Spatiotemporal dynamics of habitat suitability for the Ethiopian staple crop, *Eragrostis tef* (teff), under changing climate

Dinka Zewudie [a], Wenguang Ding [a*], Zhanlei Rong [b], Chuanyan Zhao [c] Yapeng Chang [c]

[a] College of Earth and Environmental Sciences, Lanzhou University, Lanzhou 730000, China
[b] College of Geographical Science, Qinghai Normal University, Xining 810008, China
[c] State Key Laboratory of Grassland Agro-ecosystems, College of Pastoral Agriculture Science and Technology, Lanzhou University, Lanzhou 730000, China

⬜ Wenguang Ding (Corresponding author),
wgding@lzu.edu.com

Abstract

Teff (*Eragrostis tef* (Zucc.) Trotter) is a staple, ancient food crop in Ethiopia. Its growth is affected by climate change, so it is essential to understand climatic effects on its habitat suitability in order to design countermeasures to ensure food security. Based on the four Representative Concentration Pathway emission scenarios (i.e. RCP2.6, RCP4.5, RCP6.0 and RCP8.5) set by the Intergovernmental Panel on Climate Change (IPCC), we predicted the potential distribution of teff under current and future scenarios using a maximum entropy model (Maxent). Eleven variables were selected out of 19, according to correlation analysis combined with their contribution rates to the distribution. Simulated accuracy results validated by the area under the curve (AUC) had strong predictability with values of 0.83-0.85 for current and RCP scenarios. Our results demonstrated that mean temperature in the coldest season, precipitation seasonality, precipitation in the cold season and slope are the dominant factors driving potential teff distribution. Proportions of suitable teff area, relative to the total study area were 58% in current climate condition, 58.8% in RCP2.6, 57.6% in RCP4.5, 59.2% in RCP6.0, and 57.4% in RCP8.5, respectively. We found

28   that warmer conditions are correlated with decreased land suitability. As expected, bioclimatic

29   variables related to temperature and precipitation were the best predictors for teff suitability.

30   Additionally, there were geographic shifts in land suitability, which need to be accounted for when

31   assessing overall susceptibility to climate change. The ability to adapt to climate change will be

32   critical for Ethiopia's agricultural strategy and food security. A robust climate model is necessary

33   for developing primary adaptive strategies and policy to minimize the harmful impact of climate

34   change on teff.

36   **Keywords: climate change, Ethiopia, Maxent, potential distribution, *Eragrostis tef***

1. Introduction

Climate is the key controlling factor in the distribution of species, and variations in habitat distribution patterns can be attributed to climate change (Parmesan & Yohe, 2003; Lenoir et al., 2008; Bertrand et al., 2011; Guo et al. 2016). The global average surface temperature has caused warming of 0.8 °C over the past century (Hansen et al. 2006; Yumbya et al. 2014), and is accelerating, with a 0.6°C increase in the last four decades (Hansen et al. 2010; Suwannatrai et al. 2017). International Panel on Climate Change (IPCC, 2007) reports that over the course of this century, net carbon uptake by the terrestrial ecosystem made a peak mid-century and then weakened or even reversed the increase on climate change. Global average temperature increases exceeding the 1.5–2.5 °C range and the concomitant CO_2 concentration, is projected to trigger major changes in the ecosystem structure and function, alter species ecological interactions and produce shifts in species' geographical ranges with predominantly negative consequences for biodiversity and ecosystem goods and services, e.g. water and food supply (Kumar 2012; Liao & Chang 2014; Pachauri et al. 2014). Evidence suggests that a significant impact of global warming is already discernible in animal and plant populations (Root et al. 2003).

Temperature in Africa is expected to increase faster than the global average throughout the 21st century (Christensen et al., 2007; Joshi et al., 2011; James and Washington, 2013). However, future values for Africa estimated by the International Panel on Climate Change (IPCC 2007) are relatively uncertain (Solomon et al. 2007). In particular, Ethiopia is predicted to be highly vulnerable to climate change, manifesting an increased warming accompanied by inconsistent rainfall leading to decreased crop security (Conway & Schipper 2011).

Climate change may increase the risk for food production in many African countries as their agricultural systems are mostly rain-fed. These impacts on livelihood, will undoubtedly mean that

62 countries will have to change their farming policies (Dinar 2007). In Ethiopia, agriculture plays a

63 crucial role in enhancing economic growth and contributes up to half of the Gross Domestic

64 Product (GDP) (Gebrehiwot & Van Der Veen 2013). Despite being one of the largest cereal

65 producers in East Africa, the country is still not self-sufficient; 85% of Ethiopians live in agrarian

66 areas relying on agricultural production as means of living (Gebrehiwot & Van Der Veen 2013).

67 Moreover, many rural Ethiopians face long or short seasonal droughts, leading to crop failure

68 (Tefera & Quintin 2012; Kamali et al. 2018). "Green famines" are caused in Ethiopia by a seasonal

69 pattern shift with delayed rains for several weeks or starting and stopping suddenly in critical

70 germination periods. Consequently, crops are lost while the natural vegetation is able to resume

71 normal phenological cycles, thus providing a green landscape (Evangelista et al. 2013). Changing

72 patterns of drought and precipitation in Ethiopia have already been documented by other

73 researchers, and greater changes are expected under future conditions (Deressa & Hassan 2009;

74 Viste et al. 2013). Cereal crops face an especially critical threat due to climate change (Ledig et

75 al. 2010), affecting human populations that rely on only a few edible species for nutrition and

76 sustenance out of more than 50,000 known edible species available worldwide (Cheng et al. 2017).

77 Teff (*Eragrostis tef* (Zucc.) Trotter), is an ancient and major staple food crop in Ethiopia,

78 accounting for the largest share of land cultivation for cereal crops, 24% nationwide (Taffesse et

79 al. 2012), showing a wide geographic condition and marked plasticity by growing in 10 to 18 agro

80 ecological zones (Assefa et al., 2001). Teff is a warm-season annual crop that produces very small

81 grains and is also gluten-free and high in iron (Figure 1A) (Rosell et al. 2014). Teff contains a

82 huge amount of nutrients, and moreover is tolerant of extremes such as drought, Water logging,

83 pests, and diseases (Cheng et al. 2017).

84   Teff crops occupy nearly 30,000 km^2 (CSA 2014) about 30% of the total area covered by cereals

85   in all administrative regions, predominantly on the highlands of Tigray, Amhara, Oromia, and

86   SNNPR regions (Wondimu and Tekabe 2001). Teff growth has been reported at altitudes up to

87   3000 m.a.s.l. ranging from semiarid areas with low rainfall to areas with high rainfall. Under

88   current conditions, teff is suitable in most areas of the country covering diverse agro ecological

89   regions where millions of people rely on it as a daily food--indeed, nearly 60% of the Ethiopian

90   population.

91   However, due to climate change, it is one of the most vulnerable crops in the region (Evangelista

92   et al. 2013). It is estimated that enjera, made from teff, provides up to two-thirds of the food

93   consumed by Ethiopians (Figure 1B) (Cheng et al. 2017; VanBuren et al. 2020). Therefore,

94   predicting potential teff distribution is necessary to take safe and effective countermeasures to

95   reduce its ecological risk under climate change (Kamilar et al. 2013).

96   Maxent is an ecological tool and statistical model used to examine ecological processes and

97   interactions across spatial and temporal scales (Elith et al. 2006; Phillips et al. 2006) that has been

98   employed to explore a range of species, habitats and ecosystem conditions (Alberto et al.

99   2013;Brown et al., 2014; Beltramino et al. 2015). Species distribution models (SDMs) are a subset

100 of the approaches outlined and were developed by combining current and historical species

101 distribution data with relevant environmental variables to explain both occurrence and abundance

102 of organisms in ecosystems (Peterson et al., 2006; Zimmermann et al., 2010; Caminade et al.,

103 2012; Kamilar et al. 2013;Guo et al. 2017b). A variety of SDMs have been developed to predict

104 species distributions under different climate scenarios (e.g. RCP). Commonly used SDM models

105 including the Genetic Algorithm for Rule-set Production (GARP), BIOCLIM and Ecological

106 Niche Factor Analysis (ENFA) have proved to be essential for predicting target species

107 distributions under current, and also future climate scenarios (Rong et al. 2019; Tognelli et al.

108 2009). Maxent (maximum entropy) has been widely used due to its many advantages, including

109 its ability to: deal with incomplete data, small sample size, species presence data, both continuous

110 and categorical environmental data; reduce laborious jobs in data collection; facilitate model

111 interpretation, and for its prediction accuracy and reliability (Guo et al. 2017a; Rong et al. 2019).

112 SDMs assume that available presence locations represent a random (representative) sample in the

113 geographical space, with no spatial dependencies and bolstered by data-rich technologies, such as

114 geographical information systems (GIS) (Rushton et al. 2004, Elith et al. 2011).

115 Teff had been an important crop in the past and will continue to be a staple food for the majority

116 of the Ethiopian people in the future. Being a major staple crop, teff is an essential food in Ethiopia,

117 so any impact on suitable areas for its cultivation due to climate change will have a direct impact

118 on food security. Unfortunately, there is already a huge deficit between teff production and the

119 national demand, which will be exacerbated by the effects of climate change. Therefore, as long

120 as teff production decreases against a rising demand due to Ethiopia's fast-growing population,

121 the teff price will increase. As cultural food insecurity remains widespread in Ethiopia, policy

122 makers should pay attention to areas with low habitat suitability and resilience for teff. It is

123 important to maintain nutrition and sustainable food security for the Ethiopian people with the

124 implementation of a strategy to foster diversification and avoid over reliance on this crop.

125 In a climate change context, understanding and planning for crop resilience is crucial for protection

126 of global food supplies, and therefore research on key crops is needed for decision makers to plan

127 and strategize future actions (Cowie et al. 2018). In line with this, the major objectives of this study

128 are to: (1) predict the potential distribution of teff species under current climates; (2) forecast

129 suitable areas for teff species under four future climate scenarios, and (3) evaluate the effects of

130   climate change on teff distribution. Identifying shifts in the ranges of suitable areas under future

131   scenarios is a novel approach in the study and we also shown the full workflow on which every

132   step of analyses of our work is delineated in Figure 2.

133
Figure 1. A. Teff (*Eragrostis tef)*, a fine-grain annual cereal. (Source: FAO
http://www.fao.org/traditional-crops/teff/en/); B. Teff-made enjera is a staple food product in
134 Ethiopia.

135
Figure 2 The workflow shows that data sets of two topographic data and Climatic Variables (Bio1-
136 Bio19) for multicollinearity test and Variables importance with Species occurrence presence only
data with MAXENT and then Teff distribution prediction based on multiple climate conditions
scenarios.

137

2. Materials and Methods

139   In this study, we analyzed the geographic distribution of *Eragrostis tef* occurrence from Ethiopian

140   Biodiversity Institute (EBI) (https://www.ebi.gov.et/) and Ethiopian National Herbarium, Addis

141   Ababa University with Maxent climate envelope model (CEM) under four climate change

142   scenarios.

143

2.1 Study Area

145   Ethiopia lies in northeast Africa, and is located between latitude 3.30°–15°N and longitude 33°–

146   48°E covering 1.13×10^6 km² with heterogenous landscapes including mountains, hills, and flat

147   regions with elevations from below sea level to more than 4,000 m.a.s.l. (Tilahun & Schmidt 2012)

148   (Figure 3). Due to this varied relief, Ethiopia has a variety of climates going from desert climate

149   to that typical of equatorial mountains (tropical) with three major climatological seasons: June–

150   September (called Kiremt), October–January (Bega), and February–May (Belg) (Gissila et al.

151   2004; Korecha & Barnston 2007; Fazzini et al. 2015). Annual average temperature ranges from 10

152 to 27°C and precipitations vary across the country and season from 145 to 2,100 mm annually

153 (Hordofa et al. 2008; Fazzini et al. 2015).

154

Figure 3 Locations of sampling sites and land elevation within the nine Ethiopian regional state administrations: Oromia, Amhara, Tigray, Afar, Benishangul-Gamuz, Gambella, Harari,

155 Southern Region, and Somali Region.

156 **2.2 Crop production in Ethiopia**

157 Though agricultural planning is difficult due to variable rainfall, a large proportion of Ethiopia

158 receives sufficient rain for crop production, that is mostly sown from June to October and harvested

159 from September to February (Taffesse et al. 2012). The primary crop season corresponds to the

160 summer rainy season, from June to August and in the autumn from September to November

161 (Yumbya et al. 2014). Light rains also fall during spring, from March through May. Some crops -

162 only about 8% of total crop land- are harvested between March and August, making Ethiopia's

163 crop season somewhat bimodal (Hordofa et al. 2008; Taffesse et al. 2012). Teff grows primarily

164 in the highlands where clouds are forced to release rain. The optimal growing conditions for teff

165 are 430–560 mm of rain per year and a temperature range of 10–30°C (Roseberg et al. 2005).

166 **2.3 Teff Distribution Data**

167 The distribution dataset contains 2490 verified, geo-referenced data-points (latitude, longitude and

168 altitude) belonging to germplasm collections and herbarium specimens from the gene bank of the

169 Institute of Biodiversity Conservation, and 14 specimens from the Ethiopian National Herbarium,

170 Addis Ababa University, collected between 1978 and 2019. Teff was present in all sites over the

171 nine Ethiopian regional state administrations, predominantly in the Oromia, Amhara, Tigray, the

172   Southern Nations, and Harari regions, with only a few locations in Gambela, Beninshangul-

173   Gumuz, and the Somali Region, and had no significant presence in Afar.

174   **2.4 Topographical data**

175   The Digital Elevation Model (DEM) with a 90-meter special resolution was acquired from the

176   USGS Shuttle Radar Topography Mission dataset (www.srtm.usgs.gov). Two terrain variables

177   (aspect and slope) from the DEM were re-sampled into 1 km spatial resolution using neighbor

178   sampling in ArcGIS 10.5. The two topographical variables were used as model inputs.

179   **2.5 Current and future climate data**

180   Climatic data consisting of 19 bioclimatic variables, here coded Bio1 through Bio19, were

181   obtained from the WorldClim (http://www.worldclim.org/) at 30″ resolution (1 km × 1 km) for the

182   climate from 1950 to 2000 in the study area (Fick & Hijmans 2017). The dataset comprises global

183   gridded information with 1 km spatial resolution on past, current, and future scenarios

184   (http://www.worldclim.org/).

185   Future climate data is based on the standard scenarios of the Fifth Assessment Report from the

186   IPCC (IPCC 2013). All four greenhouse gas concentration trajectories provided by the IPCC were

187   used, Representative Concentration Pathway (RCP): RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.0. In

188   2100, the total radiative forcing values in the four scenarios stated would have attained 2.6W/m2

189   ,4.5 W/m2, 6.0 W/m2, and 8.5 W/m2 over the value in the preindustrial period (Taylor et al. 2012,

190   Rogelj et al. 2012, Stocker et al. 2013). The data used was produced by interpolation of data

191   predictions for 2060 and 2080 to produce an estimate of climate condition for the year 2070.

192   Cross correlation among 19 bioclimatic variables and two independent variables was checked to

193   avoid the presence of redundant variables in the model. The input rate of the variables was

194 calculated by Jackknife test of Maxent model, and IBM-SPSS statistical software (Statistical

195 Product and Service Solutions, Version 20.0, SPSS Inc., Chicago, IL, USA) was used for Pearson's

196 correlation. From each highly correlated pair of variables, one variable was removed (> |0.8|) and

197 the ones with high contribution rate were chosen (Liu et al. 2005).

2.6 Climatic niche Modeling

199 We   used   Maxent   Version   3.4.1

200 (https://www.biodiversityinformatics.amnh.org/open_source/Maxent, (Phillips et al. 2006)) to

201 predict the current and future potential distribution of teff. Species distribution point data was

202 stored in csv file format and included coordinate data such as name, latitude and longitude of the

203 species. ArcGIS 10.5 converted all environmental variables to ASCII raster grids and species

204 presence coordinates to decimal degrees. Certain settings (500 iterations, 0.00001 convergence

205 requirement, 10,000 peak context points) were kept by default. The software ran with 75% of

206 presence locations and tested the efficiency of the model with the remaining 25% of the presence

207 points (Phillips et al. 2006, Phillips & Dudík 2008). In Phillips et al. (2006), a detailed

208 mathematical description of Maxent was mentioned.

209 A continuous probabilistic layer ranging from 0 to 1 is the output of the model. Higher-value areas

210 indicate more desirable conditions for growth of species (Phillips et al. 2006). For each case, we

211 selected the minimum performance by training presence (MTP) as a threshold or "cut-off" value

212 (Hijmans & Graham 2006). The MTP can be interpreted ecologically to include those cells that

213 are expected to be at least as sufficient as those where the species has been defined as present. We

214 have categorized four habitat suitability groups, unsuitable, low suitability, moderate suitability,

215 and high suitability by Spatial Analyst tool in ArcMap 10.5, so as to measure the niche centroid

216 from present to future climate change scenarios.

217 There are two ratification processes in the Maxent model: area under the curve (AUC) and

218 Jackknife. Area Under the Curve (AUC) of Receiver Operating Characteristic (ROC) curves was

219 used to verify the suitability of teff estimated by the model. The AUC represents the probability

220 that a randomly chosen teff occurrence exceeds that of randomly choosing an absence. The AUC

221 values lie between 0.5 and 1.0 (perfect prediction), and can be divided into five categories:

222 outstanding (>0.9), good (0.8 − 0.9), approved (0.7 − 0.8), poor (0.6 − 0.7) and invalid (<0.6) (Elith

223 2006, Suwannatrai et al. 2017).

224 Jackknife is part of Maxent model and it is calibrated with all permutations of the groups using

225 occurrence points and background data from k−1 spatial groups and then evaluated with the

226 withheld and alternate estimates of which variables are most important in the model (Hu et al.

227 2011). Variables that significantly affected the model were identified and chosen based on percent

228 contribution to the model.

229

230 **3. Results**

231 **3.1 Variable Contribution Analysis**

232 After testing for independence between climatic variables, the ones with low predictive power or

233 high similarities to other variables in prediction were identified. Eleven variables (11) were

234 selected for the model according to the contribution rate of each variable (Table 1). The potential

235 teff distribution under current projected climate change was mostly affected by the mean

236 temperature of the coldest season (Bio11 78.3%) and precipitation seasonality (Bio15 8.3%)

237 (Table 1). The potential teff distribution under the RCP scenarios was also influenced mainly by

238 Bio11 (77.8%-80.4%), Bio15 (7.3%-9.04%). The Pearson's correlation coefficients are included

239 in the supplementary material (Table S1).

240

> **Table 1.** Percent contributions of the climate variables for teff distribution in the MaxEnt model.

241

242

243   The jackknife test indicated that the bioclimatic variables Bio11, Bio14, Bio19, and Bio4 provided

244   huge gains when they were used independently to estimate potential teff distribution under current

245   conditions and under RCP scenarios 2.6 to 6.0 (Figure 4). The potential distribution of the species

246   under the RCP8.5 scenario was most strongly associated with Bio11 (gain, 0.59), Bio2 (gain, 0.12),

247   Bio19 (gain, 0.15) and Bio4 (gain, 0.13), respectively (Figure 4E).

248
> Figure 4 Jackknife test variable contributions to the potential distribution of teff distribution under:
249 (A) current climate condition scenario, (B) RCP 2.6 scenario, (C) RCP 4.5 scenario, (D) RCP 6.0
> scenario, and (E) RCP 8.5 scenario. The regularized training gain describes how much better the
250 simulated distribution fits the present data compared to a uniform distribution. The dark blue bars
> indicate the gain from using each variable in isolation, the light blue bars indicate the gain lost by
251 removing the single variable from the full model, and the red bar indicates the gain using all the
252 variables.
253

254

255

256   The response curves indicate the relationship between environmental variables and habitat

257   suitability and can provide information on teff ecological niche. The ranges of suitability for

258   environmental variables were identified by the threshold of normal suitable habitats. The response

259   curves of 8 variables of teff habitat suitability are illustrated in Figure 5, as is the suitable range

260   for each variable. The highest suitability areas for teff have a mean temperature of the coldest

261   season (Bio11) between 14-19 ∘C, an annual precipitation seasonality (Bio15) between 60% to

262   122%, precipitation of the coldest season (Bio19) between 8.5-110 mm, a slope between 0 to 3∘, a

263   temperature annual range (Bio7, Bio5-Bio6) from 11.8 to 26.6 ℃, a temperature seasonality

264   (standard deviation ×100, Bio4) from 1000-1550, precipitation of the driest period (Bio14) from

265   0.3 mm to 20 mm, an isothermality (Bio3) above 68 and an aspect from 355°to 0° (Figure 5).

266   Figure 5 Response curves of 8 environmental variables in the teff habitat distribution model.
267   A:Bio11(Mean temperature of coldest season (°C*10)); B: Bio15(Precipitation seasonality
268   (CV)); C: Bio7(Temperature annual range (Bio5–Bio6));D: Bio19(Precipitation of coldest season
269   (mm*10)); E:Bio14(Precipitation of driest period (mm*10)); F:Bio3(Isothermality
       (Bio2/Bio7×100));G:Bio4 (Temperature seasonality (standard deviation×100) (°C*10));H(Slope
270

271   **3.2 Performance and accuracy of the Maxent Model**

272   Of the climatic variables, mean temperature of the coldest quarter played the greatest role in the

273   model in both percent contribution and permutation importance, which reflects the effect of a

274   variable determined by impact to the model when the variable is absent (Table 2). However, in the

275   variable analysis, mean temperature of the coldest quarter was not independent of mean

276   temperature of the warmest quarter, or mean temperature of the driest quarter. Therefore,

277   temperature generally had the greatest effect, especially during the growing season, which would

278   logically be the highest for teff.

279   AUC values were above 0.829 under current and four projected climate scenarios (Table 3).

280   According to the performance classification standard, prediction accuracy was very good, as AUC

281   for training and testing were 0.84 and 0.83, respectively.

282   **Table 2.** Estimates of relative contributions and permutation importance of the predictor
283   environmental variables to the Maxent model.

284
285   **Table 3.** Results of receiver operating characteristic (ROC) analysis under current climate and four
286   future projected scenarios.
287
288

289 **3.3. Predicted distribution of teff under current climate condition and future scenarios**

290 The model showed that teff has a climatically suitable area of minimum annual precipitation

291 between 550 and 1770 mm. The minimum mean temperature is expected to be 14.9 ℃ with

292 maximum values of 26.75 ℃ in Ethiopia. The model showed that under such temperature

293 conditions, suitable distribution classes under the current and future scenarios showed that the

294 warmer the climate condition, there will be a greater shift from high-level to low-level suitability.

295 The distribution classes under current and future scenarios show that teff in Ethiopia is highly

296 suitable in the central region of the country. Areas with higher temperature that do not correlate

297 with suitable teff habitat lie on the eastern side of highlands and those that do not correlate with

298 higher temperature lie in the western lowlands (Figure 6).

299 Generally, teff simulated distribution includes the west part of Ethiopia in current and future

300 climate condition (Fig.7). The high suitable area lies in the northwest part of the country, related

301 to low temperature and high precipitation (Fig.6). There is no distribution of teff in the eastern part

302 of Ethiopia related to low altitude, high temperature and low precipitation (Fig.6).

303
304 Figure 6 Average annual rainfall (A) and average annual temperature (B) in Ethiopia over three decades.

305 **3.4. Teff Habitat Suitability under current and future scenarios**

306 Under current climate, the distribution area with low suitability summed up 463,453 km^2, moderate

307 suitability 296,933 km^2, and with high suitability, 14,513 km^2, giving a total suitable area of 58%

308 of our research area. Considering the four projection scenarios, the total suitable area declined with

309 climate warming in RCP 4.5 (770,139 km^2) and RCP 8.5 (767,554 km^2) while in other scenarios

310 suitable area increased (Table 4, Figure 7). A difference was found between the current suitable

311 area and the predicted habitat in RCP 2.6 and 6.0 (Figure 7). In particular, the area of suitable teff

312   habitat increased in both RCP 2.6 and 6.0 while it decreased in RCP 4.5 (-4760 km^2) and RCP 8.5

313   (-7345 km^2) (Table 4).

314

> Figure 7 Distribution of unsuitable, and low, moderate, and highly suitable teff habitats
> based on current and future distribution under four climate scenarios (Note: A: current;
> B: RCP 2.6; C: RCP4.5; D: RCP6.0; E: RCP8.5)

315

316

317

318   Suitable habitat including moderately and highly suitable areas remained roughly the same in each

319   future scenario (from 0.042 to 0.052 for RCP2.6 and 8.5 respectively). Taking the ratio of

320   moderately suitable habitat to low suitable habitat, the largest projected deviation was under the

321   RCP 4.5 scenario (ratio=0.74 vs. 0.64-0.67 for the other RCPs), resulting in a relative decrease of

322   low suitable area and an increase of moderate suitability. In the other scenarios, the model

323   predicted a slight increase of highly suitable and a decrease of moderately suitable area (Table 4).

324

> Table 4. Total area of suitable and unsuitable teff habitats based on current distribution data
> and projected four future climate scenarios.

325

326

327

328   Unsuitable area in the future decreases in RCP 2.6 and RCP 6.0 compared to the current situation

329   while it increases in RCP4.5 and RCP 8.5. Also, low suitability areas decrease in RCP 2.6, RCP

330   4.5 and RCP 8.5 while increasing in the RCP 6.0 scenario. Moderate suitability areas increase in

331   RCP 2.6, RCP 4.5 and RCP 6.0 but decline in RCP 8.5. Again, high suitability areas compared

332   with the current situation increase in area in RCP 4.5, RCP 6.0 and RCP 8.5 but not in the RCP

333   2.6 scenario (Table 4).

334   On the regional scale, the largest projected shifts in habitat suitability occur in the northwest region

335   of the country under the most extreme radiative forcing case of RCP 8.5, where a patch of currently

336   unsuitable area becomes moderately suitable (Figure 7). Despite this single projected increase in

337   area, overall, suitable land area is expected to decrease under RCP 4.5 and RCP 8.5, including a

338   decrease in total moderately suitable land. The result of a shift in suitable land towards the west

339   and away from the east contrasts with the path of rainclouds traveling from west to east.

340

341   **4. Discussion**

342   Ultimately, several studies and our own research results show it is necessary to assess the impact

343   of climate change on teff distribution and take it into account in adaptive management policies in

344   order to minimize the impact of climate change.

345   Recent research findings indicate that most updated climate projections of GCM (global climate

346   model) used in the IPCC Fifth Assessment Report were used to forecast the effect of climate

347   change on teff that was used for crop suitability (Alemayehu et al 2020). The distribution of plants

348   would be significantly affected by climate change according to the findings of several researchers.

349   For example: McSweeney et al., 2010a and Niang et al.,2014, reported that increased temperature

350   and precipitation was projected in East Africa. This had an impact by decreasing the yield of many

351   cereals by shortening the growing season length, amplifying water stress and increasing incidence

352   of weed outbreak and diseases. As (Prasad et al., 2008; Nelson et al., 2009 and Thornton et al.,

353   2009) indicated that for high altitude regions in Ethiopia, such as mountainous land where

354   temperature is the limiting factor for plant growth, a rise in temperature will possibly increase crop

355   yield, but that in lowland areas, it will increase the risk of water stress. They also indicated that

356   precipitation variability due to various effects of climate change, and the resulting heat and water

357   stress, are considered the most important factors. (Elith and Graham,2009) also reported that there

358   is always uncertainty about selecting the best fit methods to model species distributions, as

359   different models and methods change the result of the predictions under different scenarios due to

360   various mechanisms. While there remains considerable uncertainty as to the extent and pace of

361   global warming trends and their impact on plant species, preceding researchers have pointed out

362   that climate change has a significant impact on the distributions of the different species by causing

363   shifts, even contractions in species ranges, and change of terrestrial ecosystems function (Barbet

364   et al., 2012; Li et al.,2015 and Petitpierre et al.,2016). Considerable effort was made to expand the

365   collection and increase the number of species studied. Due to limiting factors, such as climatic and

366   environmental conditions, difficulty accessing some of the data and time constraints during

367   occurrence sampling, some locations that were unreachable may have been overlooked. This

368   shortcoming is believed to have slightly affected our results; hence, future studies should more

369   comprehensively focus on the climate factor and other variables such as soil organic carbon, clay,

370   bulk density (BD), Elevation, and pH. In future research, we should consider these methods to

371   improve the accuracy of the predictors.

372   Ethiopia is predicted to be highly vulnerable to climate change, manifesting an increased warming

373   accompanied by inconsistent rainfall (Conway & Schipper 2011). In that direction, potential teff

374   distribution under current conditions and projected climate change scenarios was mostly affected

375   by the temperature and precipitation. Evangelista et al. (2013) found that teff distribution depended

376   most on precipitation variables, especially precipitation of the wettest quarter. However, we have

377   found that the potential teff distribution was mostly affected by mean temperature of coldest

378   quarter (Bio11), precipitation seasonality (Bio15) and precipitation of coldest quarter (Bio19).

379   As reported by Tan et al 2016, due to increasing temperature and varying rainfall the areas suitable

380   for cultivating teff will become centralized to the plateau of Ethiopia in the future. Yet, (Gregory

381   et al., 2005, Turner and Rao, 2013) suggest that for most of the crops, including teff, suitability

382   decreased due to the warming trend of climate change. Furthermore, Thornton et al., 2009 state

383   that if temperature increases above the level suitable for a crop then it will lead to the death of that

384   crop. Teff is known to be a primary cereal, which is less tolerant of cold (Chamberlin and Schmidt,

385   2012; Yumbya et al.,2014, Sen et al.,2016). Though our model share some common data and

386   methods with preceding studies, it has arrived at different findings because it uses a wider range

387   of data and environmental variables than those earlier studies. Existing research of different

388   regions has reported variables found to have an important effect on various species. For example:

389   Evangelista et al., 2013 Studied teff by using three climate projection model that the value of

390   predictable were 0.79 (Bio16, Bio12,Bio19,Bio15) and others studied different species in different

391   geographical area including ,Elham et al.,2015 (Bio2, Bio3, Bio7, Bio8, Bio13, Bio14, Bio15,

392   Bio18), Ardestani et al.,2015 (Bio8, Bio19 ,Bio2 ,Bio13 ,Bio7), Sen et.,2016 (Bio4 and Bio19),

393   Rong et.,2019 (Bio1, Bio8 and elevation), Abdelaal et al.,2020 (elevation, precipitation,

394   temperature and soil), and Yang et.,2020 (Temp Seasonality, Precipitation, Vegetation Type, Soil

395   Type). Our results indicate that temperature of coldest quarter had a predictability value of 0.83

396   for teff, which is stronger than that of any other existing model. Mean temperature of coldest

397   quarter (Bio11), Precipitation seasonality (Bio15), Precipitation of coldest quarter (Bio19), Slope,

398   and Temperature annual range (Bio7) were the variables with the greatest effect on teff

399   distribution.

400   Our result indicates that the suitable and unsuitable area somehow varies, increasing and

401   decreasing under four climate change scenarios (i.e., RCP2.6, RCP4.5, RCP6.0 and RCP8.5).

402   Comparing unsuitable area in current condition with that in scenario RCP 2.6 and RCP 6.0,

403   unsuitable area decreased by 11058 and 16186 km^2 respectively. Also, the RCP 4.5, RCP 8.5

404   decreased by 4760, and 7345 km^2 respectively. Suitability area decreased comparing the current

405   condition with RCP 8.5, suitability area increased comparing RCP 8.5 with the other three

406   scenarios due to different climate changes under four scenarios. Future climate change scenarios

407   RCP 2.6 and RCP 6.0 provided the most favorable outcomes in terms of loss of suitable teff habitat.

408   However, RCP 2.6 resulted in a greater loss of high suitable habitat, whereas projections from

409   RCP 6.0 show the highest preservation of total potential crop area. Surprisingly, projected loss of

410   suitable habitat did not correlate with increasing projected radiative forcing. Alemayehu et al

411   (2018), in relation to future climate change from 2050-2070s, indicated that generally suitable area

412   for teff under climate change scenarios will suffer a slight increase in almost all administrative

413   regions of Ethiopia. This increase in suitability will transform marginalized currently unsuitable

414   areas to suitable area for teff under climate change scenarios. An example of these areas are Afar

415   and Somali regional states which have low precipitation and high temperature conditions, and are

416   predicted to have increased precipitation and higher temperatures. In contrast with our results in

417   the four scenarios, they demonstrate the possible future expansion of the cultivation of teff in the

418   east lowlands of Ethiopia. In 2050, the area expects a temperature range between 15 °C and 27 °C,

419   and a compensating increase in rainfall between 600 and 1900 mm where teff would be

420   climatically suitable (Yumbya 2014). Several studies indicate that changes in rainfall, temperature

421   and seasonality in Ethiopia directly affect rainfed agriculture (Evangelista et al. 2013; Gebre et al.

422   2013; Asfaw et al. 2018; Alemayehu & Bewket 2017; Worku et al. 2019). Evangelista et al. (2013)

423   predicted a 350,000 km^2 loss of suitable crop area by 2050, however, in our study, areas of crop

424   suitability showed different trends in the future climate change scenarios. In the model used by

425   Evangelista et al. (2013) rainfall was the primary climate driver (and not coupled with mean

426   temperature of the coldest season), so the model outcomes were heavily dependent on the specific

427   rainfall predictions of the climate data. The main difference in the models lies in the confidence of

428   an environmental variable versus the prediction of a climatic variable.

429   Most studies using models to predict the climate change in Ethiopia revealed that important climate

430   variables influence teff distribution. The contribution rates of precipitation of wettest quarter

431   (Bio16), annual precipitation (Bio12), precipitation of the coldest quarter (Bio19), and

432   precipitation seasonality (Bio15) are 26.6, 9.3, 8.3, and 6.1%, respectively (Evangelista et al.

433   2013). By contrast, our analysis results show that contribution rates of four environmental

434   variables (Bio11, Bio15, Bio19, and slope) are 78.3, 8.3, 3.7, 3.3 % respectively suggesting that

435   precipitation in the wettest quarter is even more important than previously thought.

436   Our model provided reasonably strong AUC predictions on the geographic changes in teff

437   suitability throughout Ethiopia under projected climate change. Several studies reveal that all

438   models have associated assumptions and extrapolation modes in time or space, and are subject to

439   violating assumptions of species distribution models (Wiens et al. 2009). We used a Maxent model

440   to show current teff distribution and to predict future climate impacts on it. Since the model relies

441   on predicted future climate scenarios, an amount of uncertainty is added. We should have

442   considered including management, soil and other teff varieties which are grown in Ethiopia in our

443   model analysis. We strongly believe that our research could be improved by including

444   management of farming practice and preparation for teff harvesting components, but we believe

445   that lack of soil and other data in our analysis did not significantly affect the results.

446   Climate change affects the teff crop both in current and future scenarios. Results indicate that the

447   differing future distributions are not uniformly affected by predicted changes in climate. Moreover,

448   the predicted future damage is so severe that the survival of the Ethiopian agricultural sector, will

449   be at stake unless adaptive policies are implemented. As Ethiopia, many other East African

450   countries are facing the erratic effects of climate change with the same projections (Deressa &

451   Hassan 2009; Di Falco & Veronesi 2013).

452 **5. Conclusions**

453 Our work presents an opportunity for the agricultural sector, modelers and policy makers to

454 examine the effect of climate change on teff so as to minimize negative impacts. Our result

455 revealed that four environmental factors have an important influence on teff distribution, namely

456 Mean temperature of coldest quarter (Bio11), Precipitation seasonality (Bio15), Precipitation of

457 coldest quarter (Bio19), Slope, and Temperature annual range (Bio7). Furthermore, based on

458 current and future climate future scenarios conditions, we found out that for teff distribution in

459 western Ethiopia the high suitable area lies on the northwest part of the county. We discovered

460 climate change is happening and influencing the teff distribution, with a total projected loss 5000-

461 7300 km^2 of suitable habitat. While this change does not pose substantial threat on the short term,

462 on the long term it may have a significant impact on the future availability to grow teff as staple

463 crop in Ethiopia.

464 **Author Attribution**

465 Dinka Zewudie wrote the paper, prepared figures and tables, reviewed drafts of the paper.

466 Wenguang Ding reviewed drafts of the paper.

467 Chuanyan Zhao conceived and designed the experiments.

468 Zhanlei Rong and Yapeng Chang analyzed the data.

469

470 ADDITIONAL INFORMATION AND DECLARATIONS

471 Funding

472 Supported by the Strategic Priority Research Program of Chinese Academy of Sciences Grant No.

473 XDA20100102

474 Conflict of Interest

475 The authors declare there are no competing interests

476 Acknowledge: We thank people who help in the manuscript, and foundation support.
477

478

479

480 **References**

481

482 *Abdelaal, M., Fois, M., Dakhil, M. A., Bacchetta, G., & El-Sherbeny, G. A. (2020). Predicting*
483 *the Potential Current and Future Distribution of the Endangered Endemic Vascular Plant*
484 *Primula boveana Decne. ex Duby in Egypt. Plants, 9(8), 957.*

485 Alberto, F. J., Aitken, S. N., Alía, R., González-Martínez, S. C., Hänninen, H., Kremer, A., ... &
486 Savolainen, O. (2013). Potential for evolutionary responses to climate change–evidence
487 from tree populations. *Global Change Biology*, *19*(6), 1645-1661.
488 Alemayehu N., Masafu M., Ebro A., Tegegne A., Gebru G. (2018) Climate Change and
489 Variability in the Mixed Crop/Livestock Production Systems of Central Ethiopian
490 Highland. In: Leal Filho W. (eds) Handbook of Climate Change Resilience. Springer,
491 Cham. https://doi.org/10.1007/978-3-319-71025-9_120-1
492 *Alemayehu N., Masafu M., Ebro A., Tegegne A., Gebru G. (2020) Climate Change and Variability in the*
493 *Mixed Crop/Livestock Production Systems of Central Ethiopian Highland. In: Leal Filho W. (eds)*
494 *Handbook of Climate Change Resilience. Springer, Cham. https://doi.org/10.1007/978-3-319-*
495 *93336-8_120*

496 Alemayehu, A., & Bewket, W. (2017). Local spatiotemporal variability and trends in rainfall and
497 temperature in the central highlands of Ethiopia. *Geografiska Annaler: Series A, Physical*
498 *Geography*, *99*(2), 85-101.
499 Anderson, R. P., Lew, D., & Peterson, A. T. (2003). Evaluating predictive models of species'
500 distributions: criteria for selecting optimal models. *Ecological modelling*, *162*(3), 211-
501 232.
502 *Ardestani, E. G., Tarkesh, M., Bassiri, M., & Vahabi, M. R. (2015). Potential habitat modeling*
503 *for reintroduction of three native plant species in central Iran. Journal of arid land, 7(3),*
504 *381-390.*

505 Asfaw, A., Simane, B., Hassen, A., & Bantider, A. (2018). Variability and time series trend
506 analysis of rainfall and temperature in northcentral Ethiopia: A case study in Woleka sub-
507 basin. *Weather and Climate Extremes*, *19*, 29-41.
508 Assefa, K., Tefera, H., Merker, A., Kefyalew, T., & Hundera, F. (2001). Quantitative trait
509 diversity in tef [Eragrostis tef (Zucc.) Trotter] germplasm from Central and Northern
510 Ethiopia. *Genetic Resources and Crop Evolution*, *48*(1), 53-61.
511 *Barbet-Massin, M., Jiguet, F., Albert, C. H., & Thuiller, W. (2012). Selecting pseudo-absences for species*
512 *distribution models: how, where and how many?. Methods in ecology and evolution, 3(2), 327-338.*

513 Barnett, T. P., Hegerl, G., Knutson, T., & Tett, S. (2000). Uncertainty levels in predicted patterns
514   of anthropogenic climate change. *Journal of Geophysical Research:*
515   *Atmospheres*, *105*(D12), 15525-15542.
516 Beltramino, A. A., Vogler, R. E., Gregoric, D. E. G., & Rumi, A. (2015). Impact of climate
517   change on the distribution of a giant land snail from South America: predicting future
518   trends for setting conservation priorities on native malacofauna. *Climatic*
519   *Change*, *131*(4), 621-633.
520 Bertrand, R., Lenoir, J., Piedallu, C., Riofrio-Dillon, G., de Ruffray, P., Vidal, C., ... & Gégout,
521   J. C. 2011. Changes in plant community composition lag behind climate warming in
522   lowland forests. Nature, 479(7374), 517-520.
523 Betts, R. A., Collins, M., Hemming, D. L., Jones, C. D., Lowe, J. A., & Sanderson, M. G. 2011.
524   When could global warming reach 4 C?. Philosophical Transactions of the Royal Society
525   A: Mathematical, Physical and Engineering Sciences, 369(1934), 67-84.
526 Brown, J. L. (2014). SDM toolbox: a python-based GIS toolkit for landscape genetic,
527   biogeographic and species distribution model analyses. *Methods in Ecology and*
528   *Evolution*, *5*(7), 694-700.
529 Caminade, C., Medlock, J. M., Ducheyne, E., McIntyre, K. M., Leach, S., Baylis, M., & Morse,
530   A. P. (2012). Suitability of European climate for the Asian tiger mosquito Aedes
531   albopictus: recent trends and future scenarios. *Journal of the Royal Society*
532   *Interface*, *9*(75), 2708-2717.
533 *Chamberlin, J., & Schmidt, E. (2012). Ethiopian agriculture: A dynamic geographic*
534   *perspective. Food and agriculture in Ethiopia: progress and policy challenges, 21-52.*

535 Cheng, A., Mayes, S., Dalle, G., Demissew, S., & Massawe, F. (2017). Diversifying crops for
536   food and nutrition security–a case of teff. *Biological Reviews*, *92*(1), 188-198.
537 Conway, D., & Schipper, E. L. F. (2011). Adaptation to climate change in Africa: Challenges
538   and opportunities identified from Ethiopia. *Global Environmental Change*, *21*(1), 227-
539   237.
540 Cowie, A. L., Orr, B. J., Sanchez, V. M. C., Chasek, P., Crossman, N. D., Erlewein, A., ... &
541   Tengberg, A. E. (2018). Land in balance: The scientific conceptual framework for Land
542   Degradation Neutrality. *Environmental Science & Policy*, *79*, 25-35.
543 CSA. (2014). Agricultural Sample Survey for 2013/14. Statistical Bulletin 532. Addis Ababa,
544   Ethiopia: Central Statistical Agency
545 Deressa, T. T., & Hassan, R. M. (2009). Economic impact of climate change on crop production
546   in Ethiopia: Evidence from cross-section measures. *Journal of African economies*, *18*(4),
547   529-554.
548 Di Falco, S., & Veronesi, M. (2013). How can African agriculture adapt to climate change? A
549   counterfactual analysis from Ethiopia. *Land Economics*, *89*(4), 743-766.
550 Dinar A (2007) Climate change: the final blow for agriculture in Africa? Research Brief.The
551 World Bank, Washington
552 Dinku, T., Connor, S. J., Ceccato, P., & Ropelewski, C. F. (2008). Comparison of global gridded
553 precipitation products over a mountainous region of Africa. International Journal of Climatology:
554 A Journal of the Royal Meteorological Society, 28(12), 1627-1638.
555 Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ. 2011. A statistical explanation of
556   MaxEnt for ecologists. Diversity and distributions 17:43-57.

557 Elith, J., H. Graham, C., P. Anderson, R., Dudík, M., Ferrier, S., Guisan, A., ... & Li, J. (2006).
558   Novel methods improve prediction of species' distributions from occurrence
559   data. *Ecography*, *29*(2), 129-151.
560 Evangelista P, Young N, and Burnett J. 2013. How will climate change spatially affect
561   agriculture production in Ethiopia? Case studies of important cereal crops. *Climatic*
562   *Change* 119:855-873. 10.1007/s10584-013-0776-6
563 Fazzini M, Bisci C, Billi P. 2015. The Climate of Ethiopia. In book: *Landscapes and Landforms*
564   *of Ethiopia* (pp.23) Ed: World Geomorphological Landscapes. Springer Verlag. Editors:
565   Billi P. doi: 10.1007/978-94-017-8026-1_3
566 Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces
567   for global land areas. *International journal of climatology*, *37*(12), 4302-4315.
568 Funk, V. A., & Richardson, K. S. (2002). Systematic data in biodiversity studies: use it or lose
569   it. *Systematic biology*, *51*(2), 303-316.
570 Gebre, H., Kindie, T., Girma, M., & Belay, K. (2013). Trend and variability of rainfall in Tigray,
571   northern Ethiopia: analysis of meteorological data and farmers' perception. *Academia*
572   *Journal of Agricultural Research*, *1*(6), 088-100.
573 Gebrechorkos, S. H., Hülsmann, S., & Bernhofer, C. (2019). Long-term trends in rainfall and
574   temperature using high-resolution climate datasets in East Africa. *Scientific Reports*, *9*(1),
575   1-9.
576 Gebrehiwot, T., & Van Der Veen, A. (2013). Farm level adaptation to climate change: the case
577   of farmer's in the Ethiopian Highlands. *Environmental management*, *52*(1), 29-44.
578 Gissila, T., E.Black, D. I. F.Grimes, and J. M.Slingo, (2004): Seasonal forecasting of the
579   Ethiopian summer rains.Int. J. Climatol., 24, 1345–1358.
580 Gleixner, S., Keenlyside, N., Viste, E., & Korecha, D. (2017). The El Niño effect on Ethiopian
581   summer rainfall. *Climate Dynamics*, *49*(5-6), 1865-1883.
582 Graham, C. H., & Hijmans, R. J. (2006). A comparison of methods for mapping species ranges
583   and species richness. *Global Ecology and biogeography*, *15*(6), 578-587.
584 *Gregory, P. J., Ingram, J. S., & Brklacich, M. (2005). Climate change and food*
585   *security. Philosophical Transactions of the Royal Society B: Biological*
586   *Sciences, 360(1463), 2139-2148.*

587 Guo Y, Li X, Zhao Z, Wei H, Gao B, and Gu W. 2017a. Prediction of the potential geographic
588   distribution of the ectomycorrhizal mushroom Tricholoma matsutake under multiple
589   climate change scenarios. *Scientific Reports* 7. 10.1038/srep46221
590 Guo Y, Wei H, Lu C, Gao B, and Gu W. 2016. Predictions of potential geographical distribution
591   and quality of *Schisandra sphenanthera* under climate change. *PeerJ* 4:e2554.
592   10.7717/peerj.2554
593 Guo, Y., Li, X., Zhao, Z., Wei, H., Gao, B., & Gu, W. (2017). Prediction of the potential
594   geographic distribution of the ectomycorrhizal mushroom Tricholoma matsutake under
595   multiple climate change scenarios. *Scientific reports*, *7*, 46221.
596 Hansen, J., Ruedy, R., Sato, M., & Lo, K. (2010). Global surface temperature change. *Reviews of*
597   *Geophysics*, *48*(4).
598 Hansen, J., Sato, M., Ruedy, R., Lo, K., Lea, D. W., & Medina-Elizade, M. (2006). Global
599   temperature change. *Proceedings of the National Academy of Sciences*, *103*(39), 14288-
600   14293.

601 Hijmans, R. J., & Graham, C. H. (2006). The ability of climate envelope models to predict the
602   effect of climate change on species distributions. *Global change biology*, *12*(12), 2272-
603   2281.
604 Hordofa, T. & Menkir, Michael & Awulachew, Seleshi Bekele & Erkossa, T. (2008). "Irrigation
605   and rain-fed crop production system in Ethiopia," Conference Papers h044065,
606   International Water Management Institute.
607 Hu, J., & Jiang, Z. (2011). Climate change hastens the conservation urgency of an endangered
608   ungulate. PloS one, 6(8), e22873.
609 Intergovernmental Panel on Climate Change. (2007). Climate Change 2007 - Mitigation of
610   Climate Change: Working Group III contribution to the Fourth Assessment Report of the
611   IPCC. Cambridge: Cambridge University Press. doi:10.1017/CBO9780511546013.
612 IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group
613   I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change
614   [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y.
615   Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United
616   Kingdom and New York, NY, USA, 1535 pp.
617 James, R., & Washington, R. (2013). Changes in African temperature and precipitation
618   associated with degrees of global warming. *Climatic change*, *117*(4), 859-872.
619 Joshi, M., Hawkins, E., Sutton, R., Lowe, J., & Frame, D. 2011. Projections of when temperature
620   change will exceed 2 C above pre-industrial levels. Nature Climate Change, 1(8), 407-
621   412.
622 Kamali, B., Abbaspour, K. C., Lehmann, A., Wehrli, B., & Yang, H. (2018). Spatial assessment
623   of maize physical drought vulnerability in sub-Saharan Africa: Linking drought exposure
624   with crop failure. *Environmental Research Letters*, *13*(7), 074010.
625 Kamilar, J. M., & Beaudrot, L. (2013). Understanding primate communities: Recent
626   developments and future directions. *Evolutionary Anthropology: Issues, News, and
627   Reviews*, *22*(4), 174-185.
628 Korecha, D., & Barnston, A. G. (2007). Predictability of june–september rainfall in Ethiopia.
629   Monthly weather review, 135(2), 628-650.
630 Kumar, P. (2012). Assessment of impact of climate change on Rhododendrons in Sikkim
631   Himalayas using Maxent modelling: limitations and challenges. *Biodiversity and
632   Conservation*, *21*(5), 1251-1266.
633 Kumar, S., & Stohlgren, T. J. (2009). Maxent modeling for predicting suitable habitat for
634   threatened and endangered tree Canacomyrica monticola in New Caledonia. *Journal of
635   Ecology and the Natural Environment*, *1*(4), 094-098.
636 Kumar, S., Spaulding, S. A., Stohlgren, T. J., Hermann, K. A., Schmidt, T. S., & Bahls, L. L.
637   (2009). Potential habitat distribution for the freshwater diatom Didymosphenia geminata
638   in the continental US. *Frontiers in Ecology and the Environment*, *7*(8), 415-420.
639 Ledig, F. T., Rehfeldt, G. E., Sáenz-Romero, C., & Flores-López, C. (2010). Projections of
640   suitable habitat for rare species under global warming scenarios. *American journal of
641   botany*, *97*(6), 970-987.
642 Lenoir J, Gégout JC, Marquet PA, de Ruffray P, Brisse H. A significant upward shift in plant
643   species optimum elevation during the 20th century. Science. 2008 Jun
644   27;320(5884):1768-71. doi: 10.1126/science.1156831. PMID: 18583610.
645 *Li, R., Xu, M., Wong, M. H. G., Qiu, S., Sheng, Q., Li, X., & Song, Z. (2015). Climate change-induced decline
646   in bamboo habitats and species diversity: Implications for giant panda conservation. Diversity and
647   Distributions, 21(4), 379-391.*

648 Liao, H., & Chang, W. (2014). Integrated assessment of air quality and climate change for
649   policy-making: highlights of IPCC AR5 and research challenges. *National Science*
650   *Review*, *1*(2), 176-179.
651 Liu, C., Berry, P. M., Dawson, T. P., & Pearson, R. G. (2005). Selecting thresholds of
652 occurrence in the prediction of species distributions. *Ecography*, *28*(3), 385-393.

653 *Mcsweeney, C., New, M., Lizcano, G., & Lu, X. (2010). The UNDP Climate Change Country Profiles:*
654   *Improving the accessibility of observed and projected climate information for studies of climate*
655   *change in developing countries. Bulletin of the American Meteorological society, 91(2), 157-166.*

656 Minten, B., Tamru, S., Engida, E., & Kuma, T. (2016). Feeding Africa's cities: The case of the
657   supply chain of teff to Addis Ababa. *Economic Development and Cultural*
658   *Change*, *64*(2), 265-297.
659 *Nelson, G. C., Rosegrant, M. W., Koo, J., Robertson, R., Sulser, T., Zhu, T., ... & Magalhaes, M.*
660   *(2009). Climate change: Impact on agriculture and costs of adaptation (Vol. 21). Intl Food Policy Res*
661   *Inst.*

662 *Niang, I., Ruppel, O. C., Abdrabo, M. A., Essel, A., Lennard, C., Padgham, J., & Urquhart, P. (2014). Africa.*
663   *Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the*
664   *Intergovernmental Panel on Climate Change. Climate Change.*

665 Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., ... & Dubash, N.
666   K. (2014). *Climate change 2014: synthesis report. Contribution of Working Groups I, II*
667   *and III to the fifth assessment report of the Intergovernmental Panel on Climate*
668   *Change* (p. 151). Ipcc.
669 Parmesan, C., & Yohe, G. 2003. A globally coherent fingerprint of climate change impacts
670   across natural systems. Nature, 421(6918), 37-42.
671 Peterson, A. T. (2006). Ecologic niche modeling and spatial patterns of disease
672   transmission. *Emerging infectious diseases*, *12*(12), 1822.
673 *Petitpierre, B., McDougall, K., Seipel, T., Broennimann, O., Guisan, A., & Kueffer, C. (2016). Will climate*
674   *change increase the risk of plant invasions into mountains?. Ecological Applications, 26(2), 530-544.*

675 Phillips SJ, Anderson RP, and Schapire RE. 2006. Maximum entropy modeling of species
676   geographic distributions. *Ecological Modelling* 190:231-259.
677   https://doi.org/10.1016/j.ecolmodel.2005.03.026
678 Phillips, S. J., & Dudík, M. (2008). Modeling of species distributions with Maxent: new
679   extensions and a comprehensive evaluation. *Ecography*, *31*(2), 161-175.
680 *Prasad, P. V., Staggenborg, S. A., Ristic, Z., Ahuja, L. R., Reddy, V. R., Saseendran, S. A., & Yu, Q. (2008).*
681   *Response of crops to limited water: Understanding and modeling water stress effects on plant*
682   *growth processes (Advances in agricultural systems modeling series 1).*

683 Rogelj, J., Meinshausen, M., & Knutti, R. (2012). Global warming under old and new scenarios
684   using IPCC climate sensitivity range estimates. *Nature climate change*, *2*(4), 248-253.
685 Rong Z, Zhao C, Liu J, Gao Y, Zang F, Guo Z, Mao Y, and Wang L. 2019. Modeling the Effect
686   of Climate Change on the Potential Distribution of Qinghai Spruce (*Picea crassifolia*
687   Kom.) in Qilian Mountains. *Forests* 10:62.
688 Roseberg, R. J., Norberg, S., Smith, J., Charlton, B., Rykbost, K., & Shock, C. (2005). Yield and
689   quality of teff forage as a function of varying rates of applied irrigation and
690   nitrogen. *Klamath Experiment Station*, *1069*, 119-136.

691 Rosell, C. M., Barro, F., Sousa, C., & Mena, M. C. (2014). Cereals for developing gluten-free
692   products and analytical tools for gluten detection. *Journal of Cereal Science*, *59*(3), 354-
693   364.
694 Rushton, S. P., Ormerod, S. J., & Kerby, G. (2004). New paradigms for modelling species
695   distributions?. *Journal of applied ecology*, *41*(2), 193-200.
696 Segele ZT, Lamb PJ, Leslie LM (2009) Large-scale atmospheric circulation and global sea
697   surface temperature associations with Horn of Africa June–September rainfall. Int J
698   Climatol 29:1075–1100
699 Seleshi, Y., & Zanke, U. (2004). Recent changes in rainfall and rainy days in
700   Ethiopia. *International Journal of Climatology: A Journal of the Royal Meteorological
701   Society*, *24*(8), 973-983.
702 *Sen, S., Gode, A., Ramanujam, S., Ravikanth, G., & Aravind, N. A. (2016). Modeling the impact*
703   *of climate change on wild Piper nigrum (Black Pepper) in Western Ghats, India using*
704   *ecological niche models. Journal of plant research, 129(6), 1033-1040.*

705 Solomon, S., Manning, M., Marquis, M., & Qin, D. (2007). *Climate change 2007-the physical*
706   *science basis: Working group I contribution to the fourth assessment report of the*
707   *IPCC* (Vol. 4). Cambridge university press.
708 Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V,
709   and Midgley PM. 2013. Climate change 2013: The physical science basis. Cambridge
710   University Press Cambridge.
711 Suwannatrai, A., Pratumchart, K., Suwannatrai, K., Thinkhamrop, K., Chaiyos, J., Kim, C. S., ...
712   & Sripa, B. (2017). Modeling impacts of climate change on the potential distribution of
713   the carcinogenic liver fluke, Opisthorchis viverrini, in Thailand. *Parasitology
714   research*, *116*(1), 243-250.
715 Taffesse, A. S., Dorosh, P., & Gemessa, S. A. (2012). Crop production in Ethiopia: Regional
716   patterns and trends. *Food and agriculture in Ethiopia: Progress and policy challenges*,
717   53-83.
718 *Tan, Z., Yang, Y., Wang, Y., Wang, L., & Sun, G. (2016). The decrease of potential suitable areas*
719   *and the distribution tendency of staple crops in Ethiopia under future climate*
720   *conditions. African Journal of Agricultural Research, 11(24), 2092-2101.*

721 Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment
722   design. Bulletin of the American Meteorological Society, 93(4), 485-498.
723 Tefera, A., & Quintin, G. (2012). Ethiopia: grain and feed annual report. *Global Agricultural
724   Information Network. USDA Foreign Agriculture Service, Report Number ET*, *1201*.
725 Tilamun, Helina & Schmidt, Emily, 2012. "Spatial Analysis of Livestock Production Patterns in
726   Ethiopia:," ESSP working papers 44, International Food Policy Research Institute
727   (IFPRI).
728 Tognelli, M. F., Roig, S. A., Marvaldi, A., Flores, G. E., & Lobo, J. M. (2009). An evaluation of
729 methods for modelling distribution of Patagonian insects.
730 *Turner, N. C., & Rao, K. P. C. (2013). Simulation analysis of factors affecting sorghum yield at*
731   *selected sites in eastern and southern Africa, with emphasis on increasing*
732   *temperatures. Agricultural Systems, 121, 53-62.*

733 VanBuren, R., Wai, C. M., Wang, X., Pardo, J., Yocca, A. E., Wang, H., ... & Messing, J.
734   (2020). Exceptional subgenome stability and functional divergence in the allotetraploid
735   Ethiopian cereal teff. *Nature communications*, *11*(1), 1-11.

736 Viste, E., Korecha, D., & Sorteberg, A. (2013). Recent drought and precipitation tendencies in
737   Ethiopia. *Theoretical and Applied Climatology*, *112*(3-4), 535-551.
738 Wei, B., Wang, R., Hou, K., Wang, X., & Wu, W. (2018). Predicting the current and future
739   cultivation regions of Carthamus tinctorius L. using MaxEnt model under climate change
740   in China. *Global Ecology and Conservation*, *16*, e00477.
741 Wiens, J. A., Stralberg, D., Jongsomjit, D., Howell, C. A., & Snyder, M. A. (2009). Niches,
742   models, and climate change: assessing the assumptions and uncertainties. *Proceedings of*
743   *the National Academy of Sciences*, *106*(Supplement 2), 19729-19736.
744 Wondimu, A. and Tekabe, F. (2001) Utilization of Teff in the Ethiopian Diet. Narrowing the
745   Rift. Teff Research and Development: Proceedings of the International Workshop on Teff
746   Genetics and Improvement, Debre Zeit, 16-19 October 2000, 239-244.
747 Worku, G., Teferi, E., Bantider, A., & Dile, Y. T. (2019). Observed changes in extremes of daily
748   rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin,
749   Ethiopia. *Theoretical and Applied Climatology*, *135*(3-4), 839-854.
750 *Yang, M., Li, Z., Liu, L., Bo, A., Zhang, C., & Li, M. (2020). ecological niche modeling of*
751   *Astragalus membranaceus var. mongholicus medicinal plants in inner Mongolia,*
752   *china. Scientific reports, 10(1), 1-18.*

753 Yumbya, J., Maria, D., Vaate, B. D., Kiambi, D., Kebebew, F., & Rao, K. P. C.
754   (2014). Assessing the effects of climate change on teff in Ethiopia: Implications for food
755   security. Technical report.
756 Zimmermann, N. E., Edwards Jr, T. C., Graham, C. H., Pearman, P. B., & Svenning, J. C.
757   (2010). New trends in species distribution modelling. *Ecography*, *33*(6), 985-989.
758
759

Pearson's correlation coefficient attached (see Table S1),
Correlation of environmental variables. Variables Bio2, Bio3, Bio4, Bio7, Bio11, Bio14, Bio15, Bio18, and Bio19 were deemed independent and used in subsequent analyses.

760

761

762

763

Figure 1

Left: The crop teff, a fine-grain annual cereal. (Source: FAO
http://www.fao.org/traditional-crops/teff/en/) Right: Injera made from teff is a staple food
product in Ethiopia.

Photo by Gamechis E. Hambisa

Figure 2

Figure 2 Workflow of the Study

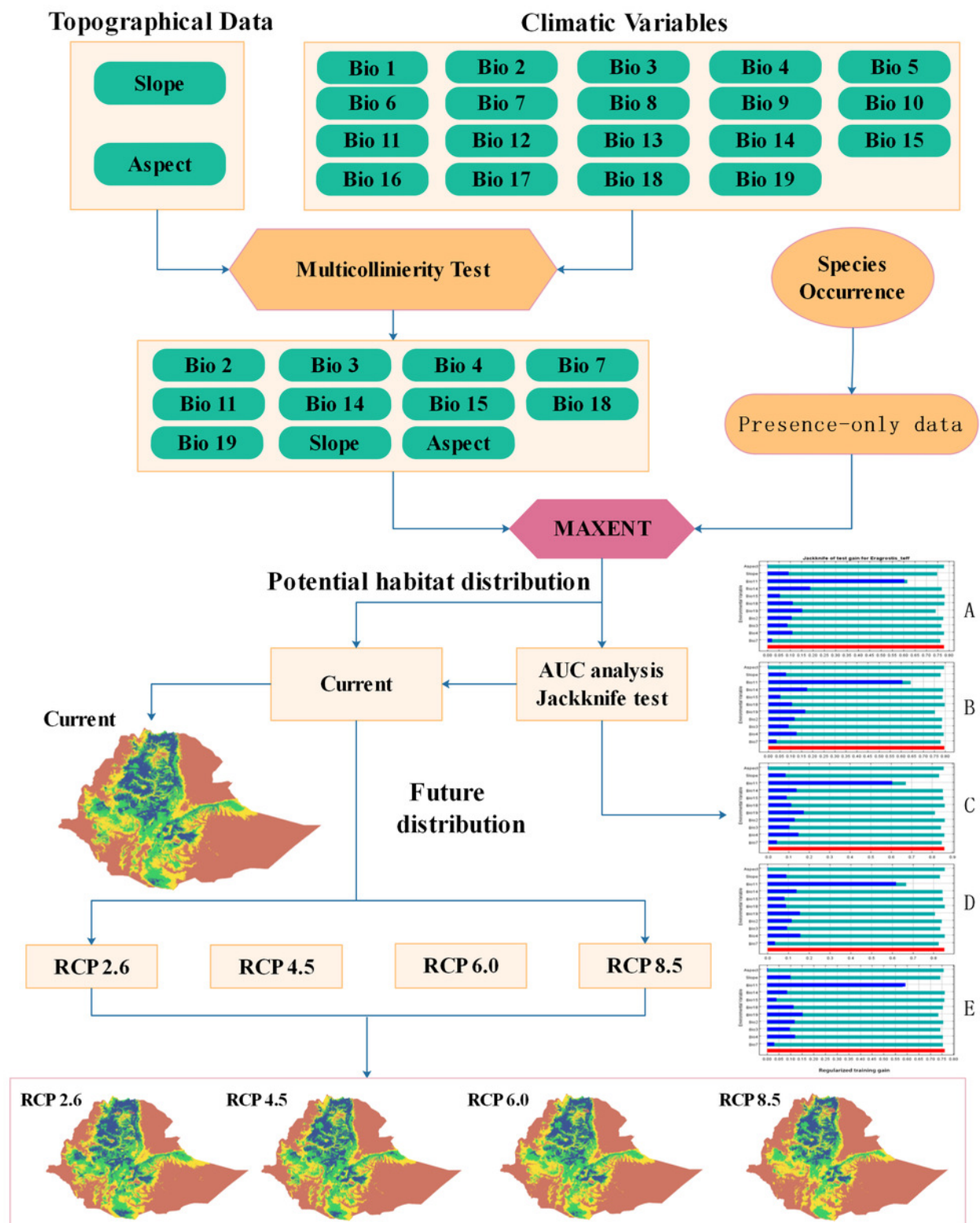



Figure 3

Locations of sampling sites and land elevation within the nine Ethiopian regional state administrations: Oromia, Amhara, Tigray, Afar, Benishangul-Gamuz, Gambella, Harari, Southern Region, and Somali Region.

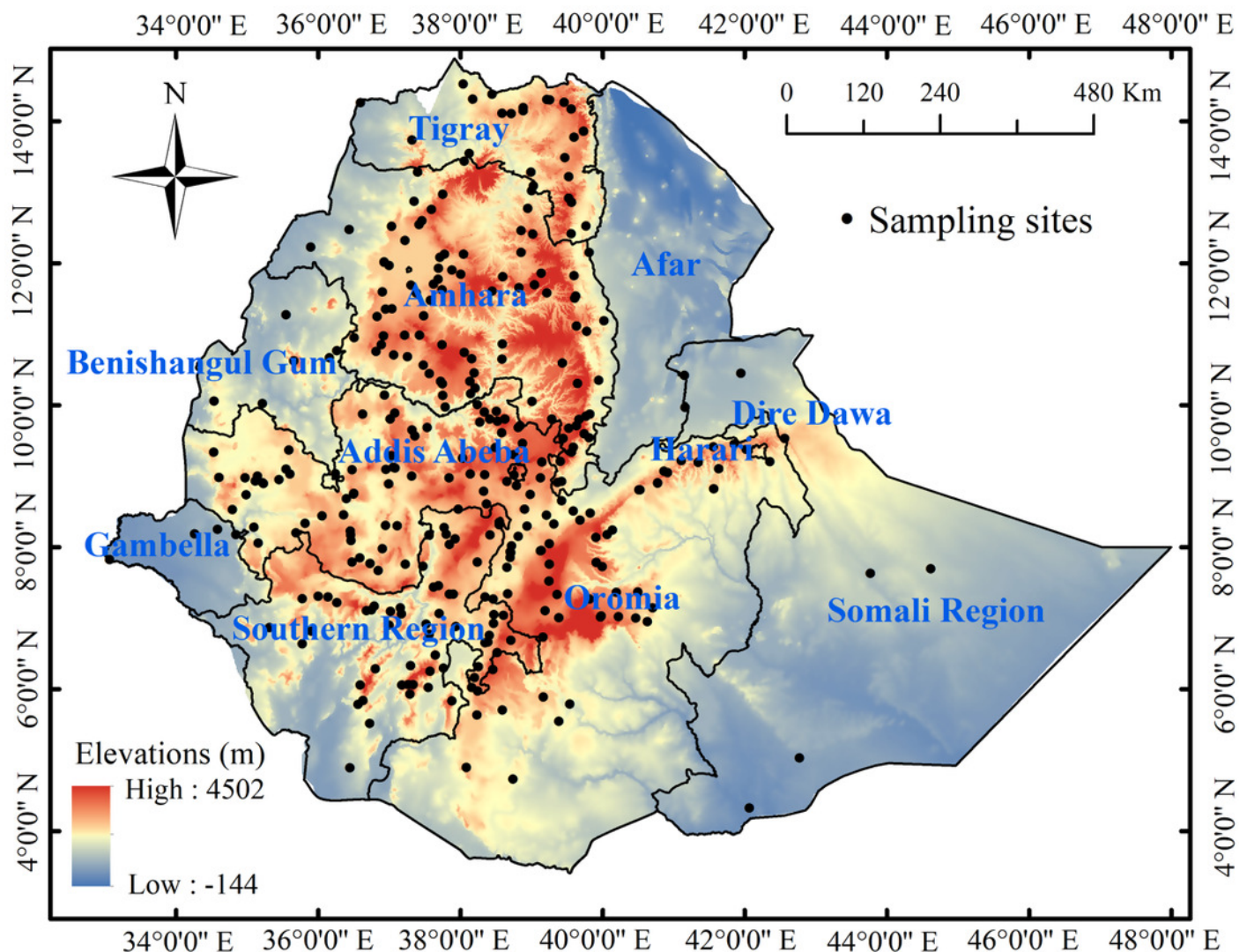



Figure 4

Jackknife test variables contributions to potential distribution of teff distribution under (A) current climate condition scenario, (B) RCP 2.6 scenario, (C) RCP 4.5 scenario, (D) RCP 6.0 scenario, and (E) RCP 8.5 scenario. (The regularized training

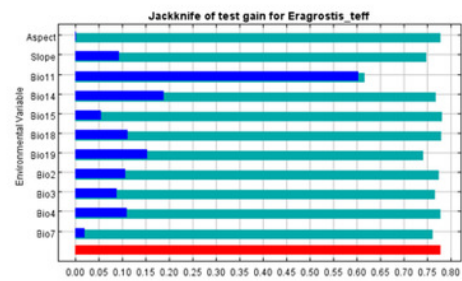
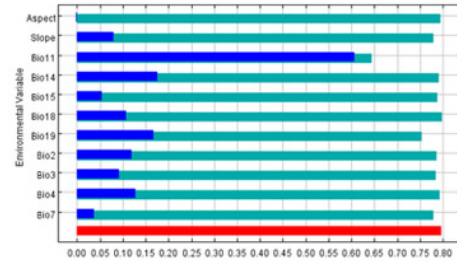
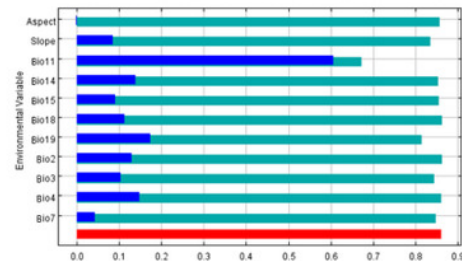
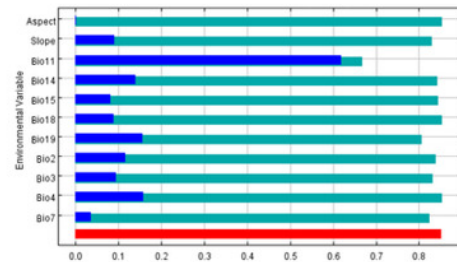
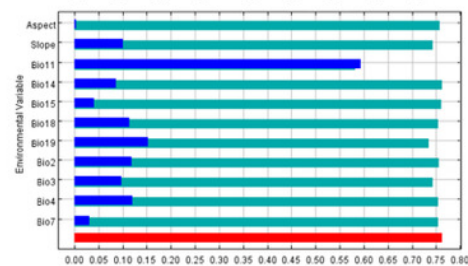



Figure 5

Figure 4. Response curves of 8 environmental variables in the teff habitat distribution model. A:Bio11(Mean temperature of coldest season (°C*10)); B: Bio15(Precipitation seasonality (CV)); C: Bio7(Temperature annual range (Bio5–Bio6));D: Bio19(Precip

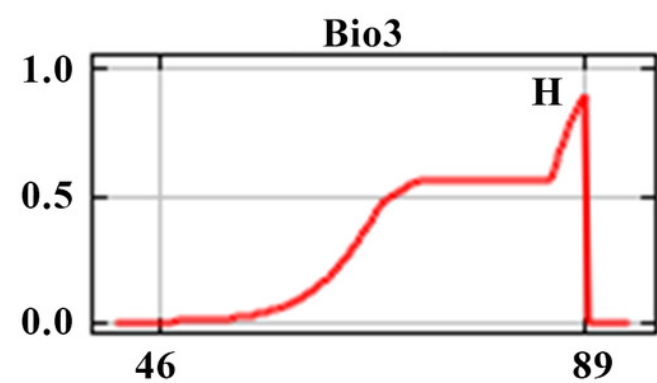
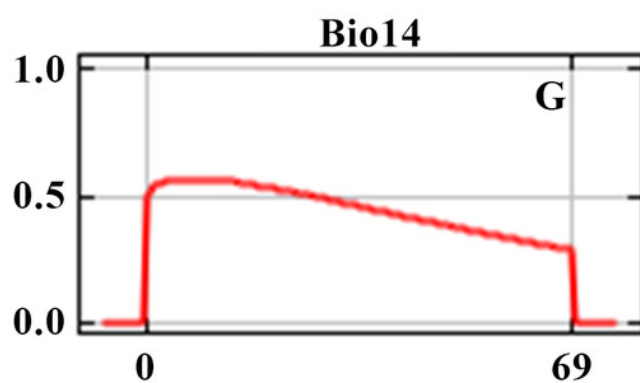
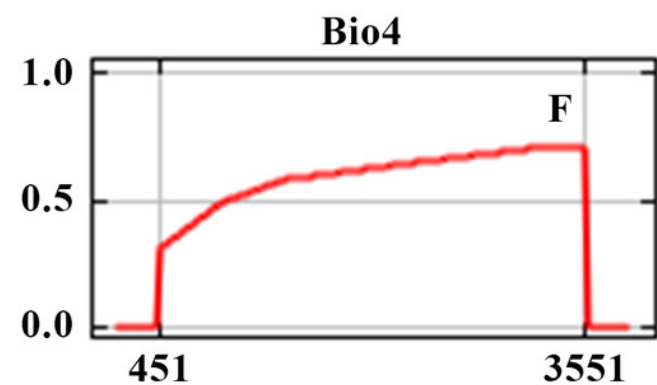
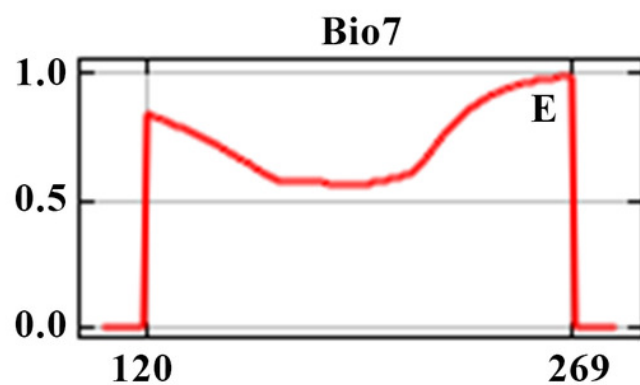
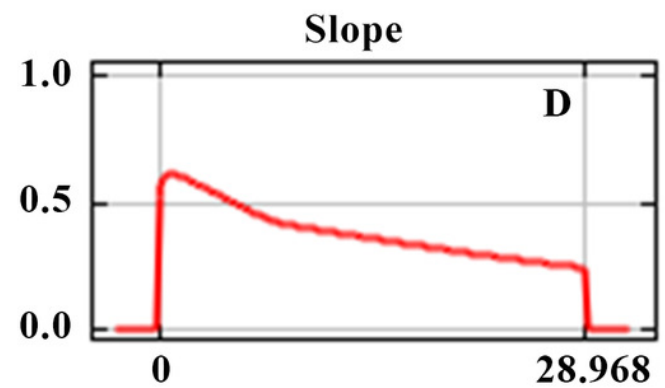
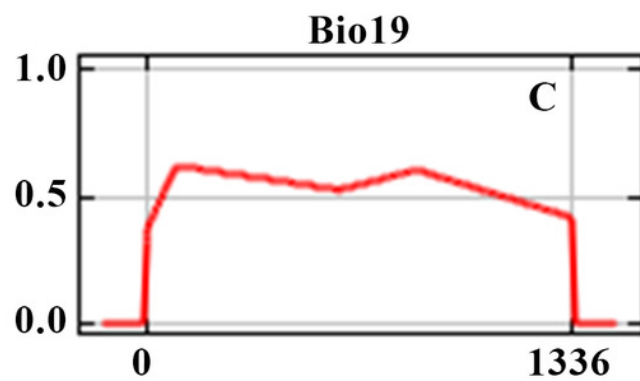
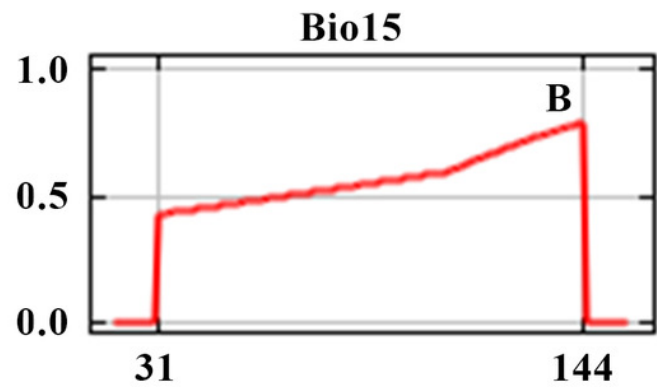
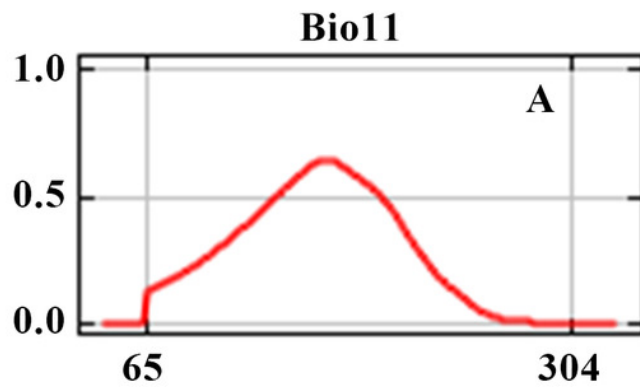



Figure 6

Average annual rainfall (A) and average annual temperature (B) in Ethiopia over three decades.

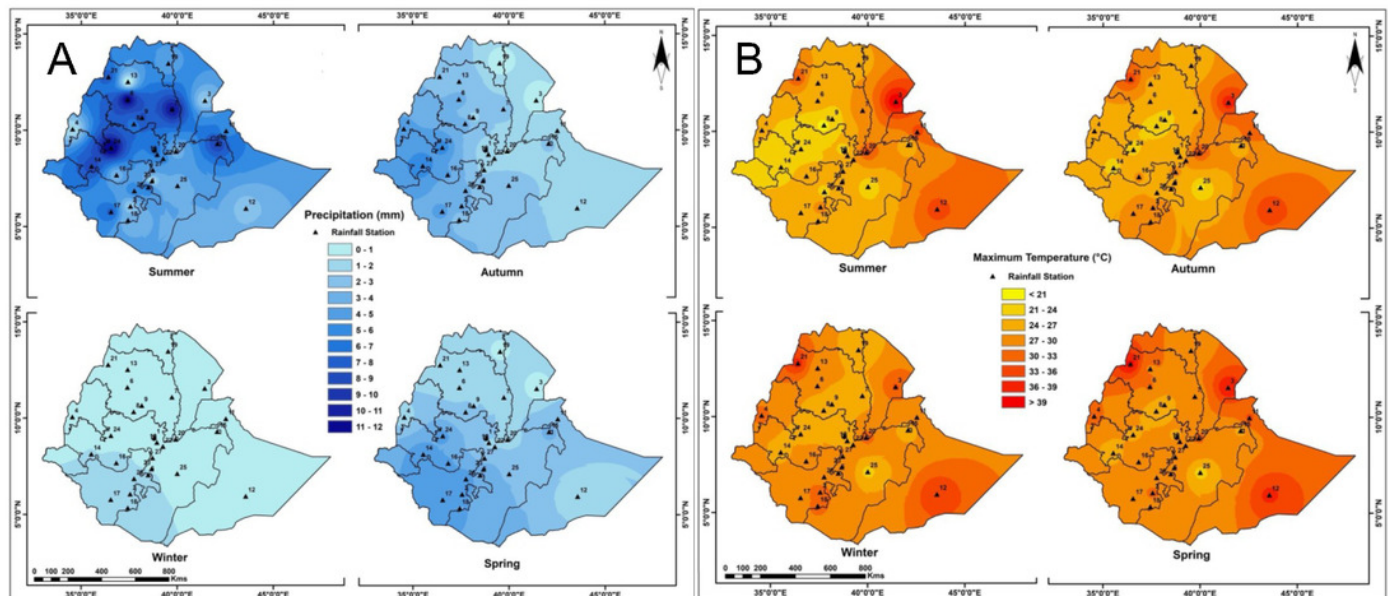
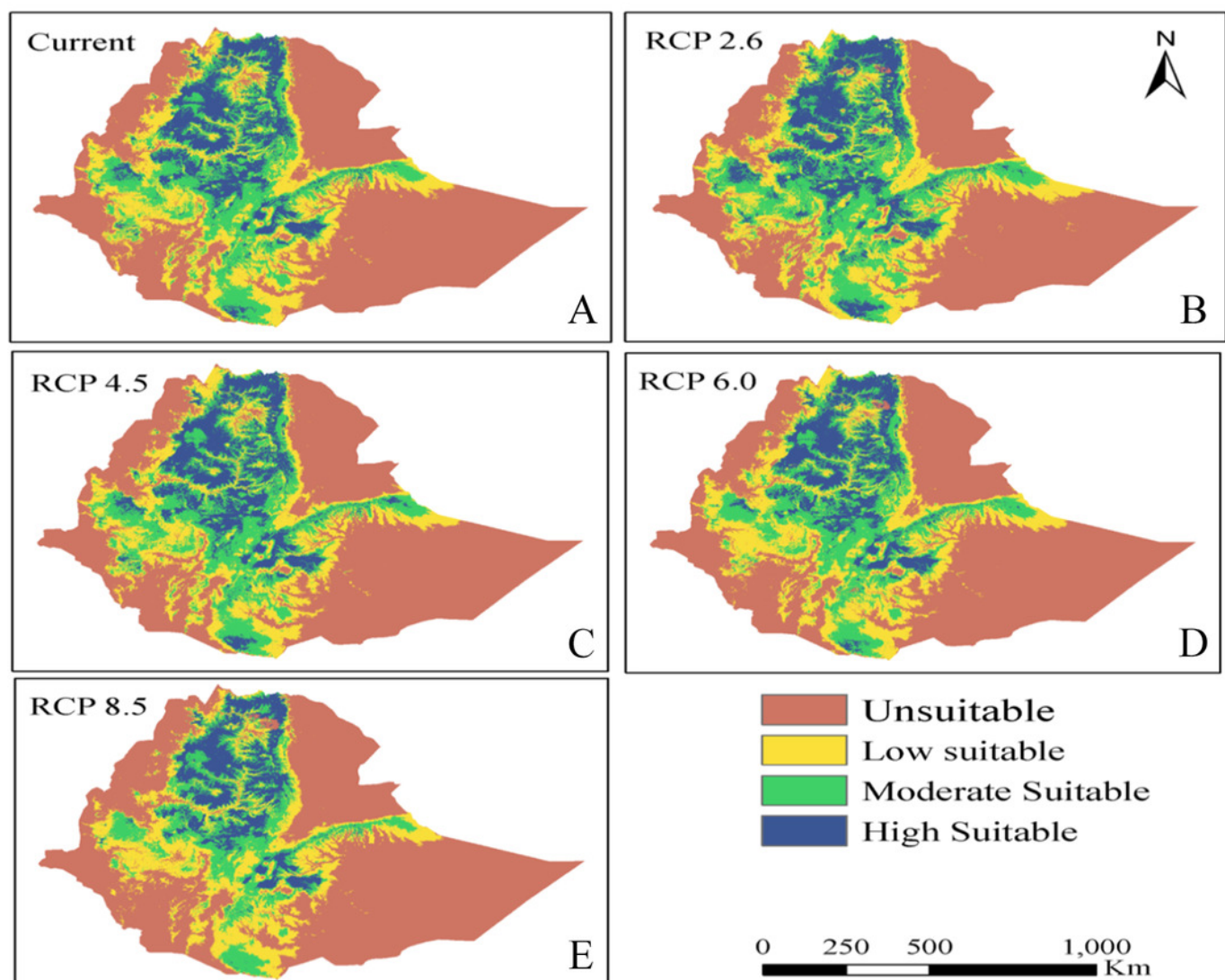



Figure 7

Figure 6. Distribution of unsuitable, and low, moderate, and highly suitable teff habitats based on current and future distribution under four climate scenarios (Note: A: current; B: RCP 2.6; C: RCP4.5; D: RCP6.0; E: RCP8.5)

Figure 6. Distribution of unsuitable, and low, moderate, and highly suitable teff habitats based on current and future distribution under four climate scenarios.

Percent contributions of the variables to teff distribution in the MaxEnt model.

1 **Table 1.** Percent contributions of the variables to teff distribution in the MaxEnt model.

Code	Environmental factor	Percent Contribution					
		Unit	Current	RCP2.6	RCP4.5	RCP6.0	RCP8.5
BIO1	Annual mean temperature	°C					
BIO2	**Mean diurnal range (Monthly max. min. and mean temp.)**	°C	0.23	0.6	0.2	0.5	0.40
BIO3	**Isothermality (Bio2/Bio7×100)**		1.11	1.3	0.9	1.3	0.81
BIO4	**Temperature seasonality (standard deviation×100)**		1.33	0.8	0.5	0.45	0.44
BIO5	Maximum temperature of warmest month	°C					
BIO6	Minimum temperature of coldest month	°C					
BIO7	**Temperature annual range (Bio5–Bio6)**	°C	2.17	2.6	2.3	2.85	2.39
BIO8	Mean temperature of wettest quarter	°C					
BIO9	Mean temperature of driest season	°C					
BIO10	Mean temperature of warmest season	°C					
BIO11	**Mean temperature of coldest season**	°C	78.3	79.7	80.4	78.5	77.8
BIO12	Annual precipitation	mm					
BIO13	Precipitation of wettest period	mm					
BIO14	**Precipitation of driest period**	mm	1.3	1.1	0.8	1.35	1.49
BIO15	**Precipitation seasonality (CV)**		8.3	7.3	7.8	7.76	9.04
BIO16	Precipitation of wettest season	mm	-	-	-	-	-
BIO17	Precipitation of driest season	mm					
BIO18	**Precipitation of warmest season**	mm	0.2	0.2	0.1	0.14	0.03
BIO19	**Precipitation of coldest season**	mm	3.7	2.9	3.5	3.90	4.32
SLOP	**Slope**	°	3.3	3.2	3.5	3.09	3.10
ASP	**Aspect**	°	0.1	0.1	0.2	0.1	0.09

4 Note: The variables in bold were key variables selected by their contribution rates and multicollinearity test.

5 RCP: (Representative Concentration Pathway).

Estimates of relative contributions and permutation importance of the predictor environmental variables to the MaxEnt model.

1 **Table 2.** Estimates of relative contributions and permutation importance of the predictor
2 environmental variables to the MaxEnt model.

Variable	Percent Contribution	Permutation Importance (%)
(Bio11) Mean temperature of coldest quarter	78.3	66.5
(Bio15) Precipitation seasonality	8.3	4.7
(Bio19) Precipitation of coldest quarter	3.7	3.8
Slope	3.3	3.9
(Bio7) Temperature annual range	2.2	5.3
(Bio4) Temperature seasonality	1.3	3.1
(Bio14) Precipitation of driest month	1.3	1.8
Bio3) Isothermality (mean diurnal range/temperature annual range)	1.1	8.4
(Bio2) Mean diurnal range (mean of monthly temp range)	0.2	1.8
(Bio18) Precipitation of warmest quarter	0.2	1.8
Aspect	0.1	0.4

Results of receiver operating characteristic (ROC) analysis under current climate and four future projected scenarios.

1 **Table 3.** Results of receiver operating characteristic (ROC) analysis under current climate and
2 four future projected scenarios.

AUC	Current	RCP2.6	RCP4.5	RCP6.0	RCP8.5
AUC (Training Data)	0.841	0.839	0.835	0.835	0.843
AUC (Test data)	0.829	0.833	0.846	0.842	0.826

The total area of suitable and unsuitable teff habitats based on current distribution data and projected four future climate scenarios.

1   Table 4. The total area of suitable and unsuitable teff habitats based on current distribution data
2   and projected four future climate scenarios.

	Current	RCP2.6	RCP4.5	RCP6.0	RCP8.5
Unsuitable area (km^2)	560960	549902	565720	544774	568305
Low suitability area (km^2)	463453	463044	434560	464483	458548
Moderate suitability area (km^2)	296933	309811	320942	311603	293716
High Suitability area (km^2)	14513	13102	14637	14999	15290
Total Suitability area (km^2)	774899	785957	770139	791085	767554
Change area (km^2)		11058	-4760	16186	-7345
Percent (%)	58	58.8	57.6	59.2	57.4