Croton macrostachyus,* and *Cordia africana* have all been reported to reach DBHs of 80-270 cm and heights of 30-46 m in the DAF (Tamrat Bekele 2003). In disturbed forests, with the exception of a few species, upper canopy species are typically removed for a variety of reasons, leaving only small trees in the middle and lower canopy with a DBH of less than 50 cm and a height of less than 21 m in the forest (Tamrat Bekele, 1993; Friis *et al.*, 2010).

DAF is divided into four distinct subtypes, but this classification is based on the characteristic species of each subtype rather than parameters such as altitude or climate (Friis *et al.*, 2010).

The subtypes are (a) undifferentiated Afromontane forest, (b) Ethiopian highland dry single-dominant Afromontane forest. (c) Afromontane woodland, wooded grassland, and grassland, and (d) the eastern escarpment transition between Afromontane vegetation and Acacia-Commiphora bush. Van Breugel et al. (2016) recognized the Transition subtype between Afromontane vegetation and Acacia-Commiphora bush on the eastern escarpment as a distinct vegetation type known as "transitional semi-evergreen bush land" more recently.

Friis et al., (2010) and van Breugel *et al.,* (2010) provide descriptions of the subtypes and characteristic species of each subtype (2016). Zerihun Woldu (1999), on the other hand, classified the DAF into five associations: *Mimusops kummel* forests, *Podocarpus falcatus forests, Juniperus procera* forests, *Juniperus procera-Podocarpus falcatus* forests, *and Acacia abyssinica* forests. The associations are more similar to the Ethiopian highlands' unique dry Afromontane forest and the Afromontane forest, woodland grassland, and grassland subtypes (*Friis et al.,* 2010). Each type of association confines 11 different species, and some examples of species lists are provided in in Hailu Sharew (1982), Sebsebe Demissew (1980), Tamrat Bekele (1993), Alemayehu Wassie *et al.,* (2005) and Alemnew Alelign *et al.,* (2007).

DAF is found in the majority of the country's northern, northeastern, northwestern, central, southern, and southeastern highlands, at elevations ranging from 1800 to 3000 m and with annual precipitation ranging from 400 to 1500 mm (Zerihun Woldu, 1999; Sebsebe Demissew & Friis, 2009; Friis *et al.,* 2010). However, the figures provided for the DAF's altitudinal ranges are inconsistent across various publications (for example, Friis, 1992; Zerihun Woldu, 1999; Sebsebe Demissew & Friis, 2009; Friis *et al.,* 2010). Friis (1992) observed a change in forest composition at about 1500 m and proposed that this represents the transition from lowland forest to Afromontane forest.

Friis et al. (2010), on the other hand, reported that the distribution of DAF was between 1800 and 3000 m, and this range was used as a vegetation mapping unit; however, the altitudinal range of the subtypes extends beyond the general distribution range of DAF. For example, the lower distribution limit of the Undifferentiated Afromontane Forest, Single-dominant Dry Afromontane Forest, and Transition between Afromontane vegetation and Acacia Commiphora bush subtypes is below 1800 m, while the upper distribution limit of the subtype A predominantly dry Afromontane forest is above 3000 m. (up to 3200 m). Friis *et al.,* (2010) have also recognized this inconsistency. Thus, the previously reported distribution

ranges for DAF (1500-3200 m) in Zerihun Woldu (1999) and Sebsebe Demissew & Friis (2009) supplement the distribution ranges for these subtypes, though this depends on the geographic locations of each. Subtype found in Ethiopia's highlands.

A number of studies have been conducted in the DAF type of vegetation. Some of them are in the central highlands of Shewa, such as the forests of Menagesha-Suba and Wof-Washa (Sebsebe Demissew, 1980; Tamrat Bekele, 1993; Demel Teketay & Tamrat Bekele, 1995), the forest of Jemjem (Hailu Sharew, 1982), Shashemene Munessa (Gemedo Dalle & Masresha Fetene, 2004; Gemedo Dalle, 2015), forests of the Church of North Gondar (Alemayehu Wassie et al., 2005), forest of the peninsula de Zege (Alemnew Alelign et al., 2007), Tara Gedam forest (Haileab Zegeye et al., 2011), Zengena forest (Desalegn Tadele et al., 2013), Kuandisha forest (Abiyot Berhanu et al., 2017), North Ethiopian Forest (Zenebe Girmay et al., 2018), Bale Mountains National Park (Haile Yineger et al., 2008), Ethiopian Afromontane Dry Forests (Demeke Teketay, 2005), Awi Zone Forest (Getaneh Gebeyehu et al., 2019) and Southeast Forest (Muktar Reshad et al., 2019).

2.4 Species distribution of Dry evergreen Afromontane forest

Olea europaea subsp. *cuspidata, Juniperus procera, Celtis africana, Euphorbia ampliphylla, Dracaena spp., Carrisa edulis, Rosa abyssinica, Mimusops kummel, Ekebergia capensis*, and other legumes is representative of this type of vegetation. *Hyparrhenia, Eragrostis, Panicm, Sporobolus, Eleusine, Pennisetum, Trifolium, Eriosaema*, and *Crotalaria* are the most important genera. There are many endemics among them. The vegetation type is found in an altitudinal range of 1500-3400 m, with an average annual temperature of 14-25 ° C and rainfall of 500-1500 mm. It is home to the majority of Ethiopia's population and has been a sedentary grain-based mixed farming area for centuries. Forests have shrunk as a result of human intervention, and in most areas, brush has taken their place. Because of centuries of soil erosion, the soils have become shallow (Demel T 2000).

Evergreen Dry Montane Forest is a type of multi-story forest. The upper floor is made up of a non-uniform, uncompressed layer of tall trees. These trees are referred to as "emergent" because they appear above the plant mass. A swarm of shorter trees of varying heights grows beneath the emergent layer. Lower down, there is a layer of short trees and tall shrubs that is much less dense than the second layer. Finally, there is a layer of shrubs, suffrutescents, and grasses at the bottom. There are many epiphytes, lianas, and parasites (Zerihun Woldu, 1999; Anonymous, 1992).

Climbers such as Smilax sp., *Rubia cordifolia, Urera hypselodendron, Embelia schimperi, Jasminum floribundum,* and *various Cucurbitaceae* species, among others, typically join the vegetation strata. The ground is covered in grasses and other herbs such as ferns and mosses. A thick layer of soil is formed by the remains of dead plants. The complexity of the vegetation is significantly reduced in the drier and lower parts of the north and east, and it can have only three layers. Upper altitudinal limits also include simpler *Hagenia abyssinica* forests with associated small trees or shrubs of *Hypericum revolutum, Rapanea simensis,* and others. *Erica arborea* scrub grows in deeper soils and *Erica arborea* scrub grows in thinner soils on slopes. Bamboo forest, *Arundinaria alpina*, is also present in some areas, with the number of individuals increasing to the west (Zerihun Woldu, 1999; Anonymous, 1992).

Human intervention has resulted in the emergence or development of grasslands, which have replaced the majority of the forest. This is especially true in poorly drained flat areas, and almost always on vertisols. Grasses include *Hyparrhenia, Andropogon, Chloris, Pennisetum*, and a variety of other genera. There are many other herbs, including geophytes. . Overgrazing, which is prevalent in most areas, tends to displace herbaceous flora from more palatable grasses eg. *Chloris gayana* and *Pennisetum cladistinum* to less palatable highly silicified herbs eg. *Pennisetum schimperi* and *P. glabrum.*

2.5 Species selected for modeling

Celtis africana is medium-sized tree up to 30–40 m tall; usually straight, cylindrical, branchless for up to 15 m but often low-branching, up to 90 cm in diameter, often slightly fluted, usually without buttresses; bark surface smooth, whitish grey, often pinkish blotched, inner bark greyish with brown blotches, rapidly becoming dark brown upon exposure; crown rounded, dark green, with branches drooping towards tips; twigs densely yellowish brown short-hairy (Bekele Tesemma, A., 2007).

Figure 2; *Celtis africana* taken from (blantbook.co.za)

Juniperus procera is an afro-montane tree often reaching 30-35 m high; can reach 50 m, actually it's the largest tree of its genus. It's straight but sharply tapered, often with a pronounced twist, commonly heavily fluted, reaches 2-3 m dbh. Bark pale brown to reddish-brown, thin, fibrous, with thin shallow longitudinal fissures, exfoliating in thin papery strips (Orwa C, A Mutua. et al. 2009).

Figure 3; *Juniperus procera* taken from (seedvendor.com)

2.6 What is species distribution modeling?

What is the definition of species distribution modeling? Species distribution models (SDMs) are a popular tool in quantitative ecology and the most widely used modeling framework in global change impact assessments for projecting potential future range shifts of species (Peterson et al. 2011). (IPBES 2016). They are popular for several reasons, including their ease of use (e.g., Thuiller *et al.*, 2009) and relatively low data requirements (e.g., Elith, Leathwick, and Hastie 2008; Elith *et al.*, 2011). SDMs require georeferenced biodiversity observations (e.g., individual locations, species presence, species counts, and species richness; the response or dependent variable) as input, as well as geographic layers of environmental data (e.g. climate, land cover, soil attributes; the predictor or independent variables). This type of data is now widely available in digital format. Online repositories, for example, provide data on species distributions (e.g., GBIF and OBIS), individual animal locations (e.g., Movebank), climate (e.g., WorldClim and CHELSA), land cover, and other remote sensing products (e.g. Copernicus).

The most common method for estimating a species' actual or potential geographic distribution is to first characterize the environmental conditions that suit the species, and then to determine where the appropriate environments are spatially distributed. For example, if we

want to model the distribution of a plant known to thrive in moist clay soils, simply identifying locations with clay soils and high rainfall can yield an estimate of the species' distribution. There are several reasons why the species may not occupy all suitable sites (e.g., geographic barriers that limit dispersal, competition from other species). However, this is the fundamental strategy shared by the majority of distribution models. A mechanistic or correlative approach can be used to characterize environmental conditions suitable for a species. The goal of mechanistic models is to incorporate physiologically limiting mechanisms into the tolerance of a species to environmental conditions. For example, (Chuine and Beaubien, 2001) estimated responses to environmental variables (including mean daily temperature, daily precipitation, and length of night) to the use of mechanistic models of factors such as frost damage, phenology, and reproductive success.

Such mechanistic models necessitate a thorough understanding of a species' physiological response to environmental factors, making them difficult to develop for all but the best-understood species. Correlative models attempt to estimate the environmental conditions suitable for a species by associating known species occurrence records with suites of environmental variables that can reasonably be expected to affect the physiology and probability of occurrence. The central premise of this approach is that observing a species' distribution provides useful information about that species' environmental requirements. For example, we can assume that our plant species of interest favors moist clay soils as it has been observed growing in these soils. The limitations of this approach are discussed later in the review, but it has been shown that this method can provide valuable biogeographic information (e.g. Raxworthy *et al.*, 2003; Bourg *et al.*, 2005).

2.6.1 Steps of Species distribution model

For SDMs, there are five major modeling stages: (a) conceptualization, (b) data preparation, (c) model fitting, (d) model assessment, and (e) prediction (figure 4). We formulate our main research objectives and decide on the study design and setup during the conceptualization phase, based on all previous knowledge about the species and the study system. Actual data on biodiversity and the environment are collected and processed during the data preparation stage. The model fitting step is critical in any SDM application. The fitted model was thoroughly examined during the model evaluation step. Strictly speaking, checking the plausibility of the adjusted species-environment relationship by visual inspection of the response curves and evaluating the model coefficients and variable importance would be part of the model evaluation. Finally, in the prediction step, after inspecting the model and

extrapolation behavior, as well as evaluating predictive performance, it is time to make predictions in space and time. Despite the fact that SDM siblings like climate envelopes, habitat models, and resource selection functions place a slightly different emphasis on different aspects of the niche and are typically used at vastly different spatial scales, the modeling steps are essentially the same. In general, different data in SDM studies will necessitate different treatment Guisan, A., and N. E. Zimmermann (2000).

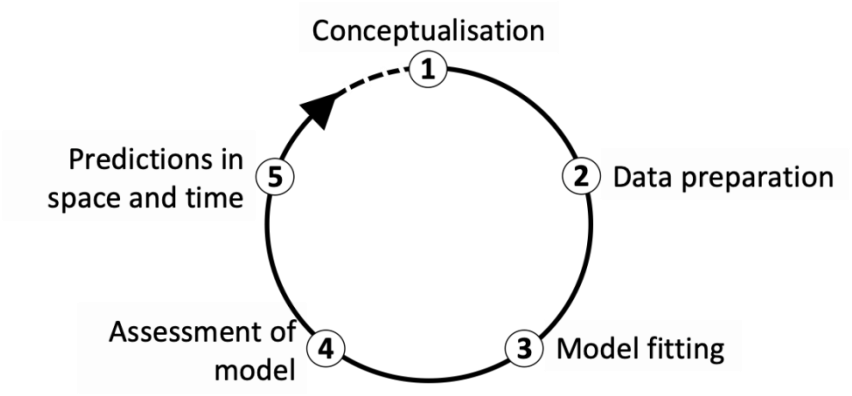


Figure 4: The main modeling cycle in species distribution modeling. Taken from (Guisan, A., and N. E. Zimmermann. 2000).

2.6.2 Types of Species distribution models

SDMs are classified into two types. Correlative SDMs, also known as climate envelope models, bioclimatic models, or resource selection function models, model a species' observed distribution in relation to environmental conditions (Elith, et al 2009). Mechanistic SDMs, also known as process-based models or biophysical models, develop a model of the environmental conditions under which a species can exist based on independently derived information about its physiology (Kearney, *et al.*, 2009).

Correlative SDMs use multiple regression approaches to model the observed distribution of a species as a function of geographically referenced climatic predictors. An algorithm finds the most likely environmental ranges in which a species lives given a set of observed occurrences of a geographically referenced species and a set of climate maps. The correlative SDMs are based on the assumption that the species are in equilibrium with their environment and that all relevant environmental variables have been sampled adequately. Interpolation between a limited numbers of species occurrences is possible using the models.

For these algorithms to be effective, observations must be collected not only of species presences, but also of absences, that is, places where the species does not live. Because species absence records are less common than attendance records, "random background" or "pseudo-absence" data is frequently used to fit these models. If records of species occurrences are incomplete, pseudo-absences may introduce bias. Because correlative SDMs are models of a species' observed distribution, they are models of the realized niche (the environments in which a species can be found), as opposed to the fundamental niche (the environments where a species can be found, or where the abiotic environment is suitable for survival).

The realized and fundamental niches for a given species may be the same, but if a species is geographically confined due to dispersion limitation or species interactions, the realized niche will be smaller than the fundamental niche. Correlative SDMs are simpler and faster to implement than mechanistic SDMs, and they can make use of existing data. However, because they are correlative, they provide little information about causal mechanisms and are not suitable for extrapolation. They will also be incorrect if the observed species' range is not in equilibrium (for example, if a species has been recently introduced and is actively expanding its range). (https://en.wikipedia.org/wiki/Environmental niche modelling).

Mechanistic SDMs have only recently been developed. Mechanistic SDMs, as opposed to correlative models, use physiological information about a species (from controlled field or laboratory studies) to determine the range of environmental conditions under which the species may persist (Kearney, et al 2009). These models seek to directly characterize and project the fundamental niche into the landscape. A simple model can simply identify the threshold values beyond which a species will perish.

A more complex model may include several sub-models, such as microclimatic conditions that account for macroclimatic conditions, body temperature that accounts for microclimatic conditions, fitness or other biological rates (e.g., survival, fertility) that account for body temperature (thermal performance curves), resource or energy requirements, and population dynamics. The model's input data is geographically referenced environmental data. Because the predictions of species distribution are independent of the species' known range, these models are especially useful for species whose range is actively moving and not in equilibrium, such as invasive species.

Mechanistic SDMs include causal mechanisms and perform better in extrapolation and non-equilibrium situations. They are, however, more time-consuming to develop than correlational models and necessitate the collection and validation of a large amount of physiological data, which may not be readily available. The models necessitate numerous assumptions and parameter estimates, and they can become quite complex. Dispersal, biotic interactions, and evolutionary processes are difficult to model because they are not typically included in either correlative or mechanistic models. To gain additional insights, correlational and mechanistic models can be used in conjunction. For example, a mechanistic model could be used to identify areas that are clearly outside the species' fundamental niche, and these areas can be marked as absences or excluded from analysis.

(https://en.wikipedia.org/wiki/Environmental_niche_modelling)

2.6.3 Use of Predictive Models in Vegetation Distribution Modeling

Predictive modeling of vegetation distribution is a process that uses occurrence records and environmental data from key species to forecast potential ranges (Heglund, 2002; Rodrguez *et al.,* 2007). The Maximum Entropy Model (MaxEnt ver. 3.3.3k) is one of the most widely used tools for predicting species/vegetation potential distributions (Phillips et al., 2006; Phillips & Dudik, 2008; Fourcade et al., 2014).

MaxEnt has the highest predictive power when using only presence data, and it is less affected by small sample sizes than other methods (Rodrguez *et al.,* 2007; Wisz *et al.,* 2008). The modeling process in MaxEnt consists of four major steps: a) The presence points and environmental layers are loaded into MaxEnt; b) the software is trained using selected species' presence points; c) randomly sampled ground points are used to determine the MaxEnt distribution; d) similar areas are modeled as potential suitable areas for the distribution of the new vegetation type, and suitability maps are produced; and and e) selected presence records are randomly sampled by MaxEnt and are used to test the strength of the suitability (AUC). Predictive modeling in MaxEnt has also been used to improve the design of a conservation reserve for endangered species (Taylor *et al.,* 2017), species habitat representation in protected areas (Alarcón & Cavieres, 2015), evaluate the impact of climate change on species (Hu et al., 2015), and quantify the impact of expected land cover change on species (Gadsden *et al.,* 2001). (Chai *et al.,* 2016; West *et al.,* 2016).

3. Methodology

3.1 Description of the study area

Dry Evergreen Montane Forest is a type of vegetation that occurs in an altitudinal range of 1500-2700 m, with average annual temperatures of 14-25° C and rainfall of 700-1100 mm, respectively (Friis, 1992). The Dry Evergreen Montane Forests are distributed in the central (east, west and north Shoa, Arsi and Gurage), north (east and west of Gojam, north and south of Gonder, south and north areas of Wello, Oromia, Agew Awi, and southern, eastern and western areas of Tigray) eastern (eastern and western areas of Hararghe, Afar and Dire Dawa) and southern (Bale, Borona and southern and northern Omo areas) of Ethiopia. They are limited to five national regions of the country namely, Amhara, Oromia, Tigray, Southern Nations, Nationalities peoples and Afar regions (Ethiopian Biodiversity Institution). Typical dry evergreen montane forests in Ethiopia are situated on highlands and mountain chains with the following locations: the Chilimo forest (38° 10′ E and 9° 05′ N), 2400 ha; the Menagesha forest (38° 35′ E and 9° 00′ N), 2720 ha; and the Wof-Washa forest (39° 45′ E and 9° 35′ N), 3600 ha (Tamrat Bekele 1994).

The shape file of the vegetation types of Ethiopia developed by Friis et al., 2010 was used to evaluate potential habitat suitability of the study area based on the vegetation type categories, as indicated in (Fig. 5). The habitat suitability of the vegetation type's ecological regions was analyzed and evaluated step by step, as some of the vegetation type's ecological zones recognized in (Friis *et al.*, 2010) have no potential habitat suitability for the distribution of the two under study species under all of the climatic conditions used in this study. Thus, we merged those vegetation types showed no tendency of potential habitat suitability for the distribution of the species with more related vegetation types and adopted five main vegetation categories for the data analysis as indicated in Table 1.

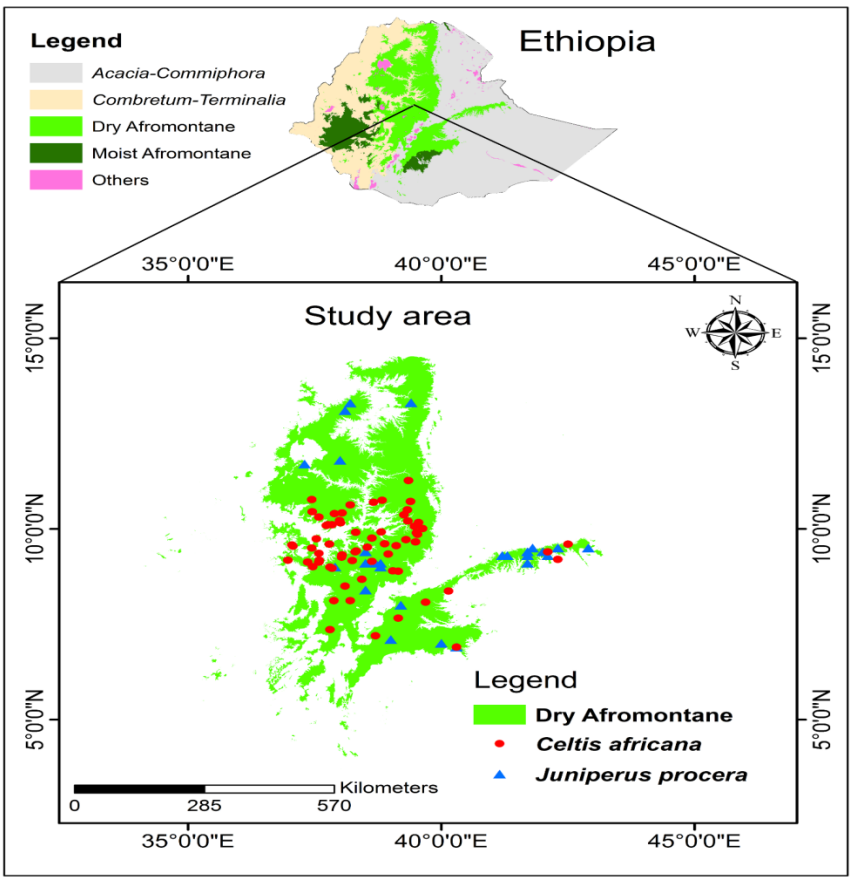


Figure 5: Biomes of Ethiopia and study area of this research

3.2 Data collection

Data of species occurrences and environmental variables were used to predict suitable habitat potential for the distribution of selected two species under the current and future climate scenarios in Ethiopia. Species occurrence data (Latitude, Longitude and Altitude) were collected from National Herbarium (ETH), Global Biodiversity Information Facility (GBIF) https://www.gbif.org/, Students thesis and Google earth collection records and website source providing their geographic location coordinates on around May. Environmental variables were obtained from appropriate website sources (http://www.worldclim.org) and used for the modeling the species suitable habitats as implemented in previous studies (Bambach *et al.*, 2013; Barbosa *et al.*, 2013; Remya *et al.*, 2015; Stalin and Swamy, 2015; Chhetri *et al.*, 2018).

3.3 Environmental parameters

The environmental parameters used in this study were current bioclimatic variables, elevation, topographic position index and solar radiation indices, and future bioclimatic projection scenarios (RCP 4.5 and RCP 8.5).

3.4 Current bioclimatic variables

Current bioclimatic variables are data compiled to represent the world's current climate condition for the period 1970-2000. (Hampe, 2004). The climatic conditions are important in understanding how living species occupy their ecological zones in appropriate habitats. It can be useful for analyzing the adaptation capacity of the species that are currently surviving in their geographical ranges. Thus, using current bioclimatic variables as a parameter and predicting their suitable distribution potentials, the effect of current climate conditions on a species distribution can be studied. Using current bioclimatic variables as a parameter, predict their appropriate distribution potentials. Downscaled 19 bioclimatic variables representing current global climatic conditions are available in 30 seconds from the website http://www.worldclim.org/ for use in modeling a species' current ecological distribution (table 2). Furthermore, elevation index (ei) and solar radiation index (sri) data are available in 30 seconds on the website, https://www.earthenv.org/topography at the global level and http://www.worldclim.org/. These data, along with the bioclimatic variables, can be used to create prediction models.

Table 2: Bioclimatic variables (Taken from https://www.worldclim.org/data/bioclim.html)

BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (×100)
BIO4	Temperature Seasonality (standard deviation ×100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter

BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

3.5 Future bioclimatic scenarios

Future bioclimatic data represents data forecasted for future global climatic conditions (Collins *et al.,* 2012). It is based on models developed from the fifth assessment report of the Intergovernmental Panel on Climate Change, which explained greenhouse gas emission trajectories; data for downscaled future climate scenarios are available from the Coupled Model Intercomparison Project Phase (CMIP5) (Diffenbaugh and Giorgi, 2012; He and Zhou, 2015). The models are available as Representative Concentration Pathways (RCP) and are represented in four trajectories based on their radiative force emissions of W/m2 and expected global temperatures to change by 2100 (Wigley *et al.,* 2002). The RCP trajectory projections are represented by values of their radiative force emissions capacities explained in W/m2 as RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5(Yin, 2012).

The RCP 2.6 model is predicated on an assumption that explains a decrease in greenhouse gas concentration. This scenario emphasizes the fact that global annual greenhouse gas emissions peak between 2010 and 2020, and temperatures are expected to rise by 0.3 to 1.78 degrees Celsius. The RCP 4.5 model proposes a moderate increase in global greenhouse gas emissions and assumes that future temperatures will range between 2 and 4.5 degrees Celsius. The RCP 6.0, on the other hand, assumes that greenhouse gas concentrations will remain stable in the future. It assumes stable emissions will peak around 2080 and then begin to decline, while temperatures are expected to rise by 0.8–3.18 degrees Celsius. The final RCP 8.5 scenario proposes that global greenhouse gas concentrations will rise in the future. It assumes that greenhouse gas emissions will continue to rise throughout the twenty-first century, with temperatures rising from 1.4 to 4.88 degrees Celsius by 2100. (Riahi *et al.,* 2011).

As a result, RCP data can be used to study the effect of future climate conditions on plant species distribution and to predict their suitable habitat potential; in this case, RCP 4.5 and RCP 8.5 were used to predict the effect of future climate conditions on the distribution of the two under study species at 2050 and 2070 (Chen, 2013). The RCP 4.5 assumes that GHG concentrations will more or less remain stable after 2100 as a result of a stabilized radiative forcing effect of approximately 4.5 W/m2 (IPCC, 2014), whereas the RCP 8.5 proposes that GHG concentrations will increase throughout the 21st century, with temperatures expected to rise from 1.4 to 4.88oC by 2100.

Zipped files of 19 bioclimatic variables and the solar radiation index were downloaded in 30 seconds from the website http://www.worldclim.org/, while data for the topographic position index and elevation were obtained at the global level from https://www.earthenv.org/ topography, for modeling the current distribution of the species using the method used in Beck et al., (2018). Similarly, zipped files containing 19 bioclimatic variables were downloaded from future climate projection scenarios downscaled in the study's Coupled Model Intercomparison Project phase (CMIP5) (He and Zhou, 2015). Following the methods used in the studies, data from two bioclimatic projections, RCP 4.5 and RCP 8.5, were used to model the future ecological distribution of the species for the years 2050 and 2070 (Diffenbaugh and Giorgi, 2012; Chhetri *et al.,* 2018).

The data were then transformed into pyramids in ArcGIS 10.5 before being clipped into a Dry Afromontane of Ethiopian boundary shape file and converted to ASCII format using SDM Toolbox 2.4 (Rahman, 2020). To eliminate redundant variables from the current data, Pearson correlation analysis was performed on the 19 bioclimatic variables, topographic position index (tpi), elevation index (ei), and solar radiation index (sri), at the maximum correlation allowed of 0.7, and highly correlated variables were removed using the methods described above (Barbosa *et al.,* 2013; Vega *et al.,* 2017; Chhetri *et al.,* 2018).

The environmental variables, BIO2 (Mean Diurnal Range (Mean of monthly (max temp - min temp), BIO3 (Isothermality), BIO4 (Temperature Seasonality (standard deviation ×100), BIO11 (Mean Temperature of Coldest Quarter), BIO15 = Precipitation Seasonality (Coefficient of Variation), BIO17 (Precipitation of Driest Quarter), BIO18 (Precipitation of Warmest Quarter), BIO19 (Precipitation of Coldest Quarter), Elevation, Topographic position index and Solar radiation index (sri) were used for modeling the ecological distribution of the species (Appendix 1).

3.6 Species presence data

The geographical coordinate system can be used to collect data on species presence to indicate the presence locations of the species on the ground (Bakuzis and Kurmis, 1978; Gibson et al., 2014). Based on this technique, geographic coordinates for the two species were collected from the National Herbarium of Addis Ababa University (ETH), as well as thesis and dissertation materials completed by university students in the country. In addition, GBIF (https://www.gbif.org) was evaluated to collect data on species presence coordinates as implemented in Beck *et al.*, (2014); Chamberlain and Boettiger, (2017). The latitude and longitude values were then saved separately in csv format in excel program as x and y coordinates, respectively. A total of 133 coordinates, 61 for Juniperus procera and 72 for Celtis Africana were used for the modeling the species distribution.

3.7 Species distribution model

A species distribution model is a technical method for creating a model that represents the range of ecological distribution of species in their ecosystems. According to Rovzar *et al.* (2016) and Dormann (2011), species distribution modeling is a scientific method used to study the ecological distribution of species across their appropriate ecosystems. Maximum Entropy (Maxent) software is a good modeling tool for predicting a species' ecological distribution by identifying the range of suitable habitats for the species' distribution. It is capable of generating a probability distribution of species occurrence over pixels in grids, beginning with the uniform suitable habitat for the species distribution and continually improving the fit to the occurrence data (Phillips *et al.*, 2006). As a result, Maxent is an important tool for assessing and drawing informative conclusions about the species in their ecological regions.

Maxent can use species presence data with environmental variables as parameters to perform a species distribution model for predicting areas of potential occurrence of species while keeping in mind that absence data is rarely reliable (Hanafi-Bojd *et al.*, 2018). It can accept a list of species presence locations as input, also known as presence-only (PO) data, as well as a set of environmental predictors (variables) spread across a user-defined landscape, i.e., area of interest (Merow *et al.*, 2013). Then it is able to extract a sample of background locations that it contrasts as absence versus presence. Accordingly, the two study species and environmental parameters used for predicting suitable ecological habitats for the distributions of the species at Ethiopia level are briefly described in the in the next sections.

So, using the Maxent programs, the effect of climate change on the ecological distribution of species can be studied by predicting their habitat suitability potential using species presence data, elevation index, solar radiation index, current and future bioclimatic variables as parameters (Phillips *et al.*, 2004; Remya *et al.*, 2015). Species presence records and environmental variables are important parameters for modeling and analyzing the extent of suitable habitats for species occurrence in areal units such as hectares or square kilometers (Pearce and Boyce, 2006; Ward *et al.*, 2009; Beaugrand *et al.*, 2011; Liu *et al.*, 2016).

3.8 Data analysis

The species distribution was modeled using Maximum Entropy software (Maxent) (Phillips *et al.*, 2006; Peterson and Soberón, 2012). It was chosen because it can use species presence-only data to calculate the probability of suitable habitat for the species' occurrence (Phillips *et al.*, 2006). The value of the ROC (AUC) graph can be used to explain the accuracy of Maxent analysis output (Ma and Sun, 2018). When the AUC value falls below 0.7, the model can be generally explained as it does not accurately represent the species distribution, whereas values 0.7-0.8 and 0.9-1 can represent good and excellent modeling technique performance, respectively (Arajo *et al.*, 2005). Thus, in this study, maxent analysis was performed with the following parameters: random test percentage of 25%, regularization multiplier of 1; maximum background points of 10,000; maximum iterations of 5000; convergence threshold of 0.00001; and 10 replicates with averaged results. Jacknife test is system generated by the software (Maxent) used to evaluate the contribution level of individual variables involved in the species distribution prediction analysis. The higher the contribution of a particular variable to the distribution of a species, the more important is the variable for predicting the occurrence of the species in its suitable habitat.

3.9 Habitat suitability analysis

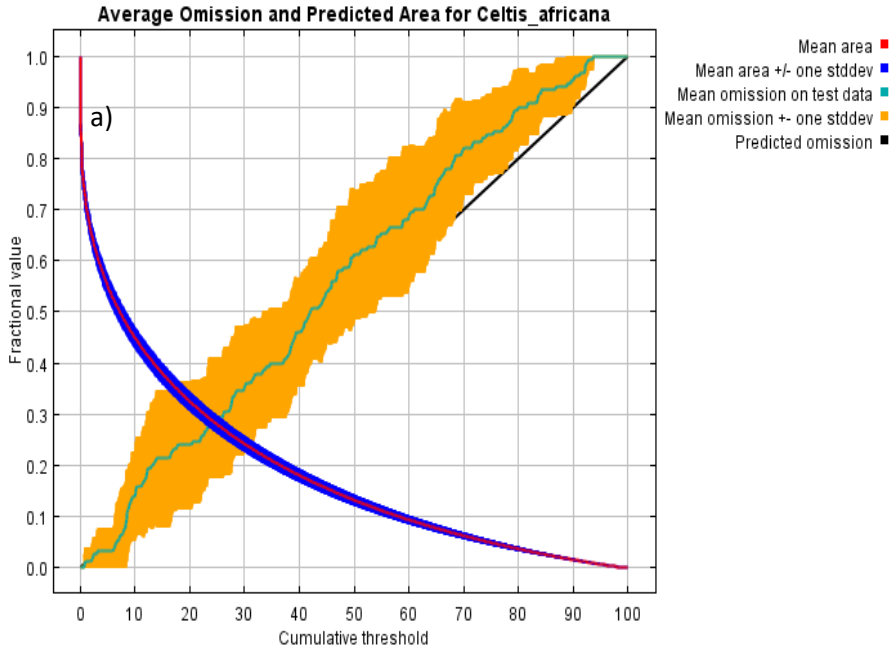
Degree of habitat suitability potential analysis was made using the average Maxent output maps of ten replicate runs, using ArcGIS algorithms. The Maxent output maps were in category classes of 0.0 − 1.0 based on the degree of habitat suitability range, which are identifiable by their color band classes, from highly suitable to unsuitable habitat classes. Based on this concept, the study area was classified into four habitat suitability classes as: A= highly suitable habitat (0.8−1.00), B= Suitable habitat (0.69− <0.8), C= Less suitable habitat (0.46− <0.69), and D= Unsuitable habitat (0.0− <0.46) for the two under study species. Then,

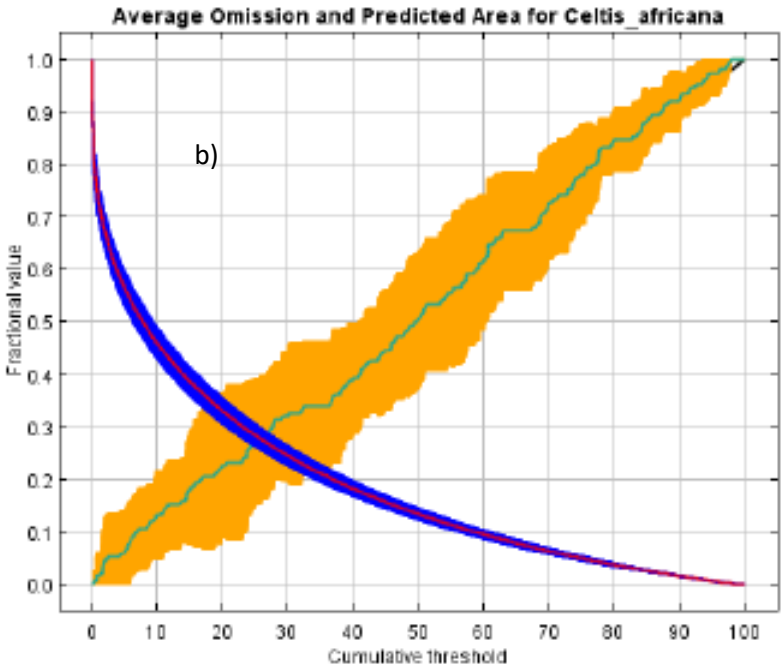
the extent of suitable habitat in each class was calculated in *ha* base from the total number of pixels distributed in each of the five habitats distribution classes.

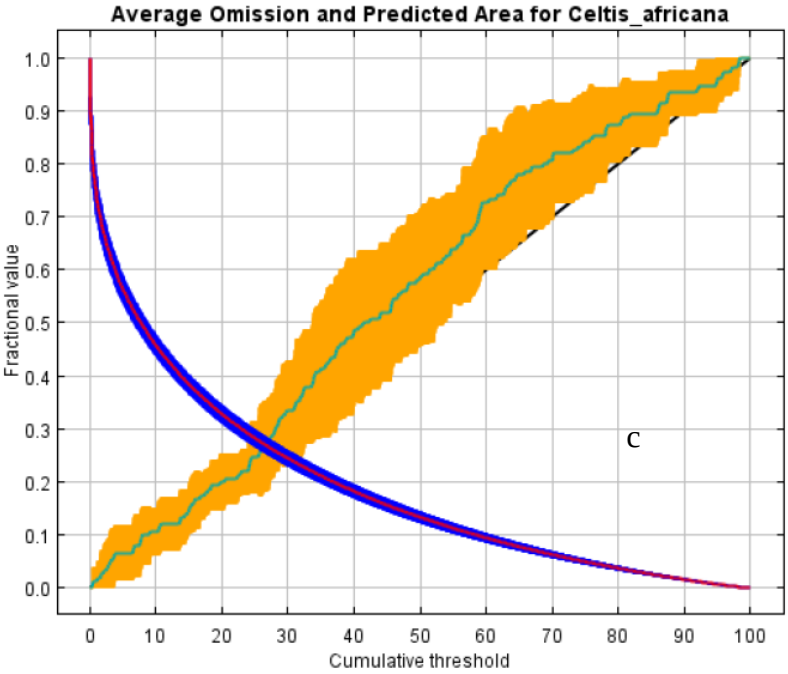
4. Results

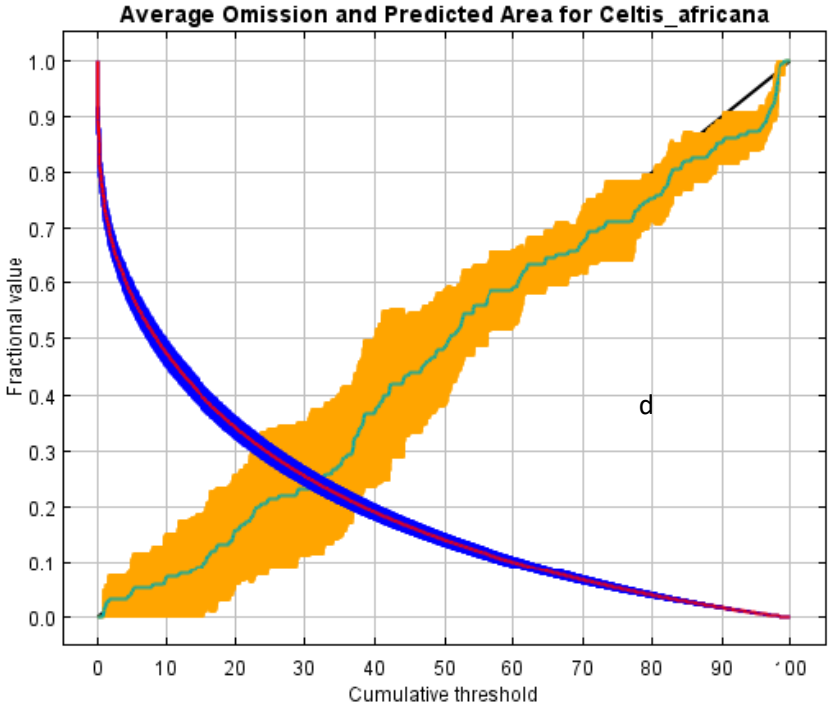
4.1 Model performance evaluation

Output of the Maxent model for *Juniperus procera* and *Celtis africana* indicated that all the test omission rates averaged over ten replicate runs were close to the predicted omission on the training and test rates for the two species under the current and future conditions.






Average Omission and Predicted Area for Celtis_africana
Fractional value
Cumulative threshold
c


Average Omission and Predicted Area for Celtis_africana
Fractional value
Cumulative threshold
d

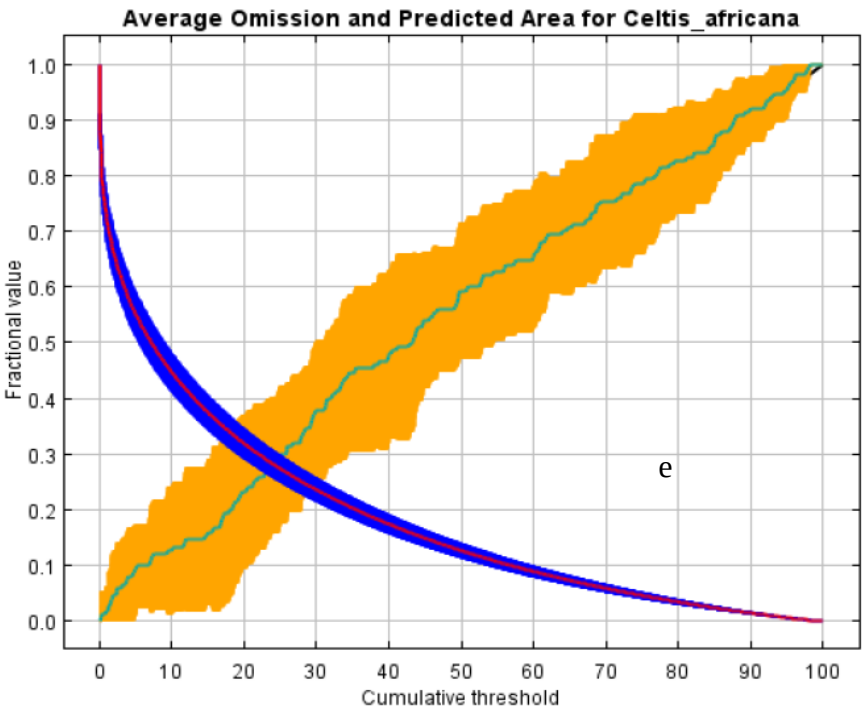
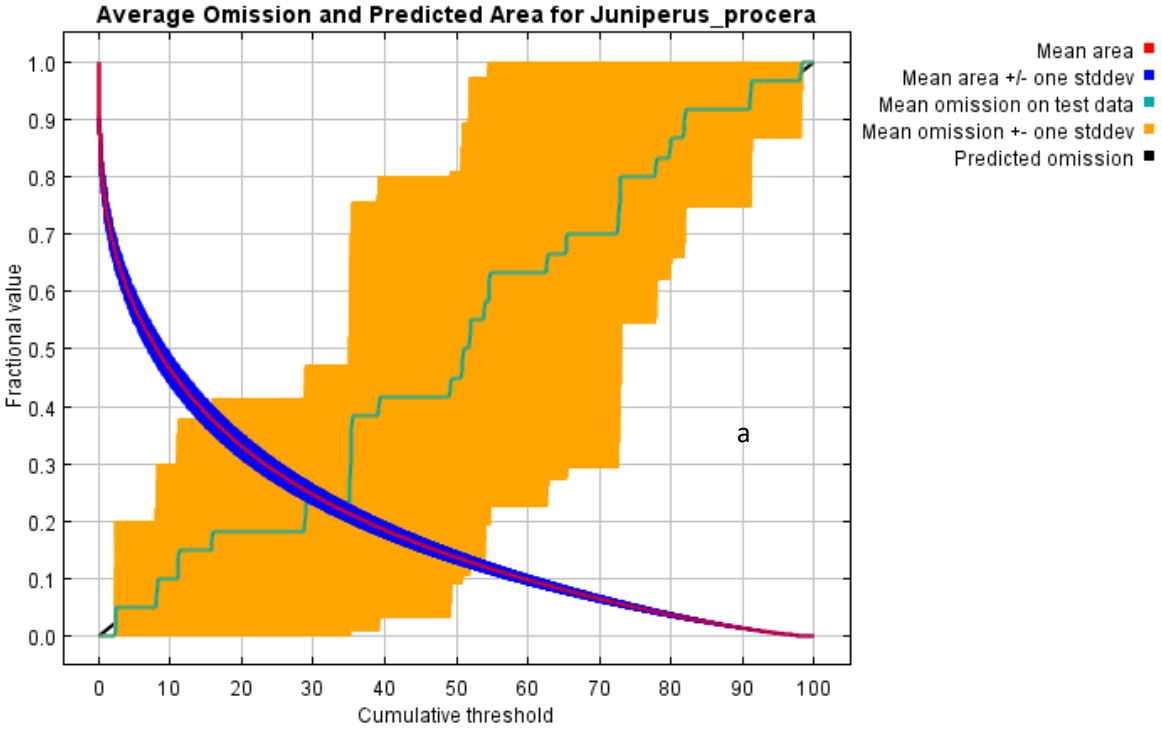
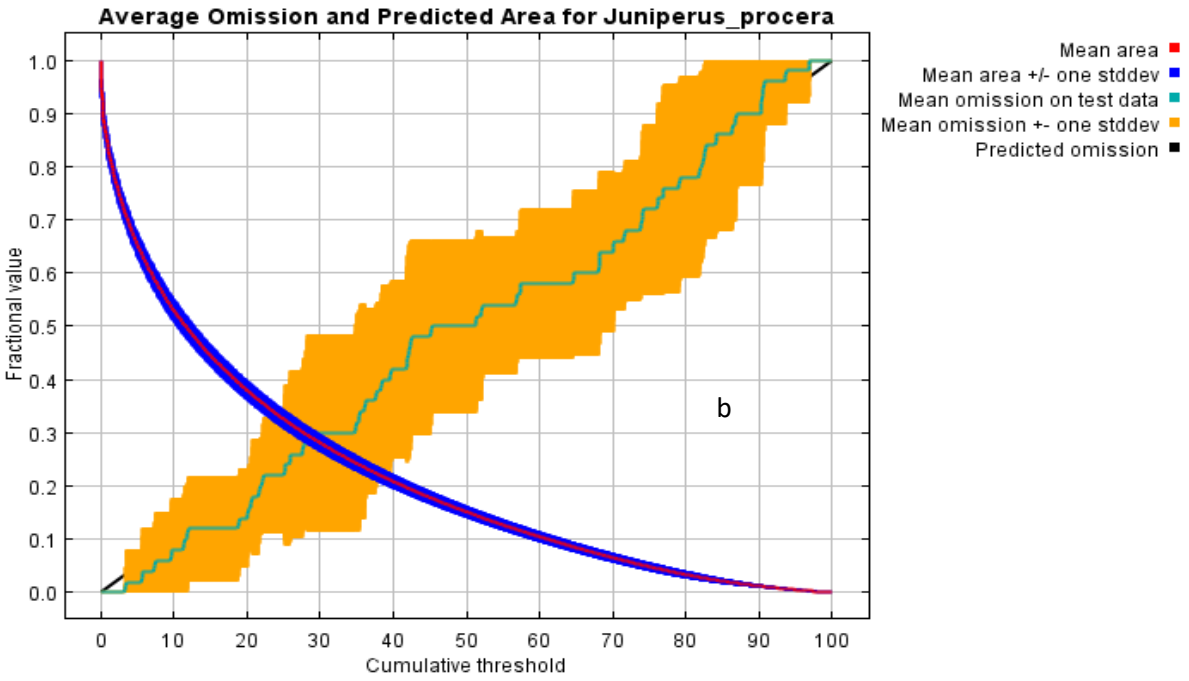
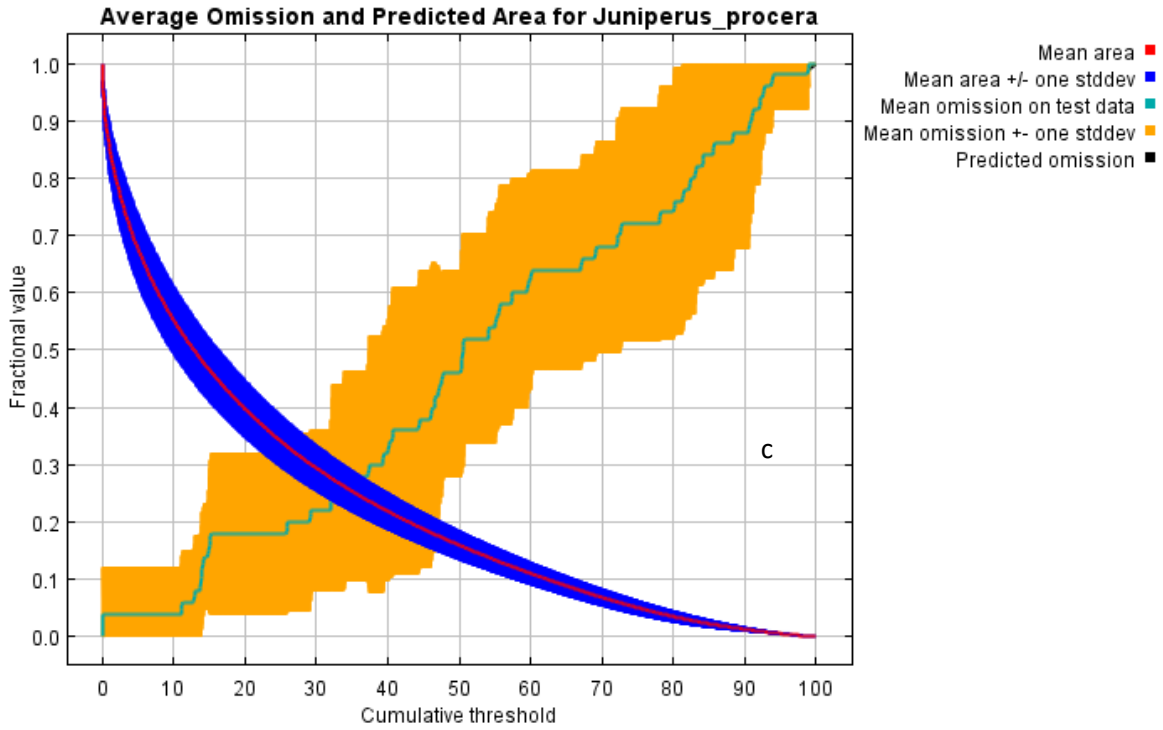
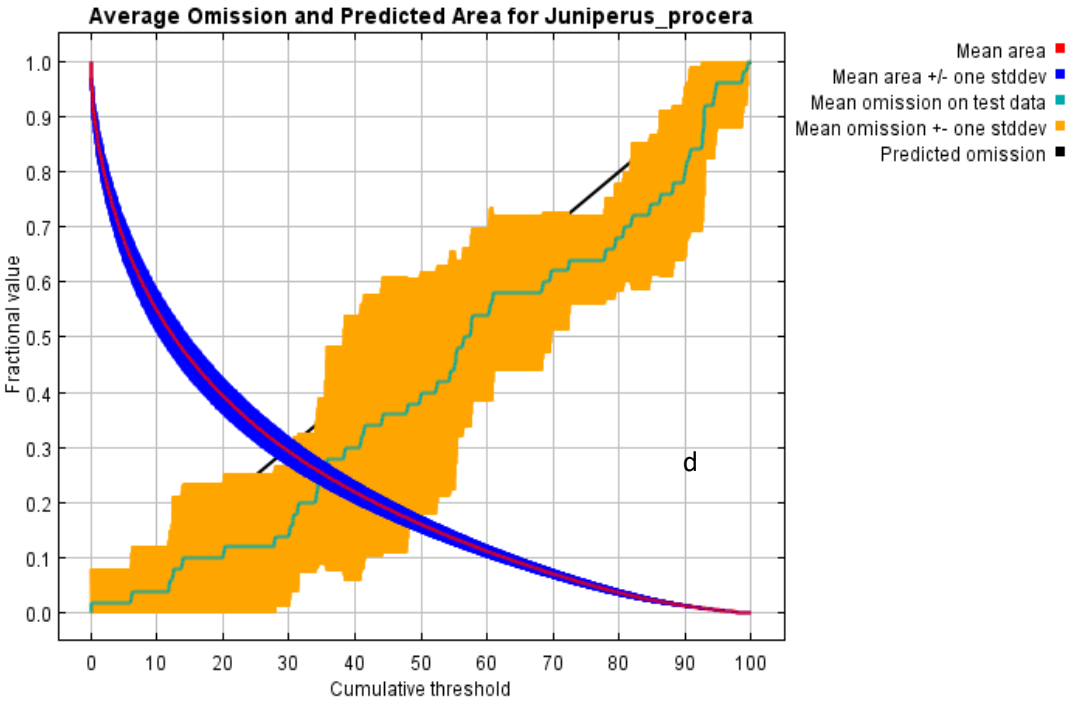


Figure 6; (a, b, c, d and e) Sample omission and predicted area curve for *Celtis africana* and *Juniperus procera.*




Average Omission and Predicted Area for Juniperus_procera
Mean area
Mean area +/- one stddev
Mean omission on test data
Mean omission +- one stddev
Predicted omission
Fractional value
Cumulative threshold
b


Average Omission and Predicted Area for Juniperus_procera
Mean area
Mean area +/- one stddev
Mean omission on test data
Mean omission +- one stddev
Predicted omission
Fractional value
Cumulative threshold
c



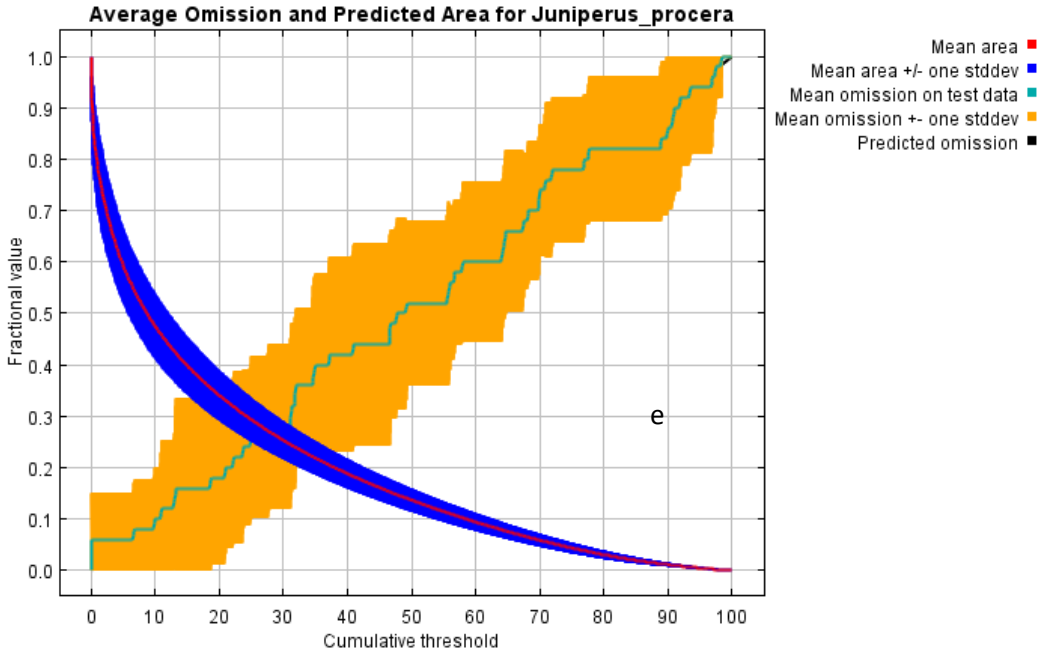
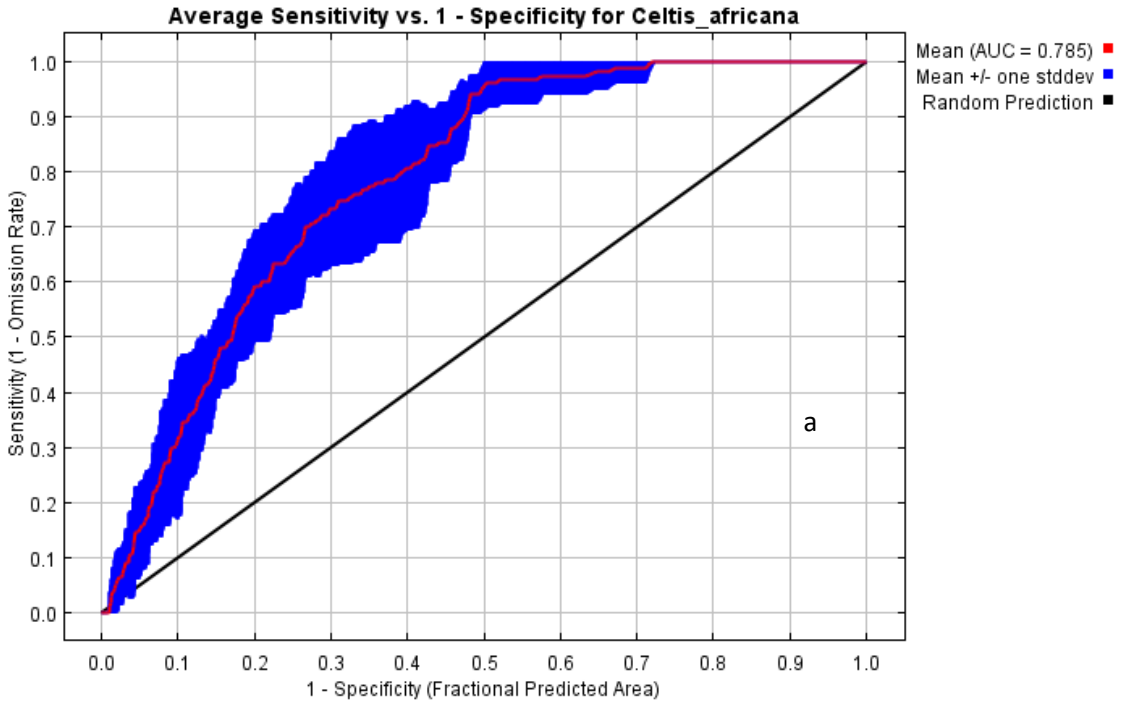


Figure 7; (a, b, c, d and e) Sample omission and predicted area curve for *Juniperus procera.*

The result indicated also that the average omission and predicted area curves for the current climate condition indicated good to great model fit on the test samples for the two study species. The average value of AUC at the current climate condition has good fit for *Celtis Africana*(0.785) while it is a great for *Juniperus procera* (0.817) (Fig. 8).



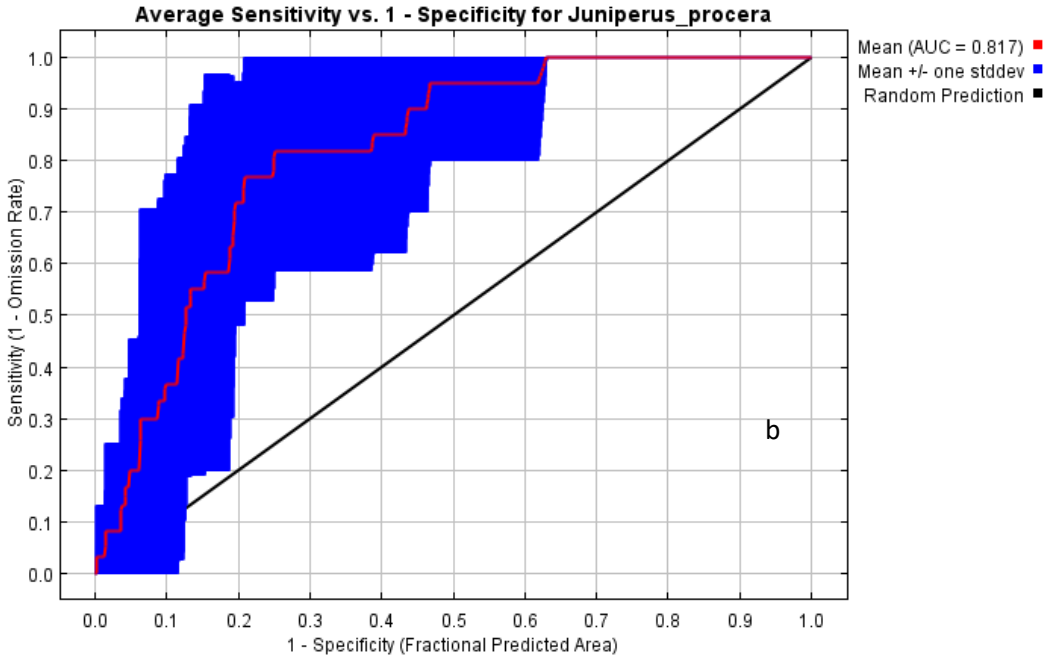


Figure 8; (a and b) Mean AUC for *Celtis africana* and *Juniperus procera* according to current climate

The mean values for AUC of the *Celtis africana* is (0.797) and for *Juniperus procera* is (0.801) according to the future climate projection scenario RCP 4.5 at the year 2050 (Fig. 9).

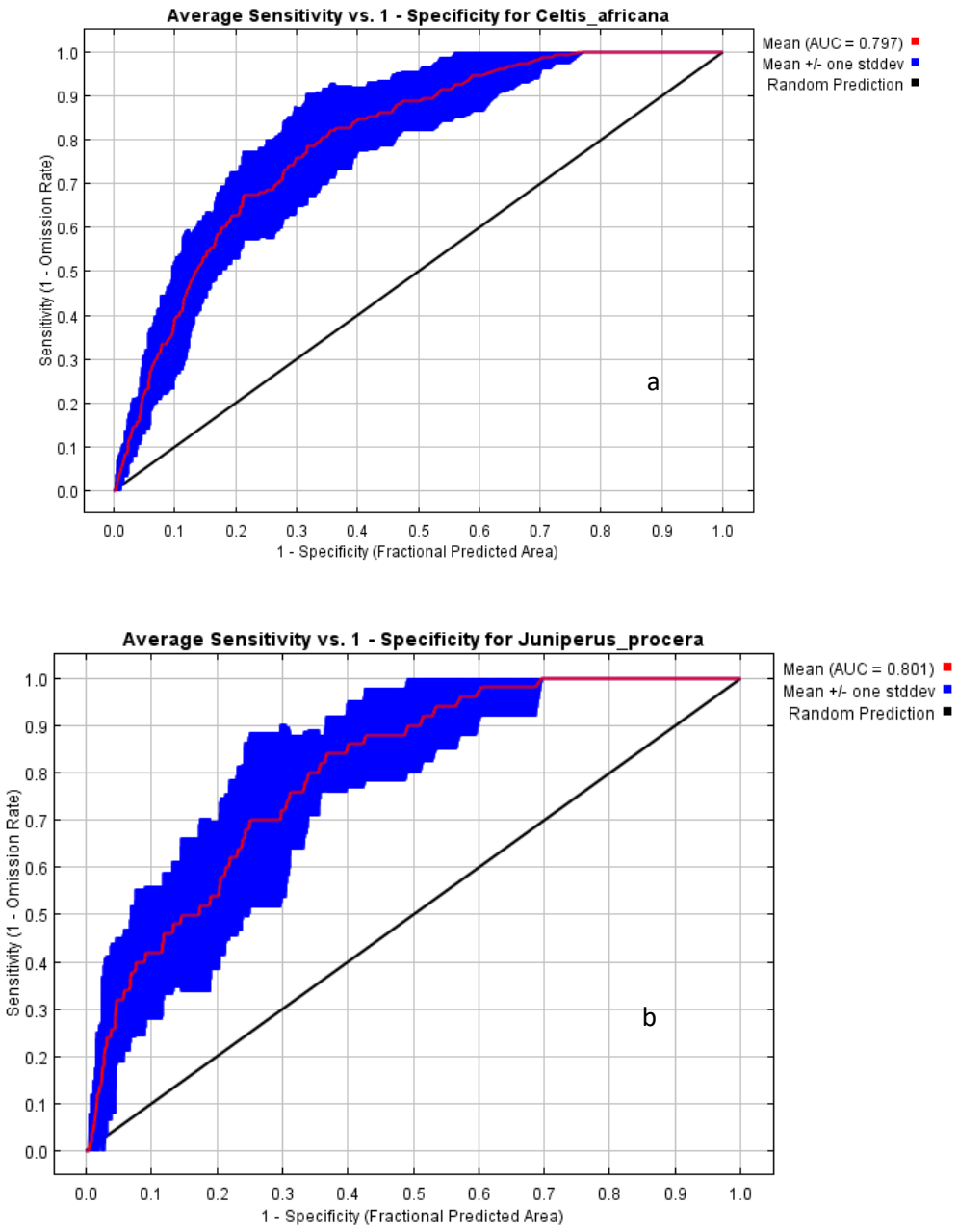


Figure 9 (a and b) Mean AUC for *Celtis africana* and *Juniperus procera* according to RCP 4.5, 2050 year

According to the future projection scenario RCP 4.5 at 2070, the average AUC is found to be best for Celtis africana (0.822) whereas it showed good value for Juniperus procera (0.796) fig 10.

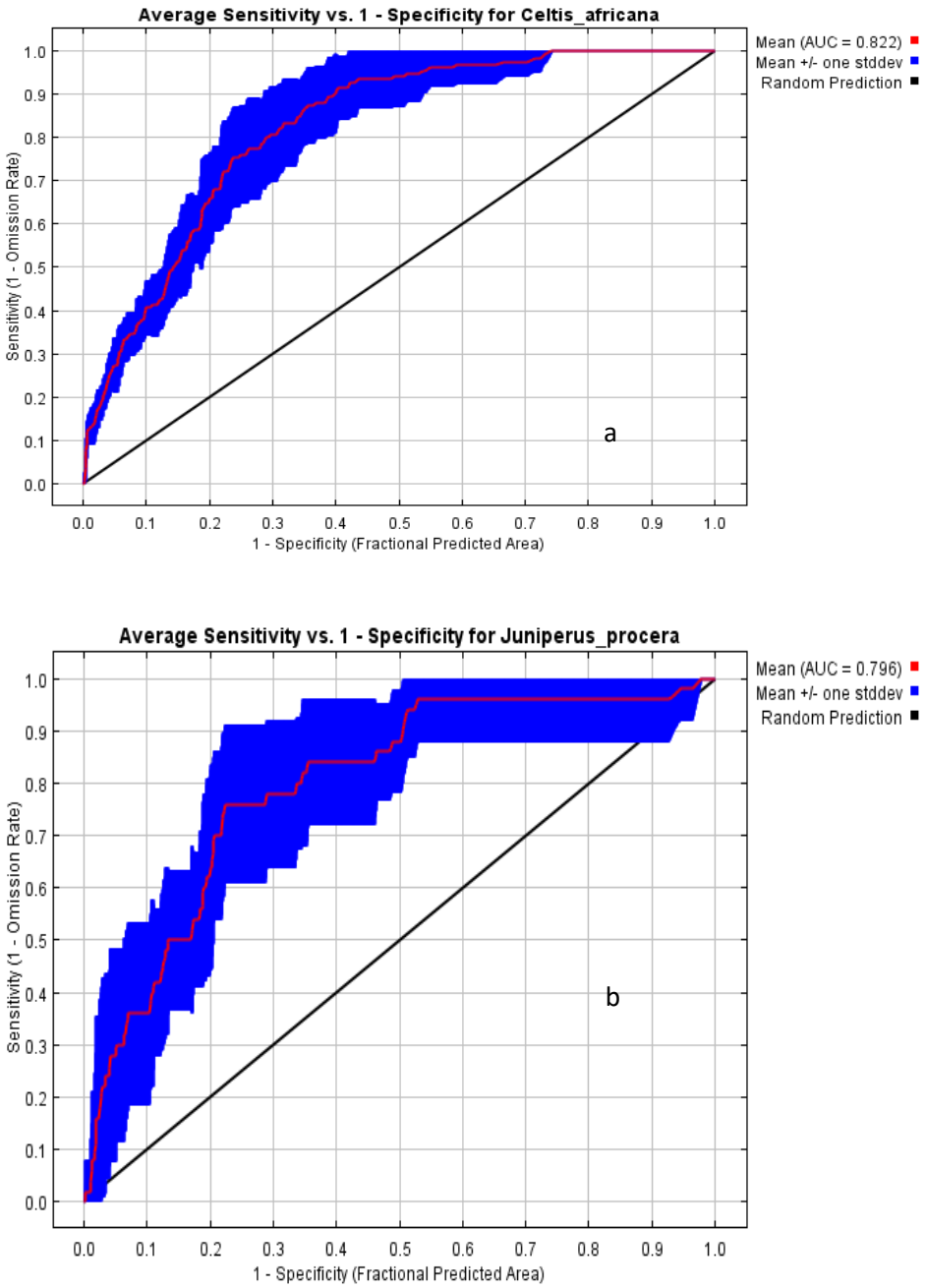
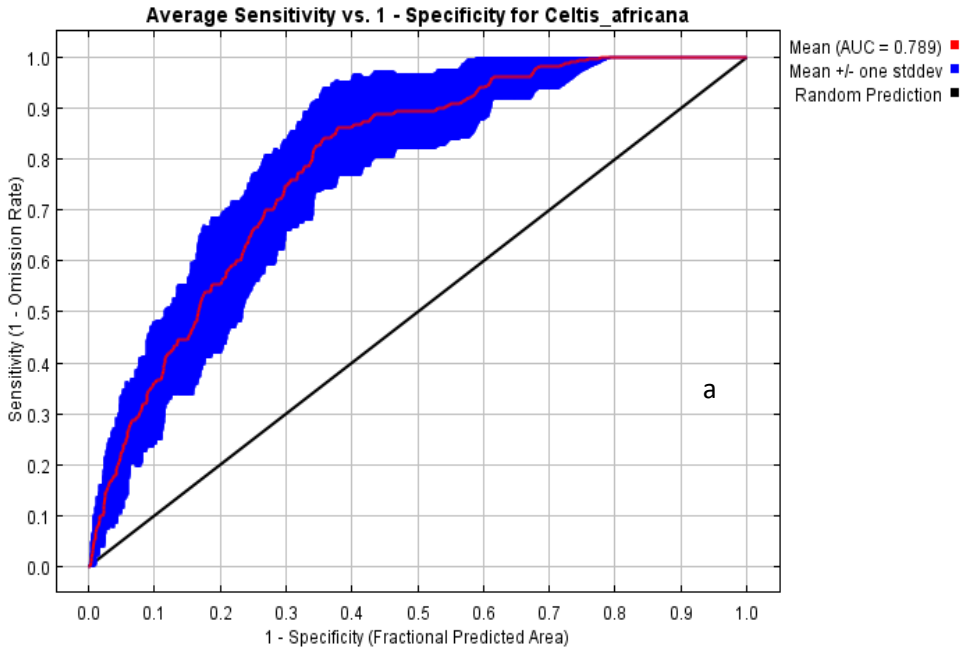


Figure 10 (a and b) Mean AUC for *Celtis africana* and *Juniperus procera* according to RCP 4.5, 2070

Here, the output indicated the mean AUC over ten replicate runs for *Celtis africana* (0.798) is best and *Juniperus procera* (0.830) is great values, as shown in Fig. 8 below, according to the future projection RCP 8.5 scenario at 2050 fig 11.



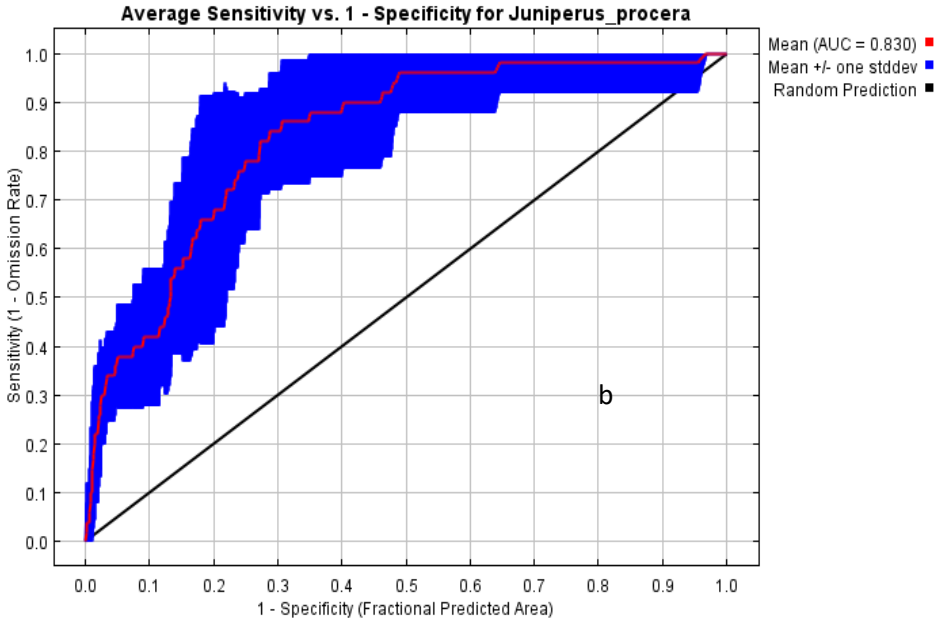


Figure 11 (a and b) Mean AUC for *Celtis africana* and *Juniperus procera* according to RCP 8.5, 2050

According to the future climate projection scenario RCP 8.5 at 2070, the average AUC value for ten replicate runs is good for the two study species as indicated in Fig. 12. The values were 0.788 for both *Celtis africana* and *Juniperus procera*.

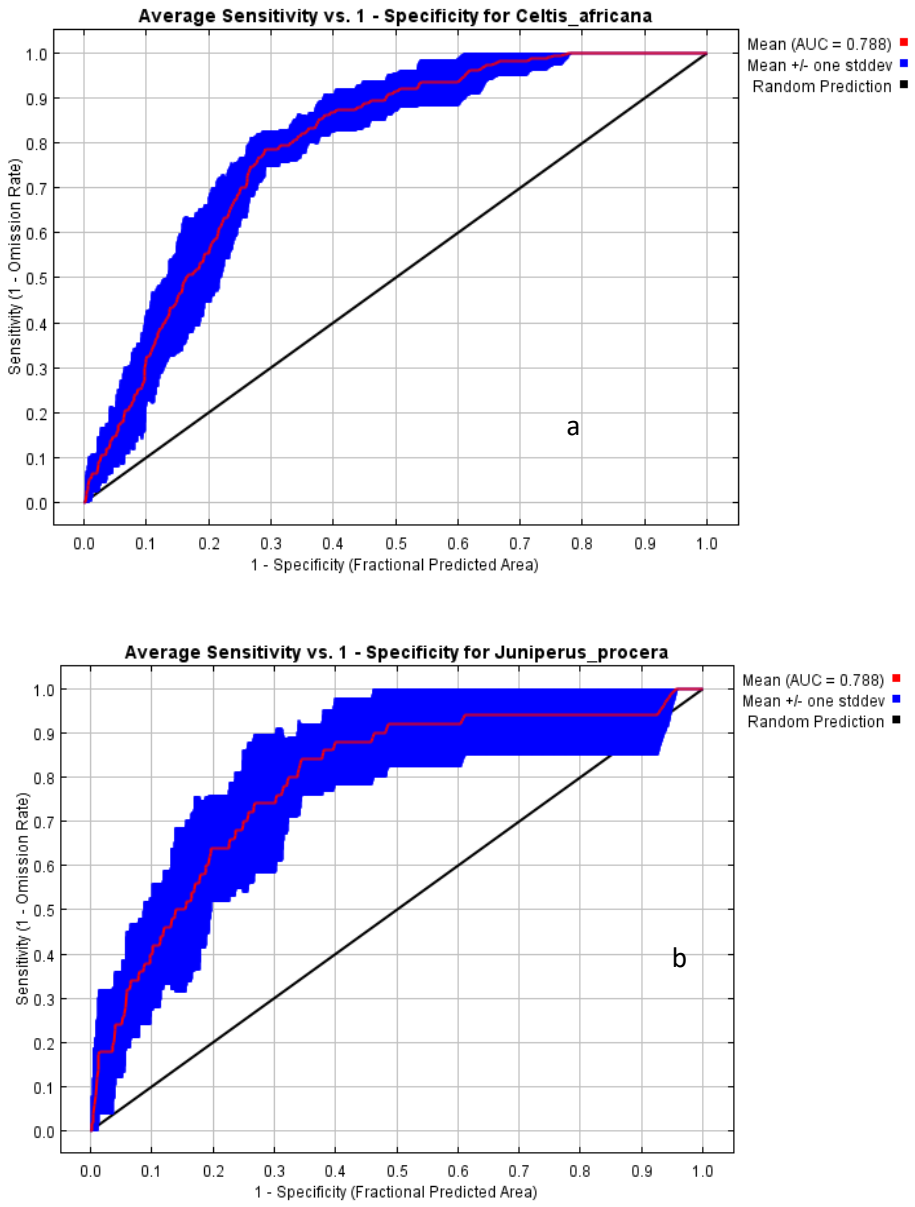


Figure 12 (a and b) Mean AUC for *Celtis africana* and *Juniperus procera* according to RCP 8.5, 2070

4.1.2 Habitat suitability pattern under current climate condition

As indicated in the output, the study area was categorized into four habitat suitability classes as highly suitable habitat, suitable habitat, less suitable habitat and unsuitable habitat potentials having different areal proportions to explain the distribution of the two study species. Based on this, *Celtsi africana* is distributed in the central and south western parts, while *Juniperus procera* is distributed in the northern, around central parts and mostly around Eastern parts of the DAF, under the current climatic condition (Fig. 13 and 14). Out of the total area of DAF, 2196.38n/10,000ha, 0.7871% (17.28504344), 3.8525%

(84.61464487), 13.2755% (291.5782928), 82.08501% (1802.898562) is recognized as highly suitable, suitable, less suitable and unsuitable habitat classes for the distribution of the *Juniperus procera* species, respectively. Similarly, highly suitable habitat for the distribution of *Celtis africana* is found to be 0.06241% (1.37062) under the current climatic condition, while the suitable, less suitable and unsuitable habitat classes are include 2.7921%(61.32256), 16.50768%(362.5713), and 80.63778%(1771.112) of the study area.

4.2 Habitat suitability potential under future climate scenarios

According to RCP 4.5 scenario, out of the total area of DAF, 0.645% (14.146) ha/10000 and 0.6405% (14.07) are recognized as highly suitable classes for the distribution of Juniperus procera at 2050 and 2070 respectively. Additionally, the proportions of suitable, less suitable and unsuitable habitat classes considered by 2050 are 3.853% (84.615), 13.275% (291.578) and 82.086% (1802.899) in respectively order. Moreover, output of the data analysis indicated that about 1.94% (42.616), 18.76% (411.97) and 78.66% (1727.718) of the study area are considered as suitable, less suitable and unsuitable habitat classes by 2070 respectively. However, according to RCP 8.5 projection, highly suitable habitat classes are found to be 0.687% (15.085) and 0.647% (14.214) at 2050 and 2070 respectively. On the other hand according to this projection 1.896% (41.652), 21.413% (470.3004) and 76.004% (1669.339) are considered as suitable, less suitable and unsuitable habitat for distribution of juniperus procera at 2050 in DAF. In addition the suitable habitat classes recognized for the species include 1.746% (38.344), 17.267% (379.255) and 80.339% (1764.563) at 2070 respectively.

Highly suitable habitat potential for the distribution of *Celtis africana* is predicted as 0.0467% (1.0237) at 2050 and 0.0437% (0.959) at 2070, according to the RCP 4.5 projection scenario. Again result of data analysis showed as the suitable, less suitable and unsuitable habitat classes include, 3.114% (68.413), 17.041% (374.28) and 79.797% (1752.65) of the area of DAF at 2050, whereas at 2070, the habitat are predicted to be 3.06% (67.211), 17.689% (388.528) and 79.206% (1739.68) following the above respectively order. In addition, according to RCP 8.5, it was found that about, 0.0578% (1.269) and 0.035% (0.753) of the proportions of the study area will comprises highly suitable habitat classes for the distribution of the species at 2050 and 2070 years respectively. But, the suitable, less suitable and unsuitable habitat classes will be considered in ha/10000 as 3.058% (67.1603), 16.0436% (352.377) and 80.84% (1775.57) at 2050, while at 2070, the suitable, less suitable and

unsuitable habitat classes will be 3.0155% (66.229), 16.27% (357.35) and 80.68% (1772.043) for *Juniperus procera* in DAF.

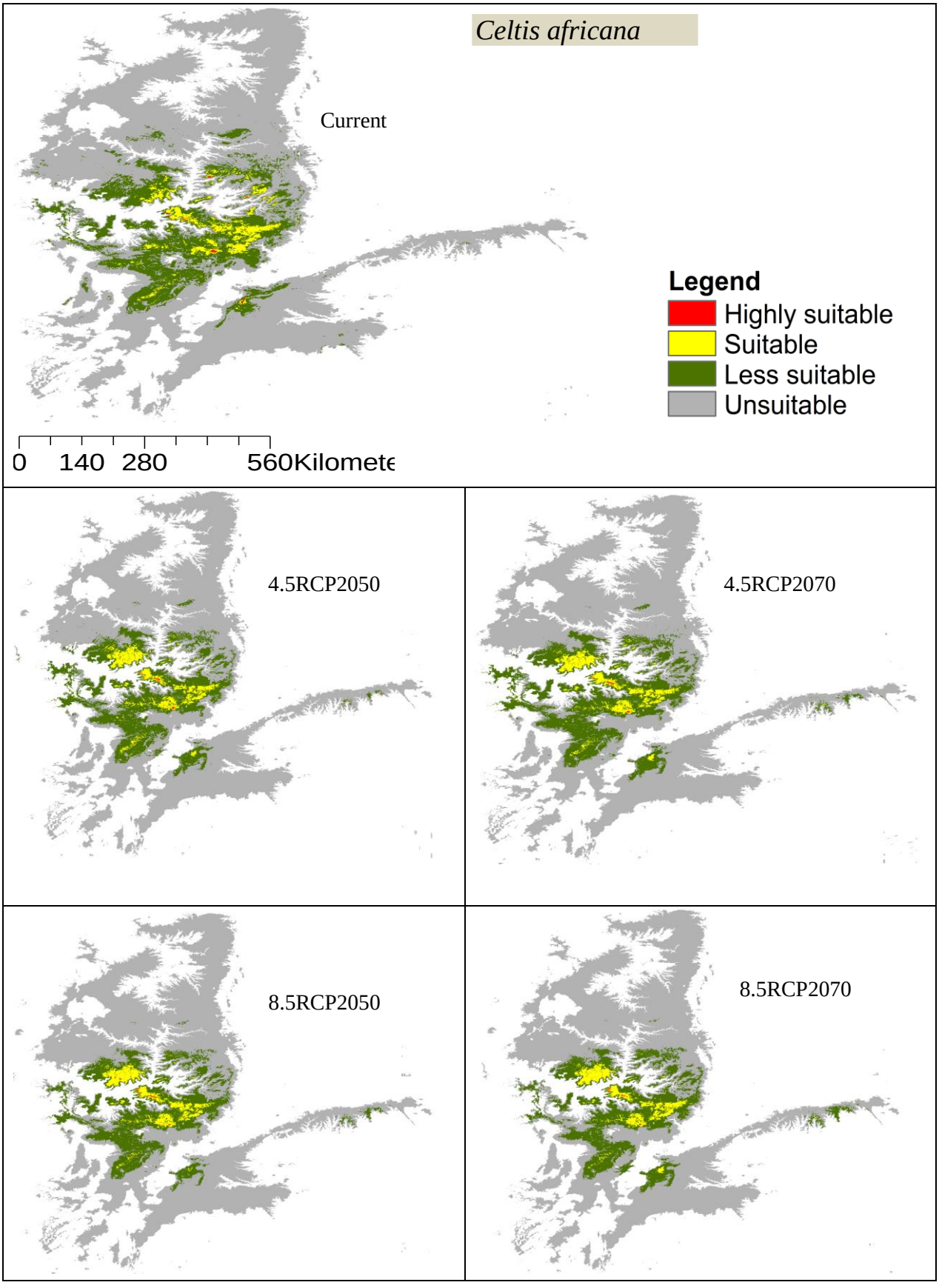
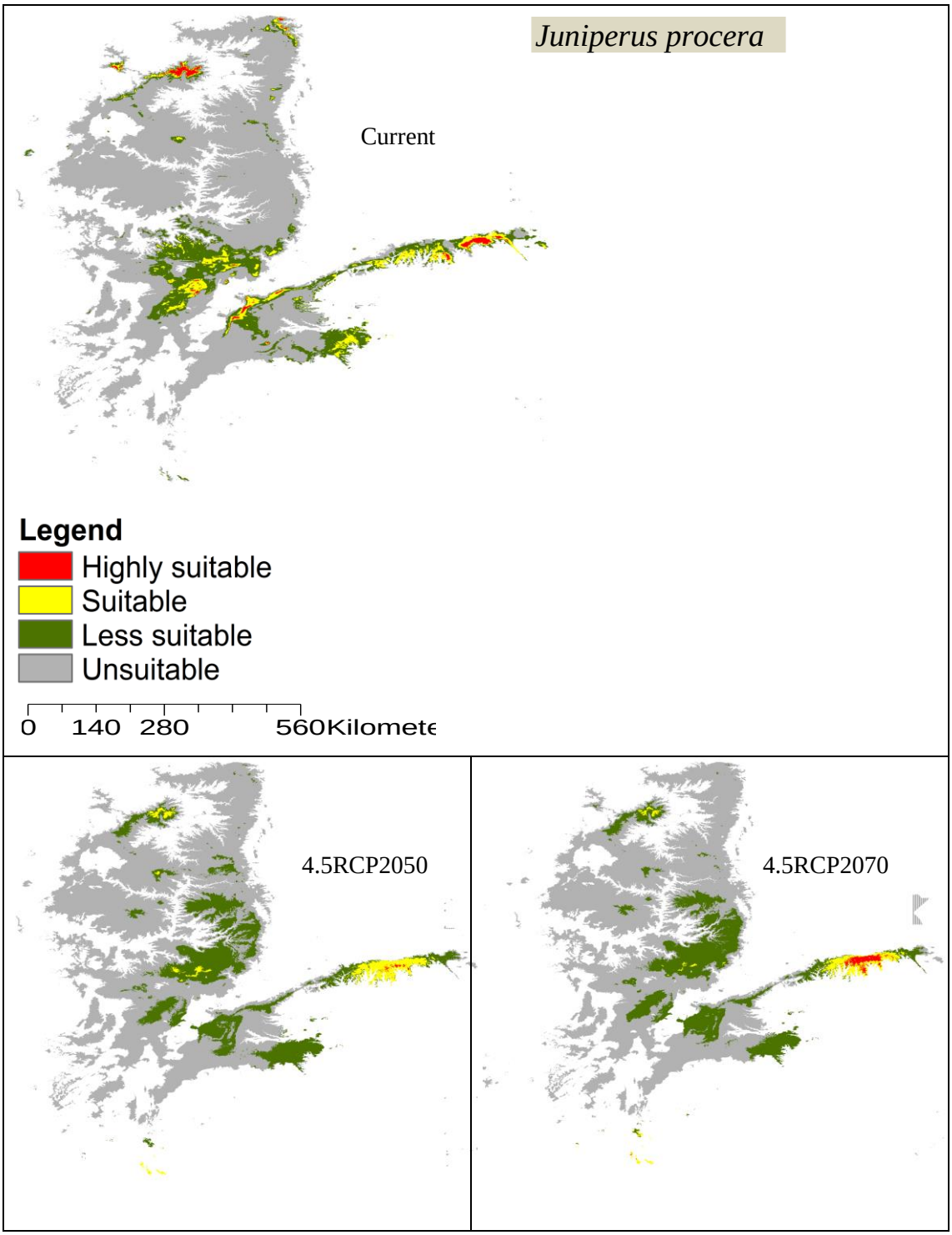


Figure 13, Potential habitat suitability for *Celtis africana* under the current and future scenarios



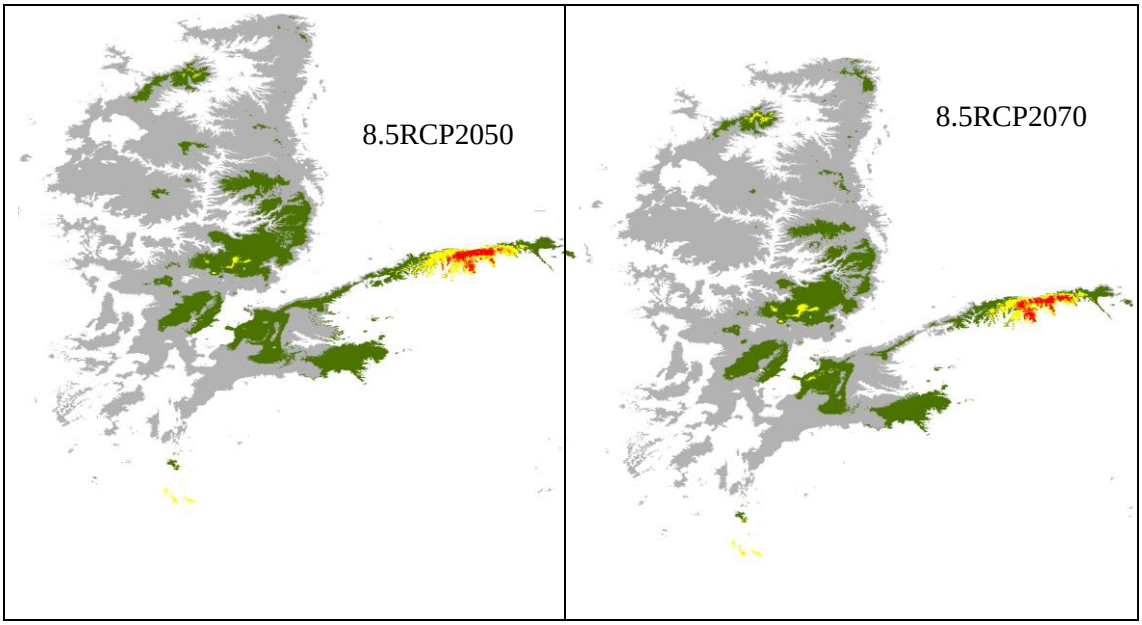


Fig. 14 Potential habitat suitability for *Juniperus procera* under the current and future scenarios

Table 3: Predicted suitable habitat for *Juniperus procera* and *Celtis africana* under the current and future climate scenarios at Ethiopia level (area is expressed in a block of 10,000 *ha* unit)

Species	Habitat Suitability Class	Habitat suitability status measurement	Current Climate	RCP 4.5		RCP 8.5	
				2050	2070	2050	2070
Juniperus procera	Highly suitable	area (ha)	17.286	14.147	14.07	15.085	14.213
		Cover (%)	0.787	0.644	0.64	0.687	0.64
	Suitable	area (ha)	84.615	42.178	42.61	41.65	38.344
		Cover (%)	3.853	1.92	1.94	1.89	1.74
	Less suitable	area (ha)	291.578	418.78	411.97	470.3	379.25
		Cover (%)	13.27	19.067	18.75	21.412	17.26
	Unsuitable	area (ha)	1802.89	1721.27	1727.71	1669.33	1764.56
		Cover (%)	82.08	78.36	78.66	76.004	80.34
Celtis africana	Highly suitable	area (ha)	1.37	1.024	0.95	1.269	0.75
		Cover (%)	0.062	0.047	0.044	0.057	0.034
	Suitable	area (ha)	61.322	68.413	67.21	67.16	66.23
		Cover (%)	2.79	3.115	3.06	3.058	3.02
	Less suitable	area (ha)	362.57	374.289	388.52	352.37	357.35
		Cover (%)	16.508	17.041	17.689	16.044	16.27
	Unsuitable	area (ha)	1771.112	1752.651	1739.681	1775.57	1772.05
		Cover (%)	80.638	79.79	79.206	80.84	80.68

4.3 Variables contribution to distribution of the species

The most influential environmental variables contributing to the distribution of celtis africana were Bio 17 (pricipitation of driest quarter), Solar radiation and Temprature while Bio11(mean temperature of coldest quarter), Bio 17 and Bio 2 (mean diurnal range) were contributing more to the distribution of Juniperus procera, under current and future climate scenrios Table 3.

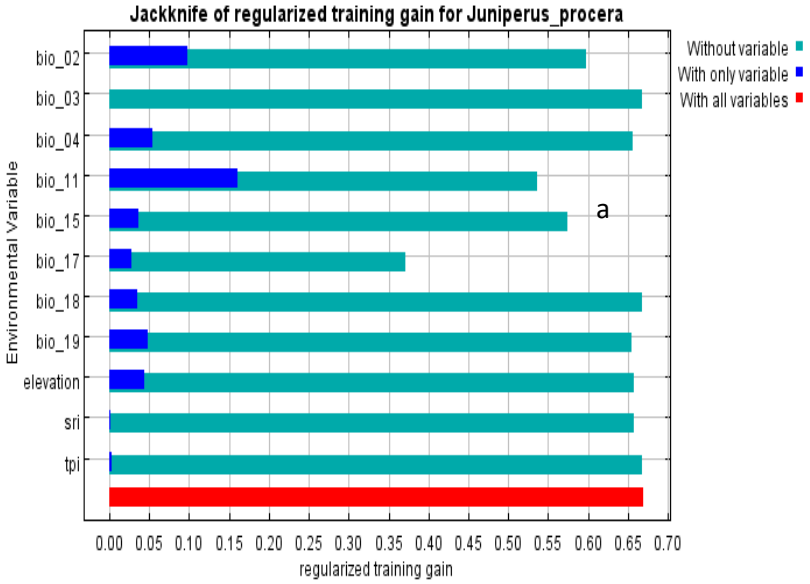
Table 4: Contribution (%) of environmental variables to the distribution of the two species

Variables	*Juniprus procera*					*Celtis Africana*				
	Current climate	RCP 4.5		RCP 8.5		Current climate	RCP 4.5		RCP 8.5	
		2050	2070	2050	2070		2050	2070	2050	2070
Bio2	22.7	24.9	30.3	23.4	18.1	0	6	7.4	8.4	10.9
Bio3	0.2	13.4	8	9.5	7.7	0.4	0.4	0.1	0.1	0.1
Bio4	0.9	0	4.5	2.3	2.6	0.5	0.2	0.4	0.3	0
Bio11	28.1	17.6	13.2	11.6	14.8	4.4	0.8	1.5	0.8	0.8
Bio15	9.3	4.3	3.9	7.6	5.6	4.1	0.7	0.8	1.2	1.3
Bio17	26.4	20.9	20.9	21.3	21.3	18.4	22.2	23.4	24	23.6
Bio18	0.2	0.4	0	0.1	0	2.4	0.1	0.3	0.4	0.3
Bio19	9.8	17.6	18.2	23.1	26.2	1.2	0.4	0.3	1.3	2.1
Sri	1	0	0.5	0.5	0.2	49.6	52.1	52	50.4	48.2
Elevation	0.8	0.2	0.3	0.2	0.1	1.3	0.4	0.8	0.5	0.3
Tpi	0.6	0.6	0.3	0.4	0.1	17.7	16.7	12.9	12.5	12.3

The output Jacknife tests indicated that solar radiation is the most important variable predicting the habitat suitability potential for *Celtis Africana* under both the current and future climate projections however for *Juniperus procera* Bio2 (mean diurnal range), Bio 11 (mean temperature of coldest quarter) and Bio 19 (precipitation of coldest quarter) are more important variables indicating the habitat suitability potential respectively. The jacknife tests indicated also that if Maxent used only Temperature Annual Range, almost no gain would be

achieved, and thus this variable is not useful for estimating the distribution of the two species, under both climatic conditions (Fig 15 and 16).

Based on the Jacknife test graphs indicated in (Fig 15 a-e), the occurrence of suitable habitats for the distribution of Juniperus procera was predicted by contributions from Bio 11, Bio 17, Bio 2 and Bio 19 under current climate condition. Also according to RCP 4.5 and RCP 8.5, Bio 11, Bio 17, Bio 2 and Bio 19 will be most contributor of *Juniperus procera* both at 2050 and 2070. On the other hand, as shown in (Fig 16 a-e), Sri, Bio 17 and Tpi are most important for the distribution of *Celtis africana* under current, RCP 4.5 and RCP 8.5 climate conditions and scenarios.


Jackknife of regularized training gain for Juniperus_procera
Without variable
With only variable
With all variables
Environmental Variable
bio_02
bio_03
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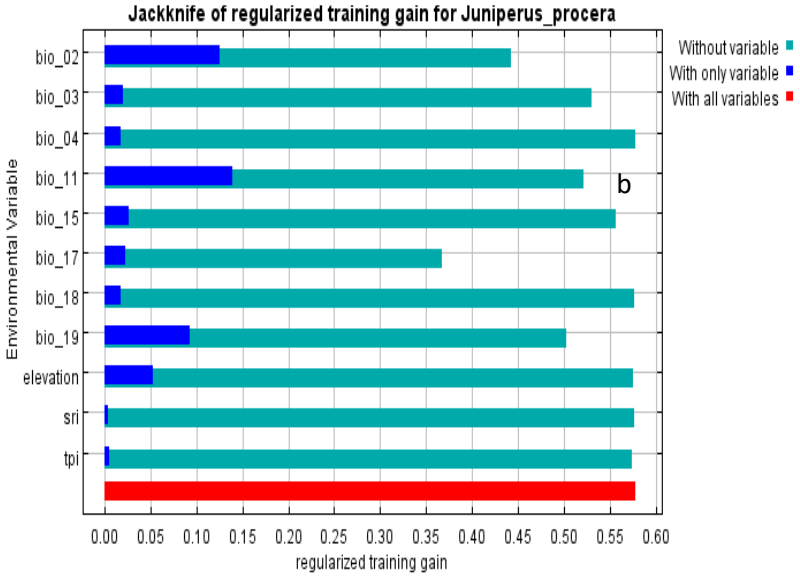
regularized training gain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Without variable
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Environmental Variable
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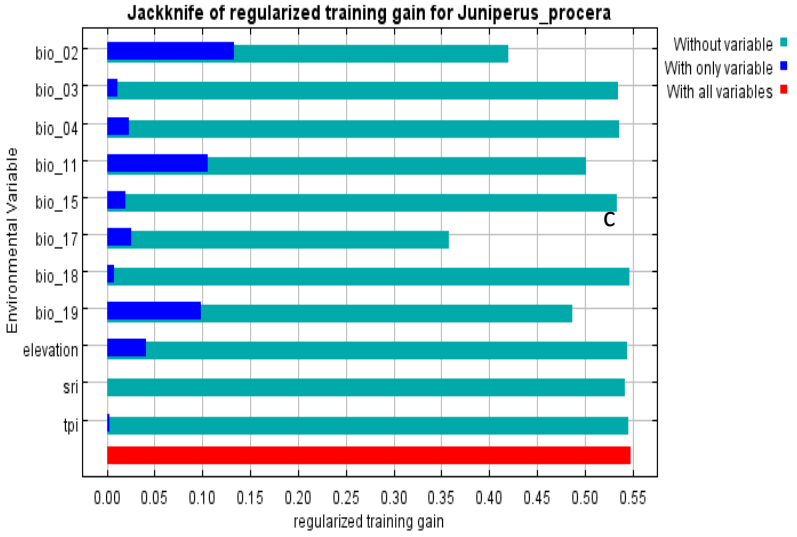
regularized training gain


Jackknife of regularized training gain for Juniperus_procera
Without variable
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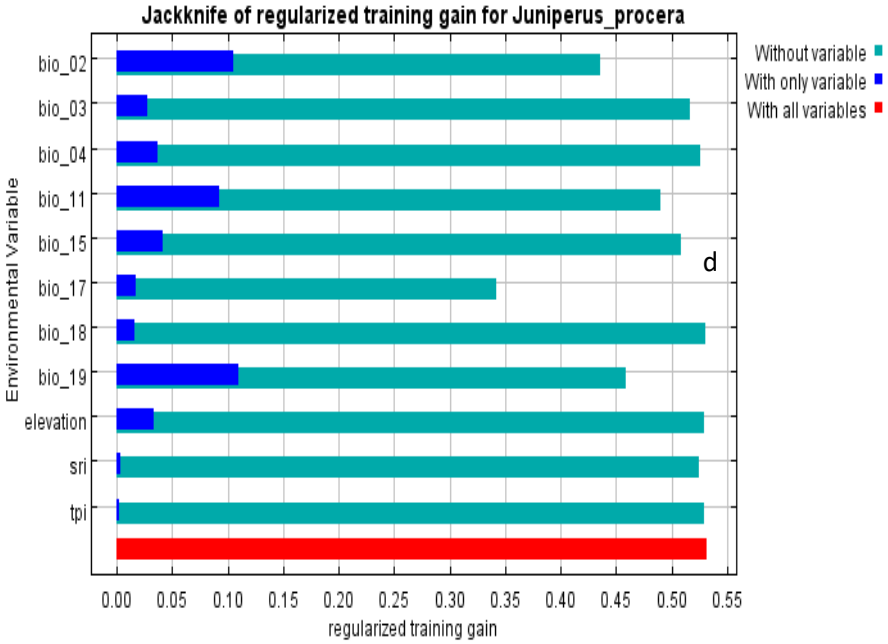


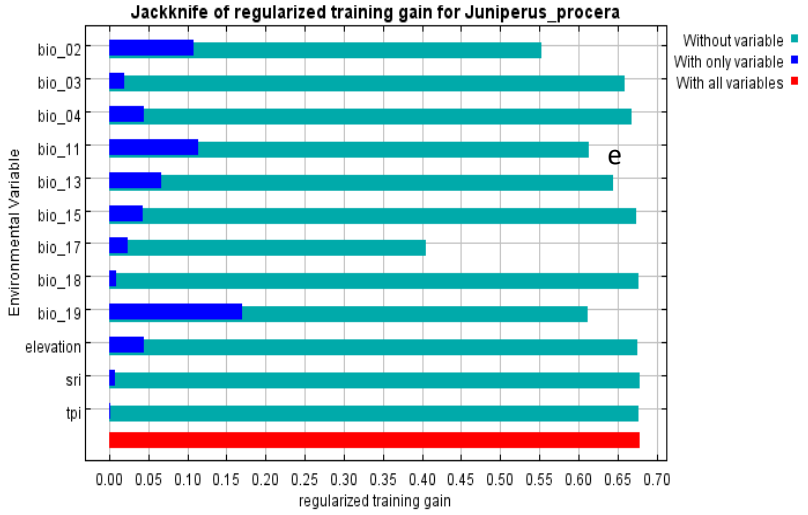
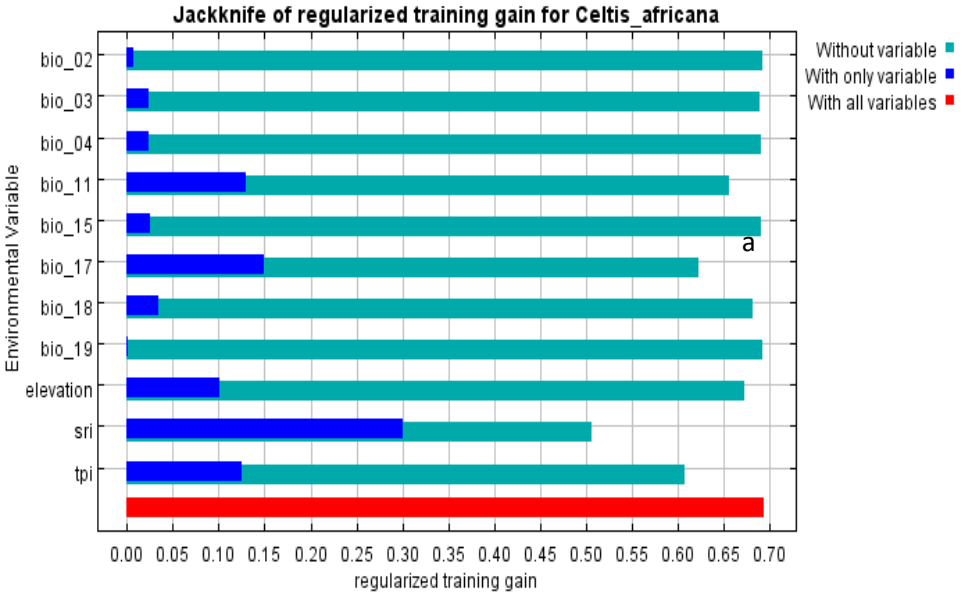


Figure 15: Jackknife of *juniperus procera* a, b, c, d, e (current, RCP4.5 (2050, 2070), RCP 8.5 (2050 and 2070)) respectively.


Jackknife of regularized training gain for Celtis_africana
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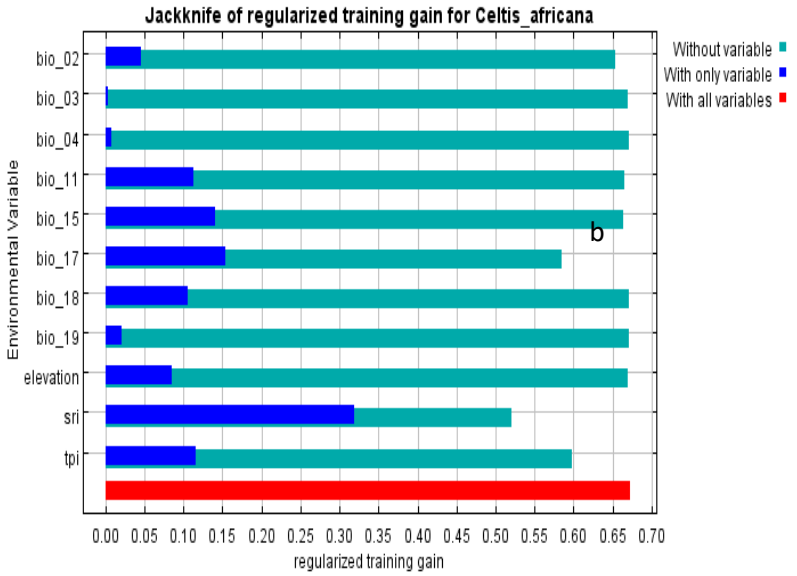
regularized training gain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Environmental Variable
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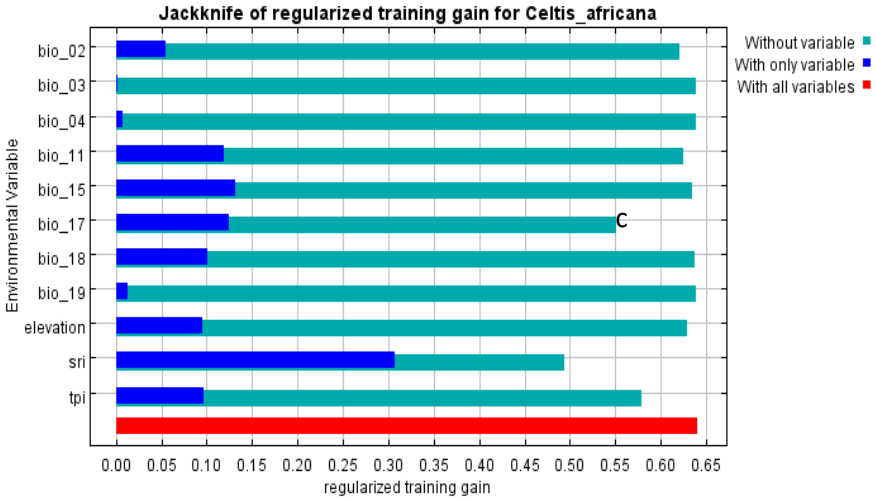
regularized training gain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With only variable
With all variables
Environmental Variable
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bio_04
bio_11
bio_15
bio_17
bio_18
bio_19
elevation
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0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50 0.55 0.60 0.65
regularized training gain

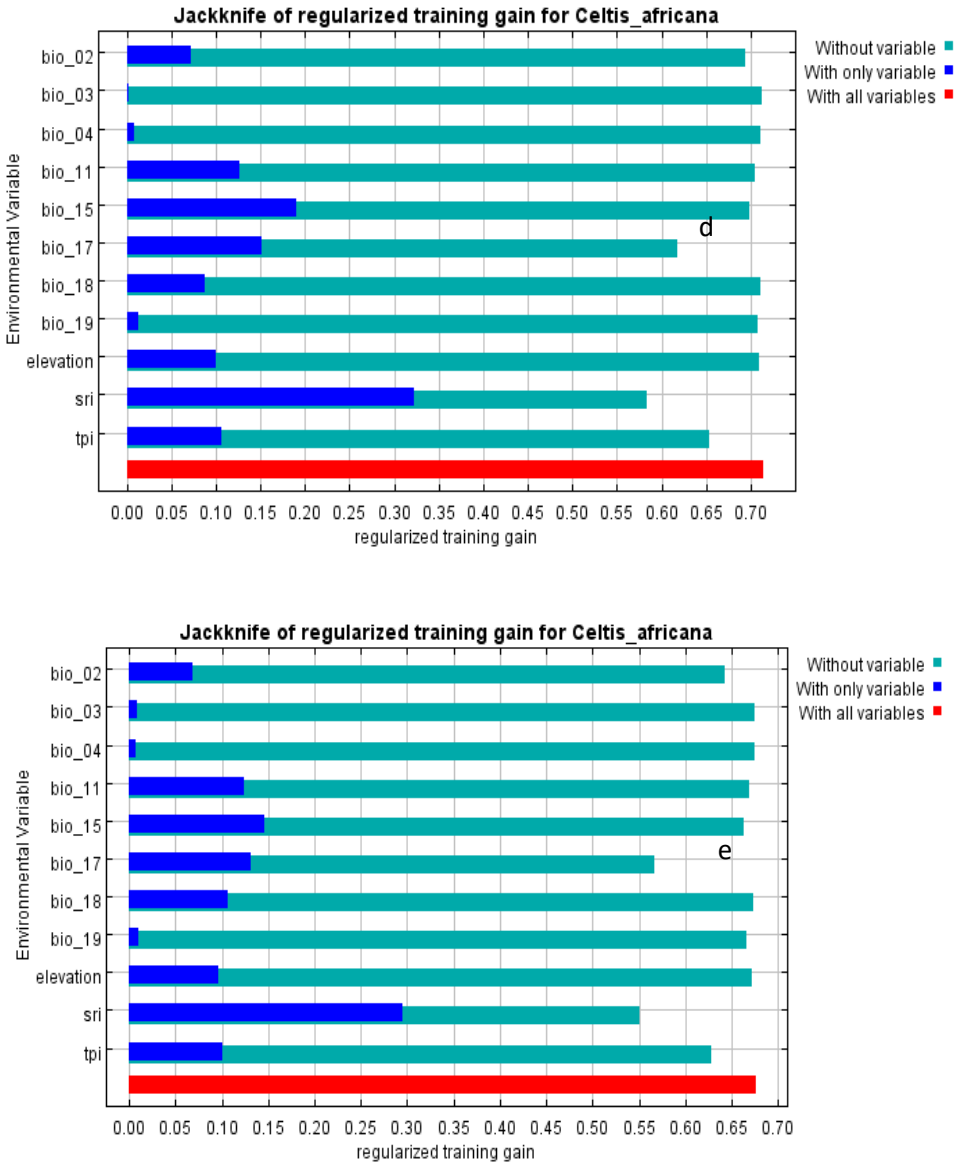

Fig 16: Jackknife for *Celtis africana* a, b, c, d, e (current, RCP4.5 (2050, 2070), RCP 8.5(2050 and 2070)) respectively.

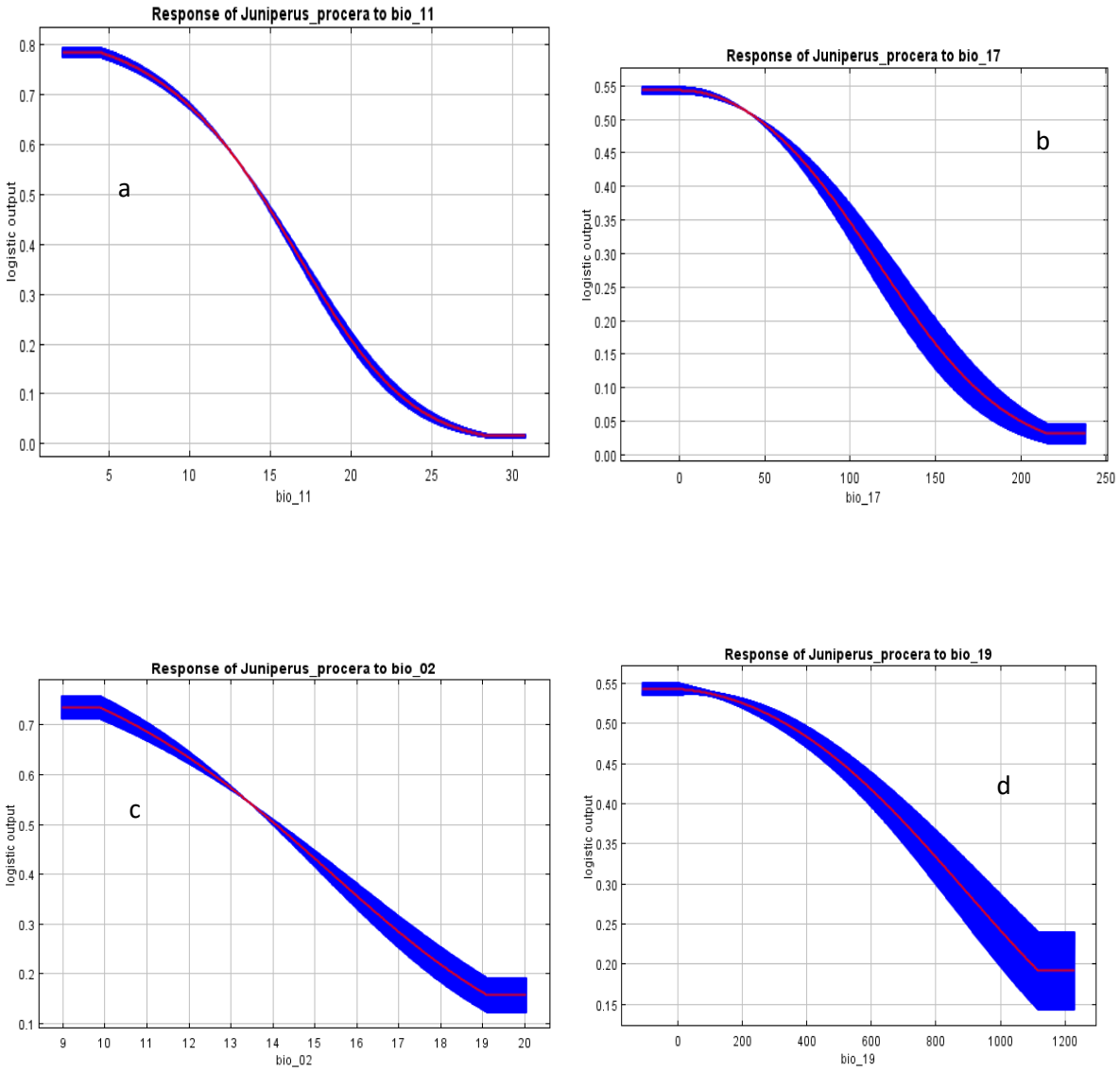

Figure 17, Response curves of four top contributing variables to distribution of *Juniperus procera*, Bio 11, Bio 17, Bio 2 and Bio 19.

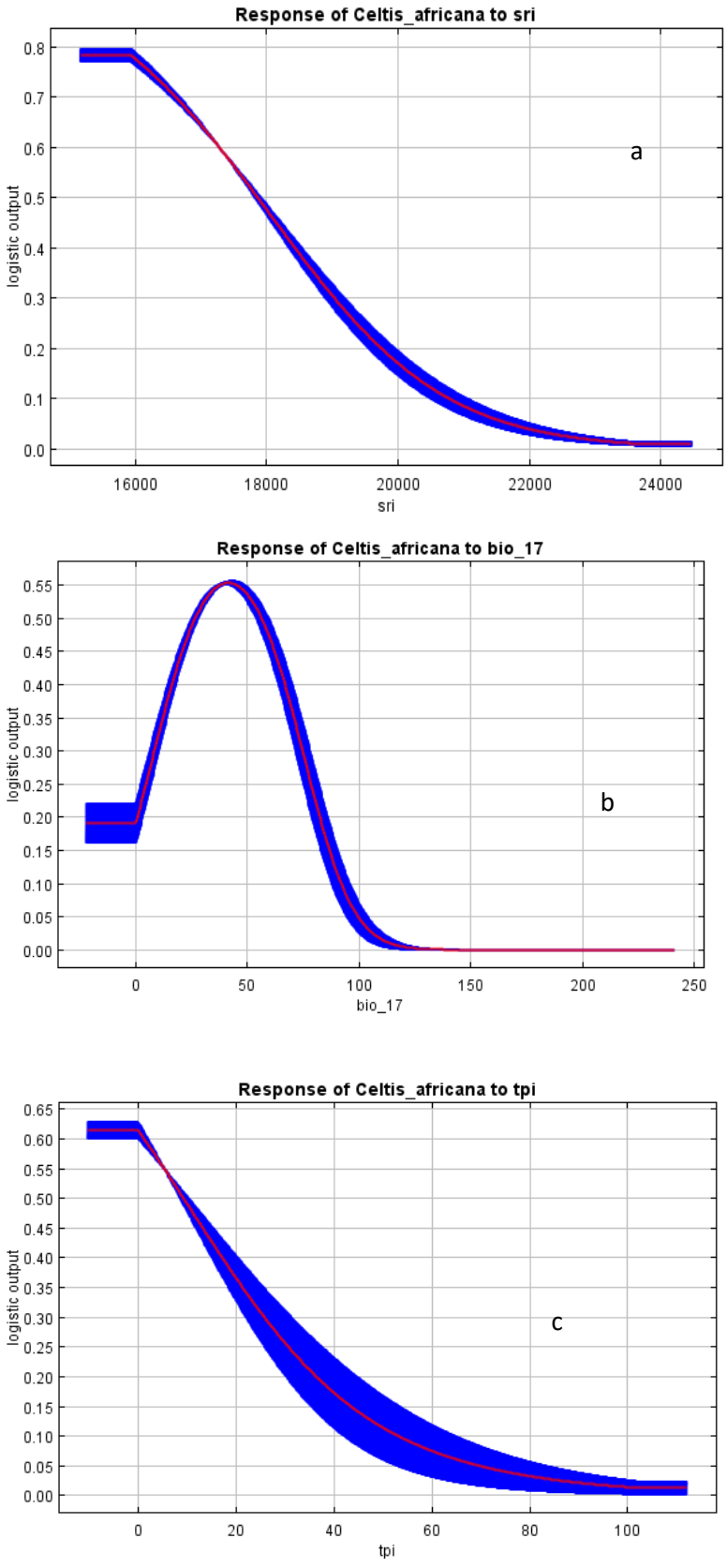

Figure 18: Response curves of three top contributing variables to distribution of *Celtis africana* solar radiation (Sri), Bio 17 and topographic position index (tpi).

The response curves in Fig. 17 and Fig. 18 are indicating the most important environmental variables contributing to the high probability of the occurrence of habitat suitability potentials for *Juniperus procera* and *Celtis africana* in DAF of Ethiopia. .

5 DISCUSSIONS

5.1 Prediction models accuracy

In our study, we used the tools for predicting models of habitat suitability potential for the distribution of *Juniperus procera* and *Celtis africana* under the current and future climate scenarios. The outputs of the models indicated that the omission rates on the training and test samples were close to the value of the predicted omission rates and this indicates that the models for predicting the distribution of suitable habitats for the species were performed better than random (Fig. 4). In our study, values of AUC are almost more than 0.7 for all the current and future climate scenarios indicating that the performance quality of the models are good to predict habitat suitability for the distribution of the two study species (Fig. 6-12).

5.2 Habitat suitability on basis of the study area

In our study, the five habitat suitability potentials for the distribution of *Juniperus procera* and *Celtis africana* are identified to occur on different ranges of scales under the current and future climate scenarios. The variation of their distribution ranges under different climatic conditions can be committed due to the contribution of climate change. Previous studies conducted to predict species distribution models at different areas (Bellard *et al.*, 2012; Barbosa *et al.*, 2013; Remya *et al.*, 2015; Stalin and Swamy, 2015; Chhetri *et al.*, 2018) have explained similar arguments as climate change can affect the prevalence of habitat suitability potentials for the distribution of plant species. The predicted habitat suitability potentials are likely to show a tendency of shifting in spatial and areal range in response to the future climate change for the study species. Species distribution range shift, which is either range expansion or range contraction can be contributed due to the effect of climate change as highlighted in the studies of (Buckley *et al.*, 2010; Shirk *et al.*, 2018). Such changes observed in species distribution ranges under different climatic conditions can be contributed from the variation in the proportion of the environmental factors like temperatures and precipitations, which play the most important roles for plant distribution (Chhetri *et al.*, 2018).

Our study has revealed that Bio 11 (mean temperature of coldest quarter), Bio 17 (precipitation of driest Quarter), Bio 2 (mean Diurnal Range (mean of monthly max temp-min temp)) and Bio 19 (precipitation of coldest Quarter) have important roles in contributing to the distribution of habitat suitability potential for the distribution of *Juniperus procera*. On the other hand solar radiation, Bio 17 (precipitation of driest Quarter) and Tpi have important

role in contributing to the distribution of habitat suitability potential for the distribution of *Celtis africana*.

Based on the results presente, we can see that the highly suitable, suitable and less suitable and unsuitable habitat potentials of *Juniperus procera* constitute 17.28504344, 84.61464487, 291.5782928 and 1802.898562 n/10000 ha is recognized under the current climate condition in the country. Due to the effect of climate change, highly suitable habitat potential for the distribution of the species will show a range contraction from the current status by 18.16 and 18.6% according to RCP 4.5, whereas it was predicted to decline by 12.72% and 17.76% according to RCP 8.5 by 2050 and 2070, respectively. Here, we can understand that the effect of climate change will be more severe to affect the distribution of the species in RCP 4.5 than RCP 8.5. Accordingly RCP 4.5 and 8.5 by 2050 and 2070, the highly suitable habitat for the distribution of *Juniperus procera* will show a considerable spatial range shifting from the north and central areas of DAF ecological regions to its eastern areas due to the impact of climate change.

But, the suitable habitat potential is expected to show a range shrink by 50.15% and 49.63% based on RCP 4.5, and 50.77% and 54.68% according to RCP 8.5, by 2050 and 2070. Whereas, the less suitable habitat class was predicted to increase by 43.62% and 41.29% from its current status, while it will show 61.29% and 30.06% on basis of RCP 8.5. Here, the results of our finding have shown the implication that the impact of climate change can negatively affect the prevalence of highly suitable and suitable habitat in the future, while the less suitable habitat potentials will be favored to show a range expansion under RCP 4.5 and 8.5. Different studies have addressed related arguments as the effect of climate change can affect the distribution of biological species by impacting the range of their habitat distribution potentials (Zhu *et al.*, 2012; Gül *et al.*, 2018; Lim *et al.*, 2018; Wei *et al.*, 2018).

Based the results presented in Table 3, we can see that the highly suitable, suitable less suitable and unsuitable habitat potentials constitute of *Celtis africana* 1.37, 61.322, 362.57 and 1771.112 n/10000 ha under the current climate condition in the country. Due to the effect of climate change, highly suitable habitat potential for the distribution of this species will show a range reduction from the current status by 25.3% and 30.02% according to RCP 4.5, whereas it was predicted to decline by 7.4% and 45.06% according to RCP 8.5 by 2050 and 2070, respectively. Here, we can understand that the effect of climate change will be more severe to affect the distribution of the species in RCP 8.5, 2070 that RCP 4.5 by the years due

to the assumptions that global temperature will be relatively stable in RCP 4.5, while it keeps increasing according to RCP 8.5 (Riahi *et al.*, 2011; Kim *et al.*, 2013; Kwon and Lee, 2015; Skougaard Kaspersen *et al.*, 2017).

But, the suitable habitat potential is expected to show a range expansion by 11.56% and 9.6% based on RCP 4.5, and 9.52% and 8.1% according to RCP 8.5, by 2050 and 2070. In the same way, the less suitable habitat class was predicted to increase by 3.23% and 7.15% from its current status, while it will decrease by 2.81% and 1.43% on basis of RCP 8.5. Here, the results of our finding have shown the implication that the impact of climate change can negatively affect the prevalence of highly suitable habitat in the future, while the suitable and less suitable habitat potentials will be favored to show a range expansion under RCP 4.5, with slightly a decreasing tendency, according to RCP 8.5. Different studies have addressed related arguments as the effect of climate change can affect the distribution of biological species by impacting the range of their habitat distribution potentials (Zhu *et al.*, 2012; Gül *et al.*, 2018; Lim *et al.*, 2018; Wei *et al.*, 2018). Therefore, we can conclude that the area with high probability of occurrence of highly suitable habitat potential for the distribution *Celtis africana* in the future will be around small parts of central region of DAF. However, even though highly suitable habitat potential for the distribution of the two species was predicted to be available out of the species current prevalence areas in the future, the species may not reach and occupy the suitable habitat areas due the limitations like lack of dispersal agents and other land future physical barriers (Bellard *et al.*, 2020).

To conclude the findings of the study, the distribution of *Juniperus procera* and *Celtis africana* will be affected by impacts of climate change in the future. Hence, the species will tend to respond to the impacts by showing spatial and areal range changes in occurrence in the future, according to RCP 4.5 and RCP 8.5 scenarios. However, it is important to suggest that this study is limited to the contribution of the bioclimatic variables, solar radiation and elevation data, and so does not include the contribution of other factors like soils, which can play important roles for the development of plant species.

6 Conclusion and Recommendation

6.1 Conclusions

Climate condition is an important factor to determine the distribution suitable habitats for plant species. Climate condition is determined by environmental factors which in turn can limit a prevalence of suitable habitat for the distribution of the species. Elevation, solar radiation, temperature and precipitation are environmental variables that can play important role to determine species' suitable habitat distribution. However, due to climate change, global temperature and precipitation are expected to change through in the future and hence can affect the distribution of plant species. The challenge can lead into species' suitable habitat expansion or contraction, or even to the extinction of the species at all when the effect exceeds the tolerating capacity of the species.

In our study, we identified highly suitable habitat potential for both species will show a range shifting in both spatial (location) and extent (area) in the future according to RCP 4.5 and 8.5 *Juniperus procera* will continue facing habitat suitability range contraction, from the present climatic condition through the future because of climate change. Its highly suitable habitat potential will show spatial range shifting from the northern, eastern and central parts of the DAF to eastern areas of DAF according to the RCPs scenarios.

Similarly, highly suitable habitat potential for the distribution of *Celtis africana* will shift from the south western and central areas of DAF to the small central regions, according to RCP 4.5 and RCP 8.5 by 2050 and 2070. In addition, our study has identified as habitat suitability potential can shift to some extent from one area category to the other under different climate conditions. However, the species may not occupy and cope up with the future climate condition soon, due to dispersal limitations and seed viability problems, as a result of which human intervention becomes very important to work on conservation aspect of these species.

6.2 Recommendation

- DAF is subjected fire and land use changes and thus it is important to look at these factors and how they affect various DAF species.
- In the future it is essential to investigate current and future distribution of other remaining species all over the DAF and all over the country.
- Governmental and NGO bodies dealing with species conservation should take into account the effect of future climate change on species distribution when planning their work strategies.

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Appendix1:

Layer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Bio1	1.000																					
Bio2	-0.457	1.000																				
Bio3	-0.532	0.403	1.000																			
Bio4	0.413	-0.053	-0.875	1.000																		
Bio5	**0.960**	-0.263	-0.626	0.582	1.000																	
Bio6	**0.961**	-0.632	-0.420	0.231	**0.856**	1.000																
Bio7	-0.049	**0.708**	-0.357	0.632	0.222	-0.314	1.000															
Bio8	**0.971**	-0.506	-0.561	0.408	**0.930**	**0.945**	-0.075	1.000														
Bio9	**0.970**	-0.476	-0.461	0.341	**0.907**	**0.948**	-0.123	**0.914**	1.000													
Bio10	**0.986**	-0.419	-0.629	0.553	**0.979**	**0.918**	0.066	**0.952**	**0.950**	1.000												
Bio11	**0.984**	-0.465	-0.392	0.254	**0.912**	**0.976**	-0.167	**0.947**	**0.970**	**0.946**	1.000											
Bio12	-0.632	0.365	0.384	-0.209	-0.608	-0.632	0.077	-0.724	-0.521	-0.595	-0.613	1.000										
Bio13	-0.617	0.460	0.343	-0.105	-0.553	-0.644	0.198	-0.712	-0.550	-0.556	-0.606	**0.858**	1.000									
Bio14	-0.329	0.108	0.293	-0.257	-0.359	-0.294	-0.105	-0.335	-0.236	-0.344	-0.305	0.570	0.212	1.000								
Bio15	0.168	0.036	0.087	-0.046	0.163	0.182	-0.043	0.153	0.103	0.158	0.206	-0.312	0.120	-0.673	1.000							
Bio16	-0.600	0.442	0.313	-0.081	-0.539	-0.633	0.204	-0.706	-0.520	-0.537	-0.594	**0.913**	**0.984**	0.264	0.010	1.000						
Bio17	-0.369	0.136	0.294	-0.265	-0.390	-0.339	-0.077	-0.367	-0.277	-0.384	-0.348	0.567	0.176	**0.974**	-0.751	0.236	1.000					
Bio18	-0.545	0.288	0.409	-0.385	-0.535	-0.514	-0.013	-0.492	-0.534	-0.575	-0.516	0.441	0.234	0.470	-0.353	0.255	0.524	1.000				
Bio19	-0.317	0.222	0.189	-0.025	-0.306	-0.341	0.082	-0.452	-0.195	-0.273	-0.310	**0.779**	**0.722**	0.300	-0.095	**0.783**	0.262	0.120	1.000			
elev.	-0.968	0.537	0.456	-0.286	-0.890	-0.968	0.191	-0.944	-0.950	-0.935	-0.973	0.611	0.638	0.301	-0.144	0.617	0.337	0.493	0.333	1.000		
sri	0.580	-0.196	-0.230	0.107	0.570	0.567	-0.022	0.645	0.486	0.531	0.584	-0.811	-0.652	-0.516	0.470	-0.708	-0.526	-0.337	-0.609	-0.552	1.000	
tpi	-0.381	0.220	0.111	-0.003	-0.331	-0.396	0.137	-0.400	-0.352	-0.341	-0.394	0.331	0.360	0.212	-0.061	0.346	0.217	0.174	0.235	0.424	-0.264	1.000

Correlation matrix among 19 current bioclimatic variables, elevation, solar radiation and topographic position indices using SDM_v2.4_AcrMap 10.5.

* elev: elevation, sri: solar radiation index, tpi: topographic position index, bolded numbers indicate variables are highly correlated ($r \geq$ **0.7**).