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, but its cultivation may be affected by climate change. It is essential to understand how climatic changes may alter habitat suitability so that appropriate cultivation countermeasures can be developed to ensure food security. We predicted the potential distribution of teff under current and potential future climate scenarios in our analysis using the maximum entropy (MaxEnt) model. Future climate scenarios were based on four Representative concentration Pathways (RCP; RCP2.6, RCP4.5, RCP6.0 and RCP8.5) outlined in the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), Twelve climate-related habitat suitability variables were used as model parameters; variables were introduced into the model, chosen from 19 variables according to the correlation analysis together with their contribution rates to the distribution. Simulated results were assessed using operating characteristic curves (AUC), which were strongly predictive of all future climate scenarios (RCPs). The primary drivers for teff habitat suitability in our study were precipitation and mean temperature in the coldest season, seasonal differences in precipitation annually, and steepness of the slope. Currently, 58% of total land area in Ethiopia is suitable for teff cultivation, compared to 58.8%, 57.6%, 59.2%, and 57.4% in RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively. We found that warmer conditions were correlated with decreased land suitability. As anticipated, temperature- and precipitation-related bioclimatic variables were highly predictive of teff cultivation suitability. Additionally, the suitability of land for teff cultivation varied across the landscape under different RCP scenarios, suggesting the use of different food security countermeasures may be required in different regions depending on future climate trajectory. A better understanding of the potential effects of climate change on teff cultivation is critical for Ethiopia's agricultural strategy and overall food security goals.

Our modelling results may inform adaptive strategies and policies for minimizing the potentially harmful impacts of climate change on teff production.

Keywords: climate change, Ethiopia, MaxEnt, potential distribution, *Eragrostis tef*

INTRODUCTION

Climate change has resulted in the warming of global average surface temperatures by 0.8 °C over the past century (Hansen et al. 2006; Yumbya et al. 2014) and is accelerating, as demonstrated by a 0.6 °C increase in the last four decades (Hansen et al. 2010; Suwannatrai et al. 2017). The International Panel on Climate Change (IPCC) has concluded that climate change is a primary driver of rising surface and ocean temperatures globally (Cabré et al. 2015; Parry et al. 2007; Solomon et al. 2007; Stocker et al. 2014); and estimates that average overall land and ocean surface temperatures have increased 0.85 ° from 1880 to 2012 0.85 ° C (Liao & Chang 2014; Pachauri et al. 2014), and that this warming is predicted to increase rapidly in the future. There is overwhelming evidence that the distribution of countless species has been, and will continue to be, affected by climate change (Root et al. 2003). Alterations to precipitation patterns, which are predicted under changing climate conditions, may affect food production in many African countries - where agricultural systems are mostly rain-fed. These impacts on livelihood will undoubtedly mean that countries will have to change their farming policies (Dinar 2007). Africa has been exposed to climate change, and population increase has led to fragility of geographical location and loss of natural resources as well as food security (Parry et al. 2007). Yet, many third world countries in Africa depend on rain water for food production, which has been dominated by small scale farmers for several decades. The absence of water for irrigation in many African countries has caused a significantly double dependency on climate for food production. Eventually, Ethiopia is one country exposed to climate change economic status and geographic location (Chen et al. 2015). Agriculture comprises nearly half of Ethiopia's Gross Domestic Product (GDP) and plays a key role in economic development. (GDP) (Gebrehiwot & Van Der Veen 2013). Eighty-five per cent of Ethiopians are considered rural and depend on agricultural production as a means of livelihood (Gebrehiwot & Van Der Veen 2013). Moreover, many

Commented [KOH1]: Revise

Deleted: with

Deleted: ,

Commented [KOH2]: Please revise

Deleted: -fed

Deleted: and

Deleted: for

Commented [KOH3]: Why not use "rain"?

Commented [KOH4]: No need

Commented [KOH5]: revise

Commented [KOH6]: ??

rural Ethiopians face crop failure during long or short droughts, which occur seasonally. Consequently, crops are often lost during natural vegetation phases (Evangelista et al. 2013). Changing patterns of drought and precipitation in Ethiopia have already been documented by other researchers, and greater changes are expected under future conditions (Deressa & Hassan 2009; Viste et al. 2013; Zeleke & Raes 1999). Moreover, while Ethiopia is one of the largest producers of cereals in East Africa, it is still not self-sufficient, as several cereal crops are grown in different agro-climatic areas in Ethiopia. Teff (*Eragrostis tef*) is one of the major preferred grown cereals and covers about 2.8 million ha of .... Cereal crops face an especially critical threat due to climate change (Ledig et al. 2010), which affects the human population because they rely on only a few edible species for nutrition and sustenance out of more than 50,000 known edible species available worldwide (Cheng et al. 2017). Understanding and planning for crop resilience are crucial for the protection of global food supplies, and therefore research on key crops is needed for decision-makers to plan and strategize in the face of climate change (Cowie et al. 2018).

Commented [KOH7]: the country's land?

Deleted: grown

Under IPCC predictions from 2007, the effects of climate change in Africa are relatively uncertain (Solomon et al. 2007). Within Africa, Ethiopia is particularly vulnerable to changing climate conditions, such as increased surface warming accompanied by inconsistent rainfall, which may decrease food security (Conway & Schipper 2011).

Commented [KOH8]: Why are you bringing in climate change issues again after moving on to discuss teff?

Teff is a staple, ancient food crop in Ethiopia, accounting for the largest share of land cultivated for cereal crops (Taffesse et al. 2012). Teff is a warm-season annual crop that produces very small grains (Figure 1A); is easily interchangeable with other staple grains, and is also gluten-free (Rosell et al. 2014). From a nutrition standpoint, teff is low in gluten and high in iron (Stallknecht et al. 1993). Teff crops occupy 988,638.5 square kilometers (Yumbya et al. 2014), however, due to climate change, it is one of the most vulnerable areas in the region (Evangelista et al. 2013). It is estimated that Injera, a food made from teff,

Commented [KOH9]: crop??

provides up to two-thirds of the food consumed by Ethiopians (Figure 1B) (Stewart & Getachew 1962). Understanding and predicting teff distribution across Ethiopia is critical for developing safe and efficient countermeasures for food security. This is particularly important given that climate-induced changes to precipitation and temperature affect teff yields and viability (Baldwin 2009; Kamilar & Beaudrot 2013). Moreover, researchers have developed a suite of ecological tools and climate models to explain ecological processes and relationships between and within spatial and temporal scales (Elith* et al. 2006; Phillips et al. 2006). Such tools have been employed to explore a range of species, habitats, and ecosystem conditions (Alberto et al. 2013; Bellard et al. 2012; Beltramino et al. 2015; Brown 2014). Species distribution models (SDMs) are a subset of the approaches outlined above and are developed by combining current and historical species distribution data with relevant environment variables to explain both occurrence and abundance of organisms in an ecosystem (Caminade et al. 2012; Guisan & Thuiller 2005; Guo et al. 2017; Kamilar & Beaudrot 2013; Peterson 2006; Zimmermann et al. 2010).

A variety of SDMs has been developed to predict species distributions under different climate scenarios (e.g., RCPs). Commonly used SDM models include: the genetic algorithm for the production of rules (GARP), BIOCLIM (the model widely fused tools to predict current and future species distribution of response) (Beaumont et al. 2005), and ecological niche factor analysis (ENFA) (Rong et al. 2019; Tognelli et al. 2009). The MaxEnt (maximum entropy) model has also been widely used due to its prediction accuracy and reliability. It has many advantages, including its ability to handle incomplete data, small sample sizes, species presence/absence and abundance, as well as both continuous and categorical environmental data. This flexibility makes efficient use of data and facilitates model interpretation (Guo et al. 2017; Rong et al. 2019). Several studies indicate that MaxEnt is a robust approach for

Commented [KOH10]: This is too old a reference. The situation may have changed.

Commented [KOH11]: ??

predicting species distributions (Elith* et al. 2006; Kumar & Stohlgren 2009; Phillips et al. 2006; Reiss et al. 2011; Tognelli et al. 2009).

In this study, the geographic distribution data of *Eragrostis tef* occurrence from the Ethiopian National Meteorological Agency was collected and predicted with the MaxEnt model under four climate change scenarios. Our major objectives were to: (1) predict the future distribution of teff species under current climate conditions; (2) forecast suitable areas for teff species under four future climate scenarios, and (3) evaluate the effects of climate change on teff distribution. Identifying shifts in the ranges of suitable areas under future scenarios is a novel approach in the study.

MATERIALS AND METHODS

Study Area

Ethiopia lies in northeast Africa, from longitude 33°E to 55°E and latitude 3.5°N to 15°N. It covers 1.13 million km^2 with various geographical units of mountainous, hilly, and flat regions encompassing elevations from below sea level to 4,000 meters (Tilahun & Schmidt 2012) (Figure 2). Ethiopia's climate is primarily composed of a tropical steppe or subtropical forest climate regime. Rainfall in the tropical zone is typically less than 510 mm per year and average annual temperature varies from 10 to 27 ° C; , the subtropical zone, covering most of Ethiopia's highlands, receives higher levels of precipitation (510 to 1,530 mm) (Hordofa et al. 2008; Mati 2006). Though agricultural planning is difficult due to variable rainfall, a large proportion of Ethiopia receives sufficient rain for crop production. The rainfall pattern in the north part of the country is generally bimodal, with a short duration rain period around March / April and a second rain period beginning around June / July. In some areas, rainfall occurs primarily between June and October, representing more of a unimodal cycle. The primary cereal crops in Ethiopia are teff, maize (*Zea mays*) and wheat (*Triticum aestivum* Linn.).

Commented [KOH12]: ??

Commented [KOH13]: If the writers compared the modeled distribution with the actual distribution obtained from the Ethiopian Meteorological Agency, then the sentence needs revision.

Deleted: s

Commented [KOH14]: Is this value above sea level?

Commented [KOH15]: ??

Teff Distribution Data

The distribution dataset contains 2490 verified, geo-referenced (latitude, longitude and altitude) data-points, including germplasms and herbariums from the Institute of Biodiversity Conservation's gene bank and the Ethiopian National Herbarium at Addis Ababa University. Teff was present in all sites over the nine Ethiopian regional state administrations, predominantly in the Oromia, Amhara, Tigray, the Southern Nations, and Harari regions, with only a few locations in Gambela, Beninshangul-Gumuz, and the Somali Region, and had no significant presence in Afar.

Teff grows primarily in the highlands where clouds are forced to release rain. Teff optimal growing conditions are 430–560 mm of rain per year and a temperature range of 10–30°C (Roseberg et al. 2005). In Ethiopia, crops are mostly sown from June to October and harvested from September to February (Taffesse et al. 2012). The primary crop season corresponds to the summer rainy season, from June to August and in the autumn from September to November (Yumbya et al. 2014). Light rain also falls during the spring, from March through May. Some crops—only about 8% of total cropland—are harvested between March and August, making Ethiopia’s crop season somewhat bimodal (Hordofa et al. 2008; Mati 2006; Taffesse et al. 2012).

Commented [KOH16]: These sentences don’t seem to fit this sub-section

Topographical data

A digital elevation model (DEM) with 90m resolution was acquired from the US Geological Survey (www.srtm.usgs.gov) (USGS, 1996). Two terrain variables (aspect and slope) from the DEM were re-sampled into 1 km spatial resolution using nearest neighbor sampling in ArcGIS 10.5. The two topographical variables were used as model inputs.

Current and future climate data

Climatic data consisting of 19 bioclimatic variables, here coded bio1 through bio19, were obtained from the WorldClim data repository. Climatic data (1-km resolution) were collected for the study region for the period from 1950 to 2000 (http://www.worldclim.org/) (Fick & Hijmans 2017; Hijmans et al. 2005). The IPCC's Fourth Assessment Report projects future climate conditions under different scenarios (Metz et al. 2007). The data were produced by interpolation of data predictions for 2060 and 2080 to produce an estimate of climate condition for the year 2070. All four greenhouse gas concentration trajectories provided by the IPCC were used: Representative Concentration Pathway (RCP) 2.6, RCP 4.5, RCP 6.0, and RCP 8.0 (I.e., the four scenarios explained for the total radiative forcing values in 2100 will be 2.6W/m^2,4.5W/m^2, 6.0 W/m^2, and 8.5 W/m^2 greater than in the preindustrial period) (Rong et al. 2019; Van Vuuren et al. 2011).

To prevent the inclusion of redundant variables in the model, all 19 climatic variables were checked for independence via a correlation test. Correlated variables were removed leaving nine climatic variables with a high degree of independence, and two independent terrain variables (slope and aspect). We used the 2070 climate projections (the average data from 2060 and 2080) as the basis for evaluating the effects different RCPs on teff cultivation. Each of the four RCPs represents possible pathways for greenhouse gas emissions, with emission peaks around 2020, 2040, 2080, and 2100 for RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively. Under each RCP, the global surface temperature is expected to increase compared to 19th-century levels. Average surface temperature is anticipated to increase by 1.61, 2.41, 2.81 and 4.31 ° C by 2080, depending on the RCP scenario (Stocker et al. 2014).

Climatic niche Modeling

We used MaxEnt Version 3.4.1(https://www.biodiversityinformatics.amnh.org/open_source/maxent) (Phillips et al.

Commented [KOH17]: Should read like this:
… according to RCP …, RCP …, RCP …, and RCP…, respectively.

Deleted: or

2006) to simulate teff distribution across Ethiopia under the different climate scenarios. We used a default setting of 10,000 for the maximum number of background points; 0.00001 for convergence threshold, 500 for the maximum number of iterations, and 0.5 for default prevalence (Phillips & Dudík 2008; Wu et al. 2017); we used a 75%/25% split for training and test data. We used the 11 variables selected after correlation analysis (9 bioclimatic and 2 terrains) as inputs in the MaxEnt model. We organized variables by Operating Characteristic Curve (AUC) values using the following five categories: 0.5–0.6 for very poor, 0.6–0.7 for poor, 0.7–0.8 for fair, 0.8–0.9 for good, and 0.9–1 for excellent (Suwannatrai et al. 2017; Wei et al. 2018), where the achievable minimum and maximum AUC values are 0 and 1 (Phillips & Dudík 2008).

MaxEnt has been used by other researchers to model current and future teff distribution using presence-only data and machine learning methods (Elith et al. 2011). This approach is particularly useful for smaller datasets, compared to other modelling approaches (Phillips et al. 2006). Furthermore, it has been demonstrated to be equally accurate under past, current, and future scenarios (Hijmans & Graham 2006). The accuracy of the MaxEnt model output was evaluated using Receiver Operating Characteristic (ROC) analysis - which utilizes AUC values. ROC analysis identifies the occurrence of true positives relative to false positives. The accuracy of our model results was assessed by inspecting plots of true positive versus false-positive rates.

RESULTS

Variable Contribution Analysis

The contribution and importance of each of the 11 variables were evaluated for each of the four climate scenarios (Table 1). The potential teff distribution under current projected climate change was significantly affected by Bio11 (78.3%), Bio15 (8.3%), Bio19 (3.7%), Slope (3.3%), Bio7 (2.2%), Bio4 (1.3%), and Bio3 (1.1%).

Deleted: differing

Commented [KOH18]: An explanation for this is absolutely necessary immediately after the sentence. Did these parameters provide the best model performance, for example? The reader needs to know.

Commented [KOH19]: Isn't AUC area under curve?

Commented [KOH20]: Did you perform any test of significance?

Commented [KOH21]: Consistency? Earlier you presented it as "bio1"

The potential teff distribution under the RCP2.6 scenario was influenced mainly by Bio11 (79.7%), Bio15 (7.3%), Slope (3.2%), Bio19 (3%), Bio7 (2.6%), Bio3 (1.3%) and Bio14 (1.1%). The significant variables under the RCP4.5 scenario were Bio11 (80.4%), Bio15 (7.8%), Slope (3.5%) Bio19 (3.5%), Bio7 (2.3%), Bio3 (0.9%), and Bio14 (0.8%) and the potential teff distribution under RCP6.0 the most constrained scenario was by Bio11 (78.5%), Bio15 (7.8%), Bio19 (3.9%), Slope (3.1%), Bio7 (2.9%), Bio14 (1.4%), Bio3 1.3%), Bio2 (0.5%), Bio18 (0.1%) and Aspect (0.1%). The potential teff distribution in the RCP8.5 scenario was most strongly related to Bio11 (77.8%), Bio15 (9%) Bio19 (4.3%), Slope (3.1%), Bio7 (2.4%), Bio14 (1.5%), Bio3 (0.8%), Bio4 (0.4%), Bio2 (0.4%), and Aspect (0.1%). The Pearson's correlation coefficients are included in the supplementary material (Table S1).

Jackknifing was used to assess the relative importance of each variable for explaining teff distribution using the "leave-one-out" method (Peterson et al. 2011). The jackknife test indicated that Bio11, Bio14, Bio119, and Bio4 were among the most important variables (high gain) for explaining teff distribution. Potential teff distribution under current conditions was significantly affected by Bio11 (gain, 0.61), Bio14 (gain, 0.18), Bio19 (gain, 0.15), and Bio4 (gain, 0.12) (Fig. 3A). Potential teff distribution under the RCP2.6 scenario was also similarly impacted by a few key variables, Bio11 (gain, 0.62), Bio14 (gain, 0.18), Bio19 (gain, 0.17), and Bio4 (gain, 0.13), respectively (Figure 3B). In RCP4.5, Bio11 (gain, 0.61), Bio19 (gain, 0.17), Bio4 (gain, 0.16), and Bio14 (gain, 0.14) were shown in Figure 3C. The variables most constraining the potential teff distribution under the RCP 6.0 scenario were the same as that under RCP 4.5 with similar gain except for Bio11(gain, 0.62), Bio4 (gain, 0.17), Bio19 (gain, 0.16), Bio14 (gain, 0.14) (Figure 3D). The potential distribution of the species under the RCP8.5 scenario was most strongly associated with Bio11 (gain, 0.59), Bio2 (gain, 0.12), Bio19 (gain, 0.15) and Bio4 (gain, 0.13), respectively (Figure 3E).

The response curves demonstrate the relationship between environmental variables and habitat suitability and provide information on factors important for cultivating teff. Suitability ranges for each environmental variable were identified by the threshold of the standard suitable habitats. Response curves of 8 primary variables explaining teff habitat suitability are illustrated in Figure 3. Habitat suitability for teff is highest in areas where mean temperature of the coldest season (Bio11) was 14-19 ◦C, annual precipitation seasonality (Bio15) was > 60% but <122%, precipitation of the coldest season (Bio19) was 8.5-110mm, the slope was 0 to 3◦, temperature annual range (Bio7, Bio5-Bio6) was 11.8 to 26.6 ◦C, temperature seasonality (standard deviation $\times$100) Bio(4) was 1000-1550, precipitation of driest period (Bio14) was 0.3mm to 20 mm, and isothermality (Bio3) above 68 and aspect from 355◦to 0◦ (Figure 4).

Mean cold-season temperature (Bio11) contributed the most to the model by far, at 78.3%. The geography of Ethiopia results in a high correlation between rainfall and temperature, due to western highlands that shape a rain shadow in the eastern half of the country (Dinku et al. 2008; Gebrechorkos et al. 2019; Gleixner et al. 2017), meaning that high precipitation has a negative relationship with temperature.

Therefore, areas with higher temperature that do not correlate with suitable teff habitat lie on the eastern side of highlands, and those that do not correlate with higher temperature lie in the western lowlands (Figure 5).

Mean cold-season temperature was not independent of the mean temperature of the warmest quarter or mean temperature of the driest quarter. Therefore, temperature generally had the greatest effect, especially during the growing season, which would logically be the highest. According to the literature (Evangelista et al. 2013), using a MaxEnt predictive model, teff distribution depended most on precipitation variables, especially precipitation of the wettest quarter, having permutation importance of 26.6%. Evangelista et al. (2013) used climatic variables only, without topographic data. In contrast, in our more comprehensive model, we found that the mean temperature of the coldest quarter was the most important variable, with permutation importance of 66.5% (Table 2).

Accuracy of the MaxEnt Model

AUC values were above 0.829 undercurrents and four projected climate scenarios (Table 3). Prediction accuracy of the MaxEnt model, based on classification standard, was very good; AUC values for training and testing were 0.84 and 0.83, respectively.

Habitat Suitability

Each teff distribution scenario (current and future RCP projections) from the MaxEnt model was mapped using ArcGIS 10.5, using the following categorized of teff cultivation suitability: unsuitable, low, moderate, and highly suitable (Figure 5). Under current climate conditions, the distribution area with moderate suitability was 296933 km^2, low suitability 463453 km^2, and high suitability, 14513 km^2. The total suitable area occupied 58% of our research area. In the four future projection scenarios, the total suitable area declined with climate warming in RCP4.5 and RCP scenarios 8.5 while it increased under other RCP scenarios (RCP2.6 and RCP6.0) and areas with warmer climate and more unsuitable for the teff were 774899 km^2 (58%), 785957 km^2 (58.8%), 770139 km^2 (57.6%), 791085 km^2 (59.2%) and 767554 km^2 (57.4%) under current, RCP2.6, RCP4.5, RCP6.0 and RCP8.5 scenarios, respectively (Table 4). The percentage of the suitable area was 58.8%, 57.6%, 59.2%, and 57.4% of the total research area under the four projection scenarios RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively. A substantial difference was found between the current suitable area and the predicted suitable area under RCP 2.6 and 6.0 (Figure 6). Specifically, the area of suitable teff habitat increased in both RCP 2.6 and 6.0 while significantly decreased in RCP 4.5 (-4760 km^2) and RCP 8.5 (-7345 km^2) (Table 4).

Surprisingly, projected loss of suitable habitat did not correlate with increasing projected radiative forcing. Rainfall projections indicate that, rather than an overall increase or decrease in volume, the primary precipitation change in Ethiopia will be a decrease in rainfall consistency. That means that year-to-year projections will capture that variation, and is reflected in the projected higher losses under RCP 4.5 and RCP 8.5. As a result, the range of projected losses should be taken as a possibility under multiple scenarios, and not as an indication that higher, rather than lower radiative forcing is better.

The area of suitable habitat between moderately and highly suitable areas remained roughly the same in each future scenario. Taking the ratio of highly suitable habitat to moderately suitable habitat, the largest projected deviation was under the RCP 4.5 scenario, resulting in a relative decrease of highly suitable area, while the other scenarios indicated a slight increase of highly suitable, relative to a moderately suitable area.

Unsuitable area under future climate conditions declines in RCP 2.6 and RCP 6.0 compared to the current unsuitable area while it rises in RCP4.5 and RCP 8.5. Also, low suitability areas decrease under RCP 2.6, RCP 4.5 and RCP 8.5 while they increase under the RCP 6.0 scenario. Moderate suitability areas increase in RCP 2.6, RCP 4.5 and RCP 6.0 but decline in RCP 8.5. Again, high suitability areas compared with the current situation increase in area in RCP 4.5, RCP 6.0 and RCP 8.5 but not RCP 2.6 scenario (Table 4).

On the regional scale, the largest projected shifts in habitat suitability occur in the northwest corner of the country under the most extreme radiative forcing case of RCP 8.5, where a patch of currently unsuitable area becomes moderately suitable. Despite this single projected increase in area, overall, suitable land area is expected to decline under RCP 4.5 and RCP 8.5, including a decrease in total moderately suitable land. The result of a shift in suitable land towards the west and away from the east contrasts with the path of rainclouds travelling from west to east (Figure 5).

Based on the current teff distribution, low suitability areas accounts for 46.88%, moderately suitable 30.03%, and highly suitable 1.47%, making a total suitable area of 78.38%. In RCP2.6, low, moderate, and high suitability areas account for 46.84%, 31.34%, and 1.33% of the actual teff distribution area, respectively. Therefore, proportional areas for the current and RCP2.6 scenarios are very similar. In RCP4.5, the proportion in low suitability decreases, but increases in moderate and high suitability proportions compared with RCP2.6. In RCP6.0, low and moderately suitable proportions are similar, and a little higher than in the highly suitable class. In RCP8.5, the proportions are similar to RCP6.0 but slightly lower in low and moderate, and higher in the highly suitable area (Table 5). Therefore, the proportion of highly suitable area will increase with warming, but areas of low and moderate suitability will remain somewhat similar.

DISCUSSION

Future climate scenarios RCP 2.6 and RCP 6.0 provided the most favorable conditions for maintaining suitable teff habitat. However, of the two scenarios, RCP 2.6 resulted in a greater loss of highly suitable habitat, thus projections from RCP 6.0 show the highest preservation of total potential crop area. While climate change is likely to affect rainfall consistency in the region, the geography will continue to define rainfall locations. With inconsistent rainfall patterns, habitat suitability will change from year to year, which explains the up and down nature of our results under increasing radiative forcing.

Evangelista et al. (2013) predicted a 350,000 km^2 loss of suitable crop area by 2050. However, our results highlight different trends under different future climate change scenarios, some increasing, and others decreasing. In the Evangelista et al. (2013) model, rainfall was the primary climate driver (and not coupled with a mean temperature of the coldest season), so model outcomes were heavily dependent on the specific rainfall predictions of the climate data. We see a similar dependency here with predictions that do not correlate linearly with radiative forcing. The main difference in the models lies in the confidence of an environmental variable versus the prediction of a climatic variable.

Previous research has shown that in some parts of Ethiopia, future teff distributional changes and yield would decrease due to climate changes. The expected average loss by 2050 was approximately 24% of the current suitable teff area (Evangelista et al. 2013). This prediction was based on a teff suitability area in 2050 having a low of 15 $^{\circ}$C, and a high of 27°C temperature, and a compensating increase in a minimum of 600mm and a maximum of 1900mm rainfall, respectively. Previous studies in Ethiopia have demonstrated that rain-fed agriculture is heavily affected by changes in rainfall, temperature and seasonality (Alemayehu & Bewket 2017; Asfaw et al. 2018; Bewket 2009; Evangelista et al. 2013; Gebre et al. 2013; Seleshi & Zanke 2004; Worku et al. 2019).

Currently in Ethiopia teff supply does not meet teff demand, and continued teff cultivation could worsen by the effects of climate change. Teff is an essential food in Ethiopia, thus any negative impact on suitable areas for its production, such as impacts due to climate change, have a direct impact on food security. Previous studies have used four environmental predictors to model teff suitability: precipitation of wettest quarter (Bio16), annual precipitation (Bio12), precipitation of the coldest quarter (Bio19), and precipitation seasonality (Bio15). Their permutation is 26.6% for Bio16 (AUC = 0.79), while our results show that the mean temperature of the coldest quarter (Bio11) has a permutation of 66.5%. This model includes six additional environmental predictors: Isothermality (mean diurnal range/temperature annual range (Bio3), temperature annual range (Bio7), precipitation seasonality (Bio15), slope, precipitation of coldest quarter (Bio19), and temperature seasonality (Bio4); the average test AUC for our model was 0.83. The highest permutation was Bio11, having a contribution of 66.5%. The second most important factor was precipitation of the driest period (Bio14).

Commented [KOH22]: revise

Deleted:

Our model provided reasonably strong AUC predictions for models of teff distribution in Ethiopia under different climate projections. Our model adequately predicted current teff conditions thus indicating our approach was sufficiently robust to model teff suitability under future scenarios. We used the MaxEnt model to show current teff distribution and to predict future climate impacts on it. Teff crop distribution differs by geographical setting in Ethiopia, which our model shows in AUC test evaluation. Furthermore, the model relies on predicted future climate scenarios. Yet literature (Barnett et al. 2000) suggests that the model should integrate multiple realization form climate and literature (Cheng et al. 2017) concluded that though bioclimatic models have a number of benefits, they need to be implemented.

Commented [KOH23]: ?? revise

Climate change affects the teff crop distribution both in current and future scenarios. Moreover, results show that the differing future distributions are not consistently affected by predicted changes in climate. Overall, data indicates that teff crop potential area decreased from 41% to 27% by climate change in Ethiopia (Tan et al. 2016). Moreover, the predicted future damage is so severe that the existence of the Ethiopian agricultural sector, in which teff, one of a staple food in the country, will be at stake unless adaptive policies are implemented. Many East African countries are facing the erratic effects of climate change, of which Ethiopia is one (Deressa & Hassan 2009; Di Falco & Veronesi 2013).

We should have considered including management, soil and other teff varieties which grow in Ethiopia in our model analysis. However, it wasn't easy to find these data for our research. While we strongly believe that our research could be improved by including management of farming practice and preparation for teff harvesting components, we believe that the lack of soil and other data in our analysis did not affect the results.

Commented [KOH24]: not at all? Perhaps it's better to say "did not significantly affect the results"

Teff has been a critical agricultural product historically, and will likely continue to be important for food security in Ethiopia. Teff is highly nutritious and is tolerant of extremes such as drought, waterlogging, pests, and diseases (Cheng et al. 2017). Ultimately, several studies and our own research results show it is necessary to understand the impact of climate change on teff distribution – such information is key for informing policymakers and implementing adaptive management to minimize the impact of climate change.

CONCLUSIONS

Climate change does not pose a substantial threat to the future ability to grow teff as a staple crop thanks to its ability to grow in an extensive range of conditions. A total projected loss of 8,000–17,000 km^2 of suitable habitat for growing teff due to climate change is undesirable, but ultimately not catastrophic. We recommend using the average temperature of local growing seasons for crop projections in agricultural modelling.

Commented [KOH25]: because of?

However, suitable teff habitats defined only by environmental parameters do not account for physical accessibility to areas, nor sociopolitical effects on land access. Suitable crop areas still need to be a protected resource, as other changes may indirectly affect total available land area. For example, increasing average temperature is expected to expedite population migrations to urban areas. Addis Ababa lies squarely within the suitable habitat for teff, and an increased population there may require a shift in neighboring land from agricultural to urban use. Advanced planning to ensure functional urban density and enforcement of land use regulations is recommended.

Our model presents an opportunity for the agricultural sector, modeler's and policymakers to examine the effect of climate change on teff to inform development of strategy and policy to minimize negative impacts. In Ethiopia today there remains widespread cultural food insecurity, but the country depends on these cereals as a staple food. Policymakers should pay attention to areas with low habitat suitability and resilience for teff, and implement a strategy to foster diversification to avoid over-reliance as it is important to maintain nutrition and sustainable food security for the Ethiopian people.

Acknowledgements: We are grateful to Prof. Zhao, Zhangle, Yapeng and Tang jia kai and Rachel, for helping directly and indirectly and guiding as well as for their continuous support throughout this project.

Funding: Priority research program of Chinese Academy of Science (XDA) (NO. 20100102)

Conflicts of Interest: The authors declare no conflict of interest.

References

Alberto FJ, Aitken SN, Alía R, González‐Martínez SC, Hänninen H, Kremer A, Lefèvre F, Lenormand T, Yeaman S, and Whetten R. 2013. Potential for evolutionary responses to climate change‐evidence from tree populations. *Global Change Biology* 19:1645-1661.

Alemayehu A, and Bewket W. 2017. Local spatiotemporal variability and trends in rainfall and temperature in the central highlands of Ethiopia. *Geografiska Annaler: Series A, Physical Geography* 99:85-101.

Asfaw A, Simane B, Hassen A, and Bantider A. 2018. Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: A case study in Woleka sub-basin. *Weather and Climate Extremes* 19:29-41.

Baldwin RA. 2009. Use of maximum entropy modeling in wildlife research. *Entropy* 11:854-866.

Barnett TP, Hegerl G, Knutson T, and Tett S. 2000. Uncertainty levels in predicted patterns of anthropogenic climate change. *Journal of Geophysical Research: Atmospheres* 105:15525-15542.

Beaumont LJ, Hughes L, and Poulsen M. 2005. Predicting species distributions: use of climatic parameters in BIOCLIM and its impact on predictions of species' current and future distributions. *Ecological Modelling* 186:251-270.

Bellard C, Bertelsmeier C, Leadley P, Thuiller W, and Courchamp F. 2012. Impacts of climate change on the future of biodiversity. *Ecology letters* 15:365-377.

Beltramino AA, Vogler RE, Gregoric DEG, and Rumi A. 2015. Impact of climate change on the distribution of a giant land snail from South America: predicting future trends for setting conservation priorities on native malacofauna. *Climatic change* 131:621-633.

Bewket W. 2009. Rainfall variability and crop production in Ethiopia: Case study in the Amhara region. Proceedings of the 16th International Conference of Ethiopian Studies: Norwegian University of Science and Technology Trondheim, Norway. p 823-836.

Brown JL. 2014. SDM toolbox: a python‐based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. *Methods in Ecology and Evolution* 5:694-700.

Cabré A, Marinov I, and Leung S. 2015. Consistent global responses of marine ecosystems to future climate change across the IPCC AR5 earth system models. *Climate Dynamics* 45:1253-1280.

Caminade C, Medlock JM, Ducheyne E, McIntyre KM, Leach S, Baylis M, and Morse AP. 2012. Suitability of European climate for the Asian tiger mosquito Aedes albopictus: recent trends and future scenarios. *Journal of the Royal Society Interface* 9:2708-2717.

Chen C, Noble I, Hellmann J, Coffee J, Murillo M, and Chawla N. 2015. University of Notre Dame global adaptation index country index technical report. *ND-GAIN: South Bend, IN, USA*.

Cheng A, Mayes S, Dalle G, Demissew S, and Massawe F. 2017. Diversifying crops for food and nutrition security–a case of teff. *Biological Reviews* 92:188-198.

Conway D, and Schipper ELF. 2011. Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global environmental change* 21:227-237.

Cowie AL, Orr BJ, Sanchez VMC, Chasek P, Crossman ND, Erlewein A, Louwagie G, Maron M, Metternicht GI, and Minelli S. 2018. Land in balance: The scientific conceptual framework for Land Degradation Neutrality. *Environmental Science & Policy* 79:25-35.

Deressa TT, and Hassan RM. 2009. Economic impact of climate change on crop production in Ethiopia: Evidence from cross-section measures. *Journal of African economies* 18:529-554.

Di Falco S, and Veronesi M. 2013. How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics* 89:743-766.

Dinar A. 2007. Climate change: the final blow for agriculture in Africa. *Research Brief*.

Dinku T, Connor SJ, Ceccato P, and Ropelewski CF. 2008. Comparison of global gridded precipitation products over a mountainous region of Africa. *International Journal of Climatology: A Journal of the Royal Meteorological Society* 28:1627-1638.

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, and Yates CJ. 2011. A statistical explanation of MaxEnt for ecologists. *Diversity and distributions* 17:43-57.

Elith* J, H. Graham* C, P. Anderson R, Dudík M, Ferrier S, Guisan A, J. Hijmans R, Huettmann F, R. Leathwick J, and Lehmann A. 2006. Novel methods improve prediction of species’ distributions from occurrence data. *Ecography* 29:129-151.

Evangelista P, Young N, and Burnett J. 2013. How will climate change spatially affect agriculture production in Ethiopia? Case studies of important cereal crops. *Climatic change* 119:855-873.

Fick SE, and Hijmans RJ. 2017. WorldClim 2: new 1 ‐ km spatial resolution climate surfaces for global land areas. *International journal of climatology* 37:4302-4315.

Gebre H, Kindie T, Girma M, and Belay K. 2013. Trend and variability of rainfall in Tigray, northern Ethiopia: analysis of meteorological data and farmers' perception. *Academia Journal of Agricultural Research* 1:088-100.

Gebrechorkos SH, Hülsmann S, and Bernhofer C. 2019. Long-term trends in rainfall and temperature using high-resolution climate datasets in East Africa. *Scientific reports* 9:1-9.

Gebrehiwot T, and Van Der Veen A. 2013. Farm level adaptation to climate change: the case of farmer’s in the Ethiopian Highlands. *Environmental management* 52:29-44.

Gleixner S, Keenlyside N, Viste E, and Korecha D. 2017. The El Niño effect on Ethiopian summer rainfall. *Climate Dynamics* 49:1865-1883.

Guisan A, and Thuiller W. 2005. Predicting species distribution: offering more than simple habitat models. *Ecology letters* 8:993-1009.

Guo Y, Li X, Zhao Z, Wei H, Gao B, and Gu W. 2017. Prediction of the potential geographic distribution of the ectomycorrhizal mushroom Tricholoma matsutake under multiple climate change scenarios. *Scientific reports* 7:46221.

Hansen J, Ruedy R, Sato M, and Lo K. 2010. Global surface temperature change. *Rev Geophys* 48.

Hansen J, Sato M, Ruedy R, Lo K, Lea DW, and Medina-Elizade M. 2006. Global temperature change. *Proceedings of the National Academy of Sciences* 103:14288-14293.

Hijmans RJ, Cameron SE, Parra JL, Jones PG, and Jarvis A. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology: A Journal of the Royal Meteorological Society* 25:1965-1978.

Hijmans RJ, and Graham CH. 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. *Global Change Biology* 12:2272-2281.

Hordofa T, Menkir M, Awulachew SB, and Erkossa T. 2008. Irrigation and rain-fed crop production system in Ethiopia.

Kamilar JM, and Beaudrot L. 2013. Understanding primate communities: Recent developments and future directions. *Evolutionary Anthropology: Issues, News, and Reviews* 22:174-185.

Kumar S, and Stohlgren TJ. 2009. Maxent modeling for predicting suitable habitat for threatened and endangered tree Canacomyrica monticola in New Caledonia. *Journal of Ecology and the Natural Environment* 1:094-098.

Ledig FT, Rehfeldt GE, Sáenz‐Romero C, and Flores‐López C. 2010. Projections of suitable habitat for rare species under global warming scenarios. *American journal of botany* 97:970-987.

Liao H, and Chang W. 2014. Integrated assessment of air quality and climate change for policy-making: highlights of IPCC AR5 and research challenges. *National Science Review* 1:176-179.

Mati BM. 2006. *Overview of water and soil nutrient management under smallholder rain-fed agriculture in East Africa*: IWMI.

Metz B, Davidson O, Bosch P, Dave R, and Meyer L. 2007. *Climate change 2007: Mitigation of climate change*: Cambridge Univ. Press.

Pachauri RK, Allen MR, Barros VR, Broome J, Cramer W, Christ R, Church JA, Clarke L, Dahe Q, and Dasgupta P. 2014. *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*: Ipcc.

Parry M, Parry ML, Canziani O, Palutikof J, Van der Linden P, and Hanson C. 2007. *Climate change 2007-impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC*: Cambridge University Press.

Peterson AT. 2006. Ecologic niche modeling and spatial patterns of disease transmission. *Emerging infectious diseases* 12:1822.

Peterson AT, Soberón J, Pearson RG, Anderson RP, Martínez-Meyer E, Nakamura M, and Araújo MB. 2011. *Ecological niches and geographic distributions (MPB-49)*: Princeton University Press.

Phillips SJ, Anderson RP, and Schapire RE. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190:231-259.

Phillips SJ, and Dudík M. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography* 31:161-175.

Reiss H, Cunze S, König K, Neumann H, and Kröncke I. 2011. Species distribution modelling of marine benthos: a North Sea case study. *Marine Ecology Progress Series* 442:71-86.

Rong Z, Zhao C, Liu J, Gao Y, Zang F, Guo Z, Mao Y, and Wang L. 2019. Modeling the effect of climate change on the potential distribution of Qinghai Spruce (Picea crassifolia kom.) in Qilian Mountains. *Forests* 10:62.

Root TL, Price JT, Hall KR, Schneider SH, Rosenzweig C, and Pounds JA. 2003. Fingerprints of global warming on wild animals and plants. *nature* 421:57-60.

Roseberg RJ, Norberg S, Smith J, Charlton B, Rykbost K, and Shock C. 2005. Yield and quality of teff forage as a function of varying rates of applied irrigation and nitrogen. *Klamath Experiment Station* 1069:119-136.

Rosell CM, Barro F, Sousa C, and Mena MC. 2014. Cereals for developing gluten-free products and analytical tools for gluten detection. *Journal of Cereal Science* 59:354-364.

Seleshi Y, and Zanke U. 2004. Recent changes in rainfall and rainy days in Ethiopia. *International Journal of Climatology: A Journal of the Royal Meteorological Society* 24:973-983.

Solomon S, Manning M, Marquis M, and Qin D. 2007. *Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC*: Cambridge university press.

Stallknecht GF, Gilbertson KM, and Eckhoff J. 1993. Teff: Food crop for humans and animals. *New crops Wiley, New York*:231-234.

Stewart RB, and Getachew A. 1962. Investigations of the nature of injera. *Economic Botany* 16:127-130.

Stocker TF, Qin D, Plattner G-K, Tignor MM, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, and Midgley PM. 2014. Climate Change 2013: The physical science basis.

contribution of working group I to the fifth assessment report of IPCC the intergovernmental panel on climate change. Cambridge University Press.

Suwannatrai A, Pratumchart K, Suwannatrai K, Thinkhamrop K, Chaiyos J, Kim C, Suwanweerakamtorn R, Boonmars T, Wongsaroj T, and Sripa B. 2017. Modeling impacts of climate change on the potential distribution of the carcinogenic liver fluke, Opisthorchis viverrini, in Thailand. *Parasitology research* 116:243-250.

Taffesse AS, Dorosh P, and Gemessa SA. 2012. Crop production in Ethiopia: Regional patterns and trends. *Food and agriculture in Ethiopia: Progress and policy challenges*:53-83.

Tan Z, Yang Y, Wang Y, Wang L, and Sun G. 2016. The decrease of potential suitable areas and the distribution tendency of staple crops in Ethiopia under future climate conditions. *African Journal of Agricultural Research* 11:2092-2101.

Tilahun H, and Schmidt E. 2012. Spatial analysis of livestock production patterns in Ethiopia.

Tognelli MF, Roig SA, Marvaldi A, Flores GE, and Lobo JM. 2009. An evaluation of methods for modelling distribution of Patagonian insects.

Van Vuuren DP, Edmonds J, Kainuma M, Riahi K, Thomson A, Hibbard K, Hurtt GC, Kram T, Krey V, and Lamarque J-F. 2011. The representative concentration pathways: an overview. *Climatic change* 109:5.

Viste E, Korecha D, and Sorteberg A. 2013. Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology* 112:535-551.

Wei B, Wang R, Hou K, Wang X, and Wu W. 2018. Predicting the current and future cultivation regions of Carthamus tinctorius L. using MaxEnt model under climate change in China. *Global Ecology and Conservation* 16:e00477.

Worku G, Teferi E, Bantider A, and Dile YT. 2019. Observed changes in extremes of daily rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia. *Theoretical and Applied Climatology* 135:839-854.

Wu X, Dong S, Liu S, Su X, Han Y, Shi J, Zhang Y, Zhao Z, Sha W, and Zhang X. 2017. Predicting the shift of threatened ungulates' habitats with climate change in Altun Mountain National Nature Reserve of the Northwestern Qinghai-Tibetan Plateau. *Climatic change* 142:331-344.

Yumbya J, de Vaate M, Kiambi D, Kebebew F, and Rao K. 2014. Assessing the effects of climate change on teff in Ethiopia. *A research project by: African Biodiversity Conservation and Innovations Centre (ABCIC) in collaboration with the International*

Crops Research Institute for the Semi-arid Tropics (ICRISAT) and Institute of Biodiversity Conservation (IBC), Nairobi, Kenya.

Zeleke K, and Raes D. 1999. Test of homogeneity, frequency analysis of rainfall data and estimate of drought probabilities in Dire Dawa, eastern Ethiopia. *Ethiopian Journal of Natural Resources* 1:125.

Zimmermann NE, Edwards Jr TC, Graham CH, Pearman PB, and Svenning JC. 2010. New trends in species distribution modelling. *Ecography* 33:985-989.

Table captions

Table 1. Percent contributions of the variables to teff distribution in the MaxEnt model. Note: The variables in bold were key variables selected by their contribution rates and multicollinearity test. RCP: (Representative Concentration Pathway).

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

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

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

Table 5. Area of teff distribution in different classes under current and projected climate scenarios and ratios of the area to current actual teff distribution area

Figure captions

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.

Figure 2. 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 3. 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 benefit explains

how much better the simulated distribution is compared to a uniform distribution that matches present data. The dark blue bars indicate the gain from using each variable in isolation, the light blue bars indicate the gain lost by removing the single variable from the full model, and the red bar indicates the gain using all of the variables).

Figure 4. Response curves of 8 environmental variables in the teff habitat distribution model. Bio11: Mean temperature of the coldest season (°C*10); Bio15: Precipitation seasonality (CV); Bio7: Temperature annual range (Bio5–Bio6); Bio19: Precipitation of coldest season (mm*10); Bio14: Precipitation of driest period (mm*10); Bio3: Isothermality (Bio2/Bio7×100); Bio4: Temperature seasonality (standard deviation×100) (°C*10); Slope (º).

Figure. 5 Average annual rainfall (left) and average annual temperature (right) in Ethiopia over three decades.

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

Supplementary table

Supplementary 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.**

Pearson's correlation coefficient attached (see Table S1)