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ORIGINAL ARTICLE

# Predicted changes in distribution and richness of wild edible plants under climate change scenarios in northwestern Kenya

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**Abstract**

Wild edible plants (WEPs) can provide diverse and nutrient-rich food sources that contribute to the health and well-being of communities worldwide. In northwestern Kenya, WEPs are vital dietary components for nomadic pastoral communities with limited access to diverse cultivated food crops. However, the increasing impact of climate change poses a threat to these valuable food resources, and their sustainable utilization remains precarious. Here, we assessed the potentially suitable habitats and richness of 23 selected WEPs in the region using a species distribution modeling (SDM) approach. We used species occurrence points from global databases, a national herbarium, and field surveys and made predictions spanning two future time intervals, 2041–2070 and 2071–2100, across three shared socioeconomic pathways (126, 370, and 585) using bioclimatic variables from five global circulation models. We also included soil and topographic variables in our models. We calibrated maximum entropy models using individually tuned parameters. Our future predictions showed a predominant decline in habitat suitability for half the studied WEPs. The richness of the selected WEPs are predicted to remain rather stable under projected future climates concentrating in southern parts of Turkana County. Conservation and management measures need to consider the changing availability of these valuable resources in order to underpin the dietary diversification of local communities.

**Keywords** Wild food plants · Ecological niche modeling · Regional climate change · Biodiversity loss

## Introduction

Northwestern Kenya is characterized by vast arid and semi-arid lands inhabited by nomadic pastoralist communities, many of whom are from the Turkana ethnic group (Ejore et al. 2020; Ratemo et al. 2020). The Turkana people depend on animal products for their protein requirements and wild edible plants (WEPs), especially their fruits, for macro and micro-nutrients (Twine et al. 2003; Agol et al. 2020; Oduor et al. 2023). The majority of Turkana communities do not have immediate access to cultivated crops and hence rely on WEPs (Ngoye et al. 2021; Shanguhyia 2021); the few strips of irrigated crop farming astride streams in the region are insufficient (Akuja and Kandagor 2019; Mbugua et al. 2020; Akall 2021). Intermittent rains within Turkana, accompanied by low flows of the Turkwel River, undermine the productivity of the irrigated riverbank strips (Korobe 2022). Occasional flash floods also devastate riparian crop farms (Chilambe et al. 2022), further increasing the nutritional insecurity problems.

Turkana is the most food-insecure county in Kenya, Kenya Economic Report (2020). The county has high levels of malnutrition among children and adults (Kuper et al. 2015; Bhavnani et al. 2023) attributable to the high food poverty rate of 66%, which is higher than the national

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average of 32% (Mbogori and Murimi 2017). Turkana has a low infrastructural development (Kihu et al. 2015) with low accessibility to remote areas hindering trade and markets. Turkana residents rely on WEPs as “safety nets,” including herbs, vegetables, and fruit trees (Oduor et al. 2023). The nutritional value of regional WEPs is similar to or superior to cultivated crops (Sarfo 2018). WEPs can support local communities to alleviate hunger and malnutrition challenges. For these resources to be used sustainably to meet the future food demands in Turkana, it is important to quantify their present and potential future spatial coverage and richness in the face of anthropogenic climate change.

We trained correlative species distribution models (SDMs) to predict the potentially suitable habitats and species richness of selected woody WEPs. Such models have been used to assess the potential distribution of socioeconomically important non-timber plants and tree species across Africa (Amoussou et al. 2022), priority multipurpose tree species in Central Africa (Ceccarelli et al. 2022) and Burkina Faso (Gaisberger et al. 2017), wild food crops in southern Africa (Wessels et al. 2021), and medicinal plants like Aloe species in East Africa (Mkala et al. 2022), among others.

Impacts of climate change on the Turkana pastoral communities have been reported, particularly in terms of livestock losses (Otieno 2020; Anno and Ameripus 2022; Imana and Zenda 2023). However, little is known about the climate change impact on the distribution and richness of nutritionally valuable WEPs. To address this gap, we adopted an SDM approach and analyzed both present and projected future climate scenarios for the years 2041–2070 and 2071–2100 under three shared socioeconomic pathways (SSPs)—SSP126, SSP370, and SSP585 (O’Neill et al. 2017). The aim of our study was to shed light on the dynamics of valuable WEPs in the face of climate change and to provide insights for policymakers and stakeholders committed to sustainable use of WEPs in northwestern Kenya. We focused on answering the following research questions:

i. What is the current extent of suitable habitats for selected woody WEPs in Turkana County, Kenya?
ii. How will future (2041–2070 and 2071–2100) climatic conditions under the three shared socioeconomic pathways (SSP126, SSP370, and SSP585) affect the distribution and extent of potentially suitable habitats of selected woody WEPs in Turkana County, Kenya?
iii. How will the species richness of selected woody WEPs respond to projected climate change scenarios in Turkana County, Kenya?

## Materials and methods

### Study area

We conducted the study in Turkana County, northwestern Kenya (Fig. 1). It covers an area of about 68,253 km$^2$. The human population in the county is 926,976 (KNBS 2019), hence a density of about 13 people per km$^2$. Literacy level is low (< 20%) according to Opiyo et al. (2015) and the county has the highest poverty rate in Kenya, about 66% (KER 2020). We used a wider geographical area spanning eastern Africa and parts of central and southern Africa (see the light green highlighted region in the inset Africa map in Fig. 1), to calibrate the models. This ensured that we obtained an adequate number of occurrence points for the studied species and captured most of the environmental conditions under which the modeled species could thrive.

During the period in which the species distribution models were calibrated, 1950 to 2022, the minimum temperature ranged from 20.0 °C (1968) to 22.5 °C (2022) and maximum temperature ranged from 32.6 °C (1968) to 35.3 °C (2022) within Turkana County according to Abatzoglou et al. (2018), as shown in Online Resource 1. Total annual precipitation ranged from 244 mm (1984) to 886 mm (1961).

### Selection of wild edible plants

We obtained a list of 23 woody WEPs from two recent studies focusing on the availability of WEPs (Oluoch et al. 2022), and threats facing the WEPs and management options (Oluoch et al. 2023) in Turkana County. The inventory consisted of woody plant species with two key attributes: well known by the local communities and producing edible fruits consumed by the local communities. We performed taxonomic validation for these WEPs by cross-referencing their names with the Plants of the World Online database (POWO 2022) (https://powo.science.kew.org/) (accessed in October 2022), checking for alternative spelling and reconciling synonyms with accepted names.

### Occurrence points of the wild edible plants

We obtained occurrence points of the WEPs from five sources: Global Biodiversity Information Facility (GBIF; https://www.gbif.org (GBIF.org 2020), accessed October 2022), Botanical Information and Ecology Network (BIEN; https://bien.nceas.ucsb.edu/bien/ (Enquist et al. 2016), accessed October 2022), Response And Impacts of Natural and anthropogenic factors on BIOdiversity in tropical forests (RAINBIO; https://gdauby.github.io/rainbio/index.html (Dauby et al. 2016), accessed October 2022), East African

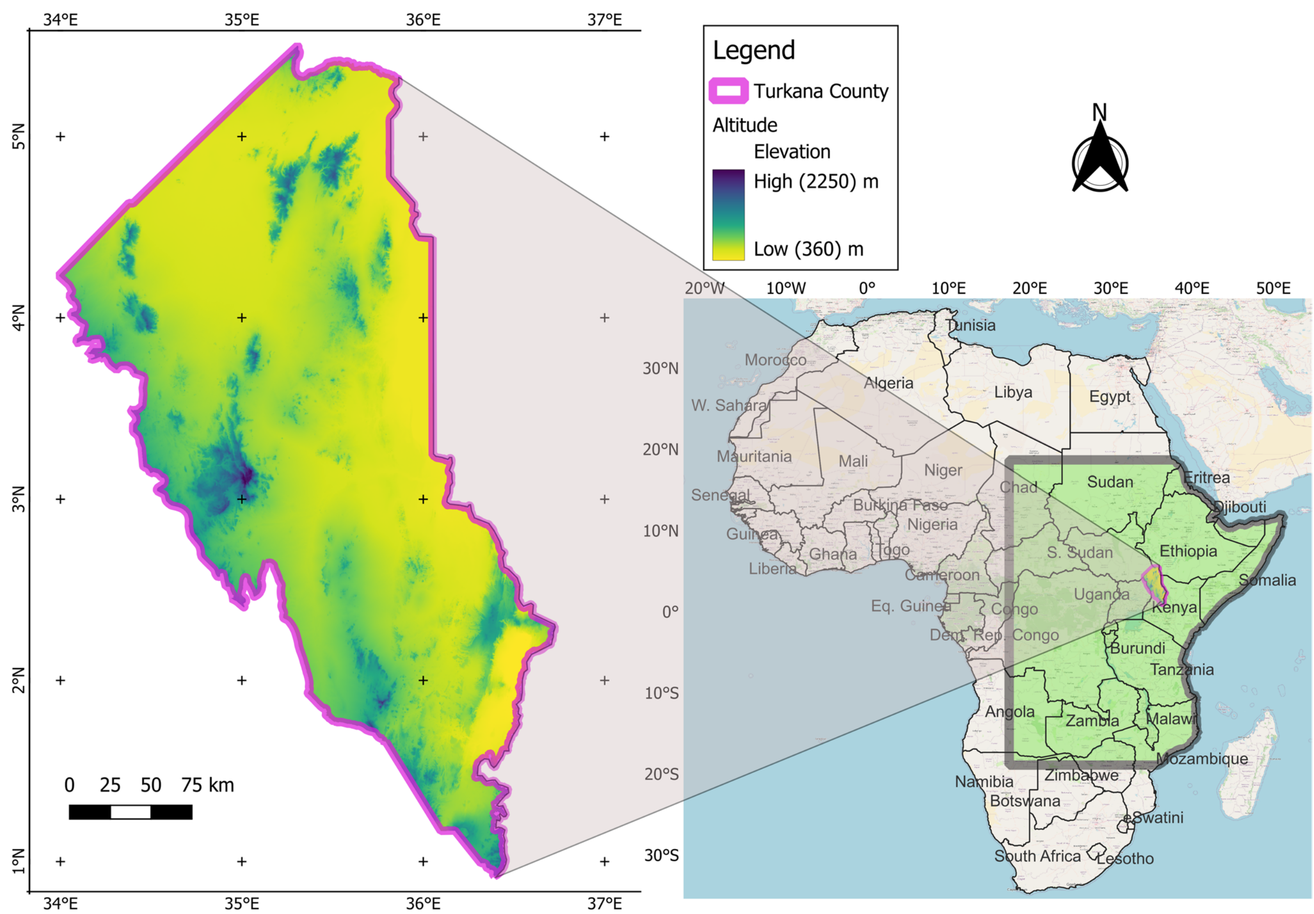


**Fig. 1** The study area (Turkana County). The model calibration area is shown in light green with a gray border spanning countries in eastern Africa and parts of and parts of southern and central Africa countries in the inset map (bottom right)

Herbarium at the National Museums of Kenya (EAH; visited in January 2023), and from field surveys within Turkana County (between April and May 2021). The field surveys were carried out in 240 plots, each 1 ha in size, for three species; *Balanites rotundifolia*, *Ziziphus mauritiana*, and *Salvadora persica*, within a 5 km radius of three communities in Turkana, Nasiger (dry lowlands, 35.437877°E 3.361547°N), Atala Kamusio (relatively less arid high altitude, 34.878133°E 2.756355°N), and Lopur (irrigated riverbanks, 35.433488°E 2.239970°N) (Oluoch et al. 2023). These three species were considered priority by the local communities for their nutrition values.

We retained occurrence points collected after 1950 to ensure congruence with the temporal resolution of our predictor variables. Further, we removed duplicated occurrence points and kept those that fell within our predetermined calibration area, see Fig. 1. This helped us minimize potential problems in our models related to the potential local genetic adaptation to environmental conditions (Kadu et al. 2013; Vinceti et al. 2013).

Finally, we spatially thinned the occurrence points using a radius of 10 km to minimize potential spatial bias. The retained occurrence points ranged from *Vatovaea pseudolablab* and *Sterculia stenocarpa* ($n=26$ each) to *Vachellia tortilis* ($n=337$) (Table 1), which we considered to be a sufficient number of occurrence points for our models (Wisz et al. 2008). The 23 WEPs comprised woody species from 11 families, mainly producing edible fruits. Fabaceae family had the highest representation ($n=5$), followed by Malvaceae ($n=4$) and Zygophyllaceae ($n=3$) (Table 1). These species are primarily distributed from southern Arabia to northern South Africa and across the west to east of Africa.

## Background points generation

We generated background points within a convex hull around occurrence points for each species. We extended the hull by 10% of the length of the longest axis from its centroid to the vertices to allow for the extraction of background points slightly beyond the presence points. We used the default

**Table 1** Comprehensive Taxonomic and Modeling Metrics of Wild Edible Plants in Turkana County, Kenya: Insights into Plant Species, Family, Occurrence Points (*n*), Sensitivity, and Mean Area Under the Curve (AUC), True Skill Statistic (TSS), and Deviance, each with Standard Deviation

| Wild edible plant | Family | *n* | Sensitivity | Mean AUC ± SD | TSS ± SD | Deviance ± SD |
|---|---|---|---|---|---|---|
| *Balanites aegyptiaca* | Zygophyllaceae | 321 | 0.503 | 0.78 ± 0.03 | 0.45 ± 0.06 | 1.04 ± 0.05 |
| *Balanites pedicellaris* | Zygophyllaceae | 35 | 0.906 | 0.62 ± 0.19 | 0.38 ± 0.22 | 0.80 ± 0.05 |
| *Balanites rotundifolia* | Zygophyllaceae | 127 | 0.944 | 0.83 ± 0.06 | 0.62 ± 0.09 | 0.48 ± 0.04 |
| *Berchemia discolor* | Rhamnaceae | 83 | 0.684 | 0.66 ± 0.05 | 0.35 ± 0.07 | 1.14 ± 0.05 |
| *Boscia coriacea* | Capparaceae | 131 | 0.701 | 0.72 ± 0.04 | 0.39 ± 0.07 | 1.19 ± 0.09 |
| *Cordia sinensis* | Boraginaceae | 259 | 0.754 | 0.80 ± 0.03 | 0.50 ± 0.05 | 0.83 ± 0.06 |
| *Dobera glabra* | Salvadoraceae | 95 | 0.663 | 0.77 ± 0.06 | 0.49 ± 0.13 | 0.88 ± 0.03 |
| *Ficus sycomorus* | Moraceae | 273 | 0.717 | 0.76 ± 0.03 | 0.44 ± 0.05 | 0.28 ± 0.03 |
| *Grewia mollis* | Malvaceae | 210 | 0.492 | 0.77 ± 0.05 | 0.46 ± 0.09 | 0.95 ± 0.07 |
| *Grewia tenax* | Malvaceae | 122 | 0.583 | 0.75 ± 0.05 | 0.43 ± 0.08 | 1.16 ± 0.06 |
| *Grewia villosa* | Malvaceae | 194 | 0.763 | 0.79 ± 0.04 | 0.50 ± 0.06 | 1.10 ± 0.16 |
| *Hyphaene compressa* | Arecaceae | 116 | 0.741 | 0.81 ± 0.07 | 0.57 ± 0.08 | 0.68 ± 0.02 |
| *Lannea triphylla* | Anacardiaceae | 63 | 0.694 | 0.71 ± 0.08 | 0.45 ± 0.10 | 1.02 ± 0.10 |
| *Maerua subcordata* | Capparaceae | 48 | 0.708 | 0.67 ± 0.08 | 0.37 ± 0.11 | 0.36 ± 0.03 |
| *Salvadora persica* | Salvadoraceae | 559 | 0.794 | 0.84 ± 0.02 | 0.53 ± 0.04 | 1.20 ± 0.02 |
| *Senegalia senegal* | Fabaceae | 567 | 0.709 | 0.77 ± 0.02 | 0.45 ± 0.04 | 0.93 ± 0.05 |
| *Sterculia stenocarpa* | Malvaceae | 35 | 0.657 | 0.68 ± 0.08 | 0.43 ± 0.10 | 0.93 ± 0.07 |
| *Tamarindus indica* | Fabaceae | 329 | 0.719 | 0.81 ± 0.02 | 0.52 ± 0.04 | 1.08 ± 0.09 |
| *Vachellia oerfota* | Fabaceae | 212 | 0.588 | 0.72 ± 0.04 | 0.40 ± 0.06 | 1.12 ± 0.05 |
| *Vachellia tortilis* | Fabaceae | 518 | 0.516 | 0.77 ± 0.02 | 0.43 ± 0.03 | 0.88 ± 0.07 |
| *Vatovaea pseudolablab* | Fabaceae | 44 | 0.705 | 0.65 ± 0.07 | 0.36 ± 0.09 | 1.02 ± 0.03 |
| *Ximenia americana* | Olacaceae | 162 | 0.682 | 0.76 ± 0.04 | 0.42 ± 0.06 | 0.56 ± 0.10 |
| *Ziziphus mauritiana* | Rhamnaceae | 163 | 0.876 | 0.87 ± 0.04 | 0.64 ± 0.08 | 0.88 ± 0.05 |

number of 10,000 background points for each WEP within our extended convex hull.

## Environmental predictors

We used 13 bioclimatic predictor variables from the CHELSA database (Karger et al. 2019) (Table 2) for present and future (2041–2070 and 2071–2100) climate conditions from all the five global circulation models (GCMs) of CHELSA database. For each of the five GCMs, we used three shared socioeconomic pathways (SSPs): SSP126 (optimistic), SSP370 (regional rivalry), and SSP585 (pessimistic) (O'Neill et al. 2014; Riahi et al. 2017). The spatial resolution of the predictor variables was 30 arc seconds (ca. 0.9 km at the equator).

We also obtained eight soil variables (Table 2) from the International Soil Reference and Information Center (ISRIC) (Hengl et al. 2017) at a spatial resolution of 250 m. We resampled them to match the extent and resolution of the bioclimatic variables. Finally, we obtained six topographic predictor variables (Table 2), topographic variables, from the Shuttle Radar Topography Mission (SRTM 2013) and the Multi-Error-Removed Improved Terrain Digital Elevation Model (MERIT DEM) (Yamazaki et al. 2017).

## Species distribution modeling

We used MaxEnt (Phillips et al. 2006) algorithm version 3.4.3 to build the models since it is appropriate for presence-only data and robust against potential geo-referencing errors (Graham et al. 2008). We tuned the MaxEnt algorithm across four feature classes (linear, quadratic, hinge, and product); we tested four combinations (linear-quadratic, hinge, linear-quadratic-hinge, and linear-quadratic-hinge-product), three regularization multipliers (1, 3, and 5), and their combinations in the *ENMeval* package version 2.0.4 (Kass et al. 2021) in R version 4.3.1 (R Core Team 2023) for ease of reproducibility of the workflow. We used a spatial block cross-validation method with four folds to calibrate the models. To obtain the best model among the tuned models, we first picked the four models with the highest Area Under the receiver-operating characteristic Curve (AUC) (using testing data), and then chose the model with the smallest difference between training and testing AUC ($AUC_{diff}$), which is a measure for overfitting. We then used this model to make predictions over geographic space for current and future times. For transparency and reproducibility, we adhered to the Overview, Data, Model fitting, Assessment, and Predictions (ODMAP) protocol by Zurell et al. (2020), Fitzpatrick et al. (2021), and the checklist by Feng et al. (2019) during the modeling process.

**Table 2** Environmental predictor variables used in modeling potentially suitable habitats of wild edible plants in Turkana County, Kenya

| Data | Code | Description | Units | Source |
|---|---|---|---|---|
| Climatic variables used in modeling | bio_2 | Mean diurnal range (mean of monthly [max temp—min temp]) | °C | CHELSA V2.1 (Karger et al. 2019) |
| | bio_3 | Isothermality (BIO2/BIO7) (×100) | °C | |
| | bio_4 | Temperature seasonality (standard deviation × 100) | °C/100 | |
| | bio_5 | Maximum temperature of warmest month | °C | |
| | bio_7 | Temperature annual range (BIO5-BIO6) | °C | |
| | bio_8 | Mean temperature of wettest quarter | °C | |
| | bio_9 | Mean temperature of driest quarter | °C | |
| | bio_12 | Annual precipitation | kg $m^{-2}$ $year^{-1}$ | |
| | bio_13 | Precipitation of wettest month | kg $m^{-2}$ $month^{-1}$ | |
| | bio_14 | Precipitation of driest month | kg $m^{-2}$ $month^{-1}$ | |
| | bio_15 | Precipitation seasonality (coefficient of variation) | kg $m^{-2}$ | |
| | bio_18 | Precipitation of warmest quarter | kg $m^{-2}$ $month^{-1}$ | |
| | bio_19 | Precipitation of coldest quarter | kg $m^{-2}$ $month^{-1}$ | |
| Climatic variables removed | bio_1 | Mean annual air temperature | °C | |
| | bio_6 | Mean daily minimum daily air temperature of the coldest month | °C | |
| | bio_10 | Mean daily mean air temperatures of the warmest quarter | °C | |
| | bio_11 | Mean daily mean air temperatures of the coldest quarter | °C | |
| | bio_16 | Mean monthly precipitation amount of the wettest quarter | kg $m^{-2}$ $month^{-1}$ | |
| | bio_17 | Mean monthly precipitation amount of the driest quarter | kg $m^{-2}$ $month^{-1}$ | |
| Soil variables | bdod | Bulk density of the fine earth fraction | $cg/cm^3$ | ISRIC SoilGrids250m version 2.0 (Hengl et al. 2017) |
| | cec | Cation exchange capacity of the soil | mmol(c)/kg | |
| | cfvo | Volumetric fraction of coarse fragments (> 2 mm) | cm3/dm3 (vol‰) | |
| | clay | Proportion of clay particles (< 0.002 mm) in the fine earth fraction | g/kg | |
| | phh2o | Soil pH | pHx10 | |
| | sand | Proportion of sand particles (> 0.05 mm) in the fine earth fraction | g/kg | |
| | silt | Proportion of silt particles (≥ 0.002 mm and ≤ 0.05 mm) in the fine earth fraction | g/kg | |
| | soc | Soil organic carbon content | dg/kg | |

**Table 2** (continued)

| Data | Code | Description | Units | Source |
|---|---|---|---|---|
| Topographic variables | HLI | Heat load index | W | Derived from Shuttle Radar Topography Mission (SRTM) elevation data (available at http://srtm.csi.cgiar.org/) and calculated with the 'raster' package version 3.6.20 (Hijmans 2023) in R version 4.3.1 (R Core Team 2023) |
| | NO | Negative openness | ° | Derived from MERIT DEM (Yamazaki et al. 2017) |
| | PO | Positive openness | ° | |
| | SLO | Slope | ° | |
| | TPI | Topographic position index | m | |
| | TWI | Topographic wetness index | NA | |

### Model outputs analysis

To assess the performance of our models, we used two suitable widely used metrics for presence-only models, AUC and Continuous Boyce Index (CBI) (Manzoor et al. 2018). AUC is a measurement of discriminatory capacity of classification models (Jiménez-Valverde 2012; Shabani et al. 2018) with values close to 0.5 being close to random classification while those approaching 1 are better classification capacity (Hao et al. 2020; Lissovsky and Dudov 2021). Positive values of CBI indicate that the predicted distribution by the model is congruent with the occurrence points data. Values approaching 0 indicate random model prediction, while negative values imply counter-predictions (Manzoor et al. 2018; Maruthadurai et al. 2023). We converted the predicted suitability values to binary presence-absence maps using the suitability threshold that maximized the sum of sensitivity (true positive rate) and specificity (true negative rate) (Table 1).

From the five GCM binary outputs for each time interval and SSP, we used a majority vote rule (that is, conditions were deemed suitable when three out of the five GCMs predicted suitable conditions) to generate a single output for the future projections. We used these maps to determine the potentially suitable habitats for future climate scenarios by calculating the areas of pixels with value 1 (present) and those with value 0 (absence). We also compared the pixel values of the present binary with the future binaries for each species to obtain change maps. This enabled us to estimate potential suitable habitats' persistence, loss, absence, and gain.

To estimate changes in species richness, we summed the presence-absence maps for all WEPs to obtain a layer that expresses species richness for the present and future scenarios separately. We then calculated the change in species richness by subtracting the present richness layer from the future richness layer and expressed it as a percentage change.

## Results

### Present and future climate of Turkana County

The climate conditions of CHELSA dataset used in this study fell within the conditions previously experienced by the WEPs in Turkana County (Online Resource 1) (Table 3; see Online Resource 2 for means of the climatic variables and Online Resource 3 for their standard deviations across all the five GCMs of CHELSA). Hence, we considered the models appropriate for predicting into the future climate change scenarios.

### Model performance

The predictive power of the MaxEnt models was very good ($0.8 < \text{AUC} < = 0.9$) for four WEPs, good ($0.7 < \text{AUC} < = 0.8$) for 13 WEPs, moderate ($0.6 < \text{AUC} < = 0.7$) for four WEP species, and low for two species ($\text{AUC} = 0.57$) (Table 1). The six WEPs with $\text{AUC} < 0.7$, primarily due to their small number of occurrence records, included in descending order of their AUC values *S. stenocarpa*, *Berchemia discolor*, *Maerua subcordata*, *Lannea triphylla*, *Boscia coriacea*, and *V. pseudolablab*, and hence their predictions should be interpreted cautiously (Table 1). Values of CBI were also positive and ranged between 0.05 (±0.59 sd) for *B. coriacea* and 0.83 (±0.08 sd) for *Cordia sinensis* (Table 1). Given these metrics, we considered the models appropriate for making predictions on the potential suitable habitats of WEPs under current and projected future climates. The threshold values

**Table 3** Average climatic variables values and deviations about the averages for the present and projected future climate scenarios for Turkana County, Kenya. The future values are averaged from five global circulation models (GFDL, IPSL, MPI, MRI, and UKESM1) of the CHELSA database. The description of the abbreviated columns is provided in Table 2

| Metric | SSPs and times | bio_12 | bio_13 | bio_14 | bio_15 | bio_18 | bio_19 | bio_2 | bio_3 | bio_4 | bio_5 | bio_7 | bio_8 | bio_9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | Present | 369.82 | 66.06 | 08.97 | 55.40 | 63.63 | 95.55 | 9.57 | 75.76 | 82.92 | 34.99 | 12.54 | 28.79 | 29.07 |
| | SSP126_2041–2070 | 412.48 | 80.72 | 10.12 | 60.36 | 75.99 | 100.51 | 9.00 | 74.25 | 87.98 | 31.91 | 12.04 | 30.27 | 30.32 |
| | SSP126_2071–2100 | 414.83 | 75.39 | 10.96 | 57.71 | 90.59 | 101.99 | 9.11 | 74.98 | 83.45 | 30.91 | 12.07 | 30.33 | 30.35 |
| | SSP370_2041–2070 | 428.87 | 78.83 | 10.46 | 57.54 | 80.75 | 109.56 | 8.63 | 70.95 | 95.68 | 32.18 | 12.10 | 30.45 | 30.53 |
| | SSP370_2071–2100 | 458.27 | 84.17 | 11.56 | 57.61 | 102.6 | 118.93 | 8.32 | 70.24 | 94.37 | 31.09 | 11.77 | 30.53 | 30.55 |
| | SSP585_2041–2070 | 450.73 | 84.02 | 10.32 | 58.80 | 85.16 | 116.01 | 8.59 | 71.51 | 91.58 | 32.13 | 11.93 | 30.51 | 30.54 |
| | SSP585_2071–2100 | 486.08 | 92.97 | 12.95 | 58.89 | 108.74 | 122.36 | 8.85 | 71.92 | 94.11 | 31.15 | 12.18 | 30.59 | 30.60 |
| ± Standard deviations | Present | 113.50 | 15.58 | 3.26 | 10.02 | 20.90 | 49.88 | 1.41 | 3.89 | 11.16 | 1.72 | 1.43 | 2.07 | 1.76 |
| | SSP126_2041–2070 | 123.92 | 18.83 | 3.94 | 10.37 | 23.35 | 51.50 | 1.41 | 4.62 | 10.24 | 0.49 | 1.40 | 0.55 | 0.48 |
| | SSP126_2071–2100 | 127.50 | 17.52 | 4.43 | 10.57 | 26.85 | 51.80 | 1.40 | 4.35 | 9.75 | 0.17 | 1.41 | 0.19 | 0.17 |
| | SSP370_2041–2070 | 131.32 | 18.79 | 4.19 | 10.62 | 25.68 | 55.40 | 1.38 | 5.13 | 10.30 | 0.49 | 1.35 | 0.60 | 0.51 |
| | SSP370_2071–2100 | 140.88 | 20.00 | 4.77 | 10.35 | 30.05 | 55.15 | 1.35 | 5.61 | 8.92 | 0.18 | 1.33 | 0.20 | 0.17 |
| | SSP585_2041–2070 | 137.37 | 19.38 | 3.90 | 10.59 | 26.85 | 55.20 | 1.36 | 4.86 | 9.38 | 0.50 | 1.37 | 0.59 | 0.49 |
| | SSP585_2071–2100 | 150.74 | 21.86 | 5.46 | 10.89 | 33.45 | 53.78 | 1.39 | 5.08 | 7.45 | 0.18 | 1.37 | 0.19 | 0.17 |

that maximized sensitivity and specificity ranged from 0.274 for *Vachellia oerfota* to 0.719 for *V. pseudolablab* (Table 1).

## Current potentially suitable habitats of priority wild edible plants

Under the present climatic conditions, the proportions of potential suitable habitats for the studied WEPs within Turkana County ranged from 2.8% for *Grewia mollis* to 99.9% for *B. rotundifolia* with an average potentially suitable habitat for the species being 64.5% of Turkana County land area (see Online Resource 4 for areal values of presence and absence for the WEPs). About 74% ($n = 17$) of the studied WEPs had a current potentially suitable habitat of at least 50% of the area of Turkana County (Fig. 2).

The southern part of the county was potentially suitable for most of the WEPs during current climate conditions (Online Resource 5). Generally, the high elevation areas in the South, Southeast, and Northwest of the county (Fig. 1) showed higher suitability for the selected WEPs, while the central part, with low altitude areas up to Lake Turkana, was less suitable, though this varied among the WEPs.

## Change in potentially suitable habitat of selected wild edible plants in Turkana County, Kenya

### The period 2041–2070

Under SSP126, our models predicted that by 2041–2070, up to 39% ($n = 9$) of the WEPs will experience a reduction in their current potentially suitable habitats (Fig. 3a). About 61% ($n = 14$) of the WEPs maintained or expanded their current potentially suitable habitats. During the same period but under SSP370, we predicted a decrease in potentially suitable habitats of up to 43% ($n = 10$) of the WEPs (Fig. 3b). Similarly, under SSP585 for the same period, 43% ($n = 10$) of the studied WEPs are predicted to experience a decrease in their potentially suitable habitat (Fig. 3c). This indicated a progressive decline in the size of potentially suitable habitat for about 50% of the studied WEPs with about three WEPs losing their potential suitable habitats by over 40% of the current suitable habitat under the SSP585 for the period of 2041–2070. Spatial distributions, corroborating the predicted changes (persistence, suitability loss, suitability gain, and absence) for the period, are shown in Online Resource 6 a—c.

### The period 2071–2100

For SSP126 of this period, 39% ($n = 9$) of the WEPs were predicted to experience a decline in their potentially suitable habitats, similar to 2041–2070 under the same SSP. For SSP370, however, 48% ($n = 11$) of the WEPs were predicted to shrink their potentially suitable habitats (Fig. 3e) which was one more species as compared to the same SSP under the 2041–2070 period. Under SSP585, a similar number of the studied WEPs as SSP370 showed a decline in their potentially suitable habitats by the end of the century (Fig. 3f). Among the species that expanded their potentially suitable habitats, most of the expansions did not exceed 40% of their present suitable habitat. This was comparable to the decline, where we observed a localized complete loss of potentially suitable habitat for one WEP while most WEPs did not lose more than 40% of their suitable habitats (Fig. 3a–f). The observed spatial changes in habitat suitability of the WEPs are shown in Online Resource 6 d—f.

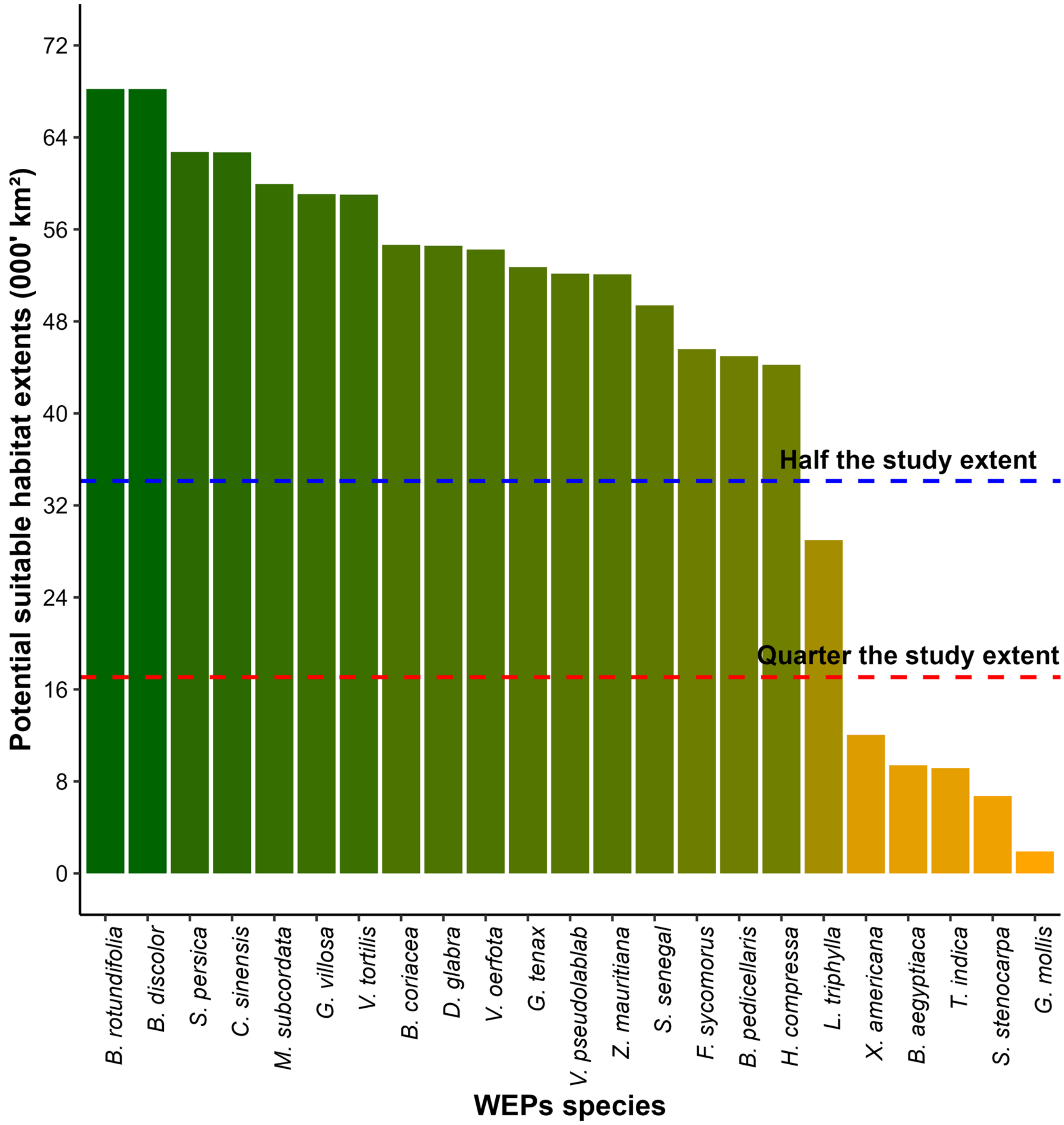


**Fig. 2** Predicted potentially suitable habitat ($km^2$) of the studied 23 wild edible plants in Turkana County, Kenya. Bars representing plants with larger area cover are darker green, while those smaller area cover are orange. The blue and red dashed horizontal lines depict 50% and 25% the study area extent, respectively

## Current richness of woody wild edible plants in Turkana County, Kenya, and future changes

### The period 2041–2070

Under SSP126, about 27,900 $km^2$ of Turkana County was predicted to undergo a decline in the richness of the studied WEPs by 2041–2070. The average slight decline in the studied WEPs' richness over Turkana County was predicted to be 0.2% of the current number of species per pixel (spatial resolution is ~ 0.9 km). For SSP370 and the same time period, the decline was predicted to be an average 1.13%. Under SSP585 for the same period, our models predicted an average slight gain in species richness by up to 0.16% of the current number of species per pixel (Online Resource 7 a—c).

During this time period and irrespective of the SSPs, the species richness was predicted to concentrate in the southern part of the county that is relatively elevated as well as the western border with Uganda and parts of the Northeast (Fig. 4a–d). Despite the small average changes in potentially suitable habitats reported in previous sections, individual

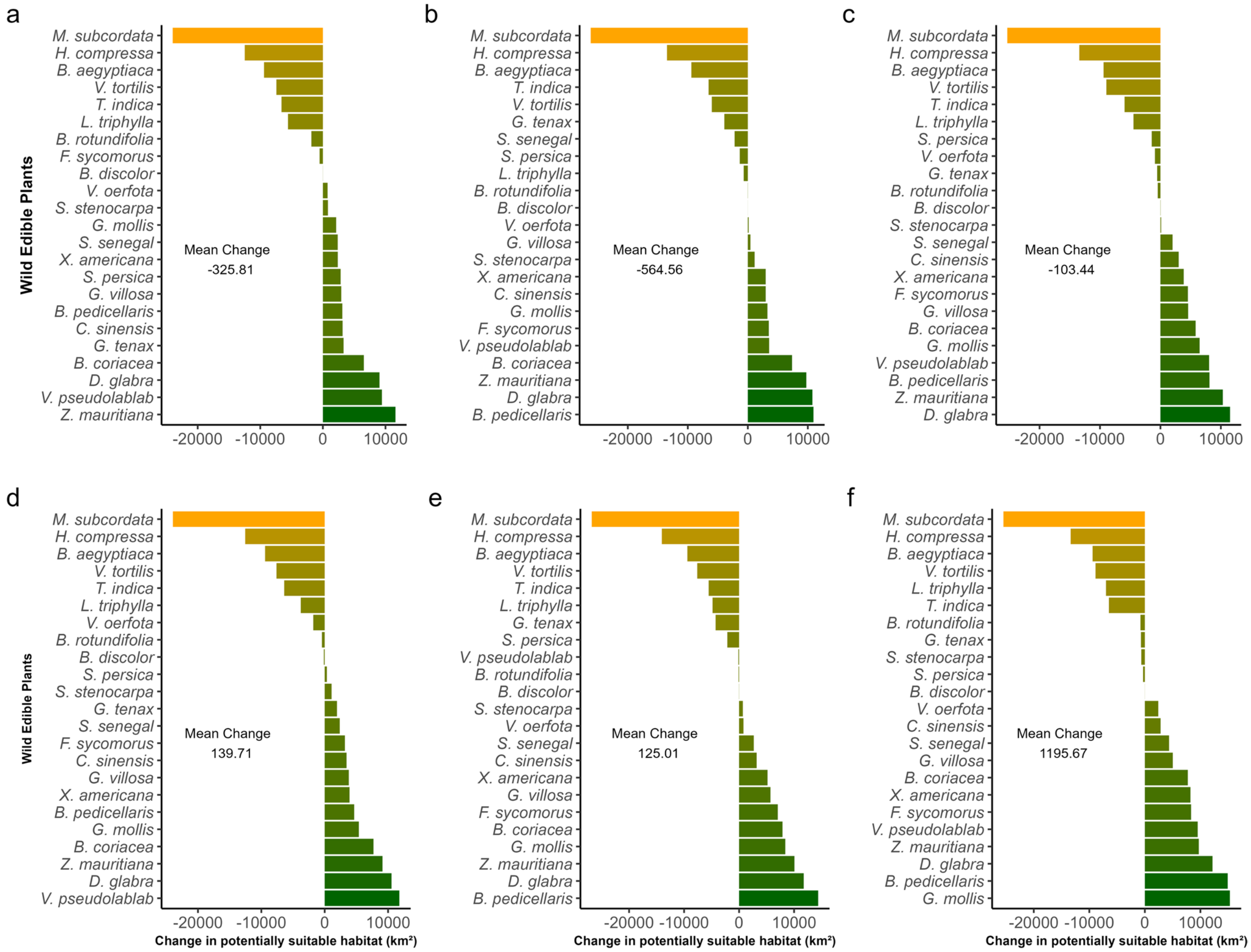


**Fig. 3** (**a**)–(**f**) Change in potentially suitable habitat of 23 wild edible plants species during two time intervals (2041–2070 and 2071–2100) for three shared socioeconomic pathways (SSP126, SSP370, and SSP585). (**a**) is 2041-2070 for SSP126, (**b**) is 2041-2070 for SSP370, (**c**) is 2041-2070 for SSP585, (**d**) is 2071-2100 for SSP126, (**e**) is 2071-2100 for SSP370, and (**f**) is 2071-2100 for SSP585. Brighter shades of orange indicate more decline while darker shades of green colors represent more gain in potentially suitable habitat. Mean changes for all the species under each time and SSP are indicated on the respective plots

pixels still showed large changes in species richness such as increase in southern parts of the county (Fig. 4b–d).

### The period 2071–2100

During this period and under SSP126, our models predicted an average gain in WEPs' richness by about 0.79% of the current number of species per pixel though 41% (28,000 km$^2$) of the area was predicted to record a decline in richness. Recoveries were predicted to continue for SSP370 with an average rise in richness by 0.64% of the current number of species per pixel (Online Resource 7 d—f). The recovery in richness continued under SSP585 by 3.47% of the current number of species per pixel, for the period. Over 2071–2100, the 23 WEPs' richness showed a similar trend as 2041–2070 and can be generally termed stable with respect to current richness values (Fig. 4e–g).

## Discussion

### Variability in climatic parameters in northwestern Kenya

Total annual precipitation (bio_12) in Turkana County is projected to increase over the two time intervals (2041–2070 and 2071–2100) and across the three SSPs (SSP126, SSP370, and SSP585). A similar pattern was reported by Omolo (2010) and Gebrechorkos et al. (2019) for parts of Ethiopia and Kenya especially during the short rainy seasons. There is also a projected corresponding increase in variability in the annual rainfall as indicated by the rising rainfall seasonality values (bio_15) (Online Resource 2). However, increasing variability of the rainfall could imply prolonged drought periods and shorter but

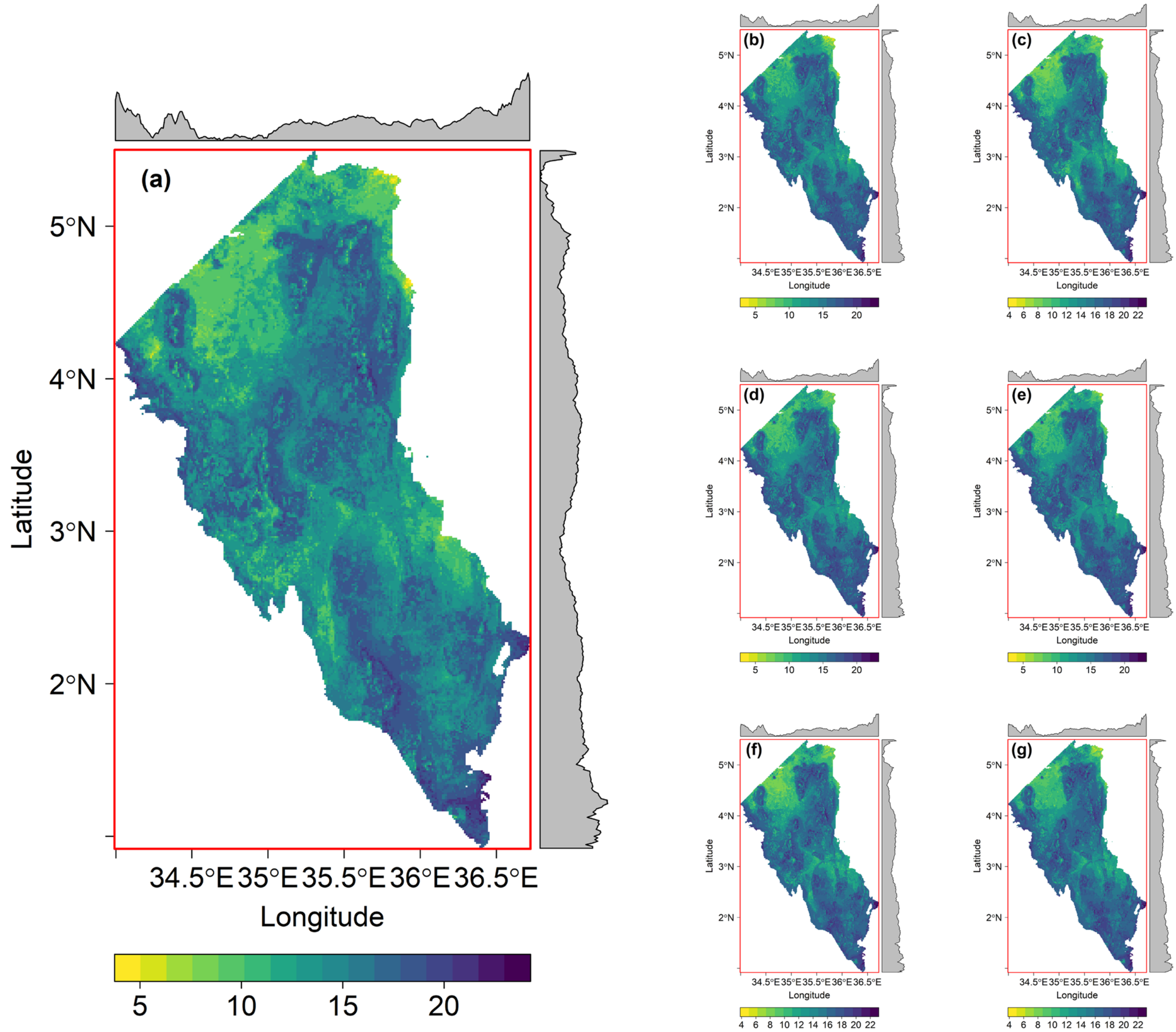


**Fig. 4** (**a**)–(**g**) Species richness of the 23 wild edible plants in Turkana County (area size: 68,253 km2), Kenya, under present and projected future climates. (**a**) represents the current climate, (**b**) the period 2041-2070 under SSP126, (**c**) 2041-2070 under SSP370, (**d**) 2041-2070 under SSP585, (**e**) 2071-2100 under SSP126, (**f**) 2071-2100 under SSP370, and (**g**) 2071-2100 under SSP585. Gray margin plots show distribution of the richness values along both latitudinal and longitudinal gradients

more intense rainy episodes (Gebrechorkos et al. 2019; Palmer et al. 2023). Projecting the future climate of eastern Africa as a whole is faced with a lot of challenges including limited rainfall stations for calibrations, the El Niño–Southern Oscillation and the Indian Ocean Dipole (Gebrechorkos et al. 2019; Palmer et al. 2023). The future maximum precipitation of the wettest (bio_13) and the driest (bio_14) months are within their present ranges, but the combined CHELSA models shows a general rise in their means. This should be interpreted cautiously as previous findings acknowledge the difficulties inherent in predicting future rainfall variabilities in eastern Africa (Nicholson 2017; Palmer et al. 2023). As with other precipitation related variables we used, precipitation of the warmest (bio_18) and the coldest (bio_19) quarters of the year showed an increasing pattern. While we could not determine the trend since the time intervals were not linear, visual appraisal of the plots indicated a stronger rise in precipitation of the warmest than that of the coldest quarter.

Regarding temperature variables, we observed future distributions of ranges overlap with those of the present, hence suited their use in building our models. However, under future times and SSPs, we observed varied distribution trends as reported in other studies (Gebrechorkos et al. 2019). Diurnal range in temperature first declined then plateaued over time and SSPs. Similar trends emerged for isothermality (bio_3), which corresponds to the increasing trend for temperature seasonality (bio_4). This indicated a rise in variability among the observed temperature values, implying intermittent heat stress imposed on the WEPs regardless of the increasing seasonal or annual precipitation. We observed declining maximum temperature values for the warmest month (bio_5). In contrast, annual temperature ranges for the area remained rather stable over the study period and SSPs (Online Resource 2). Both mean temperature of the wettest (bio_8) and driest (bio_9) quarters showed an increasing trend relative to the current climatic conditions. These warming quarters, coupled with the increasing rainfall seasonality, could negatively impact habitat suitability and richness of the studied WEPs.

We observed varied trends of the major climate variables guiding the distribution of the WEPs over space. The difficulties in explaining the variability of the climate conditions in East Africa is well documented (Nicholson 2017). This is even more challenging when making future projections (Cook et al. 2020; Palmer et al. 2023). This is because most of the observed seasonal variabilities cannot be fully explained by the known drivers of climate in the region. This calls for enhanced monitoring of the patterns to enable more accurate future predictions (Palmer et al. 2023). We visually appraised that the ranges of the variables under future scenarios fell within those of the calibration sets.

## Current potentially suitable habitats for selected wild edible plants in Turkana County, Kenya

Up to 17 WEPs currently have potentially suitable habitat areas that cover more than half of Turkana County (Online Resource 5). However, we are aware that our predictions only reflect Turkana County rather than the full distribution range of the species which stretches well beyond the county. For suitability maps for the whole model calibration area, see Online Resource 8. All of the 23 studied WEPs have potentially suitable habitats beyond the borders of Turkana County.

For five species, the potentially suitable habitat covered less than 25% of the study area. Out of those, *B. aegyptiaca* showed a complete loss of its local suitable habitat within Turkana County for future climate scenarios. The species has been reported to thrive in rain-fed conditions with 400–800 mm per annum and mean temperature of 20 °C (Hall 1992) that could be rare under current and future climate conditions. About 50% of the WEPs showed a decline in potentially suitable habitat, with their distribution concentrated in the South end of the county, the western edge bordering Uganda, and in some parts of the Northeast (Online Resource 5). These areas are at relatively higher elevation (about 900 m in altitude) areas and have been characterized by conflicts with neighboring communities over pasture and livestock in the past (Shanguhyia 2021; Anno and Ameripus 2022). Hence, for communities to better utilize WEP resources at present and in the future, fostering peace in the area could be essential (Omolo 2010) as the plants are more distributed adjacent to the shared borderlands.

## Future changes in potentially suitable habitats of selected wild edible plants in Turkana County, Kenya

Our models show that the size of potentially suitable habitat for half of the studied WEPs could experience considerable decline in the future and across SSPs, with *Balanites aegyptiaca* losing local (within the county) suitable habitat even under SSP126 of 2041–2070 period. Some species that will expand their current ranges within the county include *Dobera glabra*, *G. mollis*, and *V. pseudolablab*. These species are largely native to arid and semi-arid conditions, and could possess a high degree of heat stress tolerance as reports from South Africa suggest (Midgley and Thuiller 2007; Wessels et al. 2021).

Several studies on the impact of climate change on the distribution of plants in East Africa pointed out that most species will likely narrow the area of their current suitable habitat (Kalisa et al. 2019; Kidane et al. 2019). However, some localized studies, for example, within a 50 by 50 m plot in Tigray region of Ethiopia, showed likely expansion of the range of *Tamarindus indica* under future climate scenarios (Gufi et al. 2022), while the species showed steady decline in potentially suitable habitat in this study. Further, decline in potentially suitable habitats of some species in this study could be exacerbated by impacts of land cover and land use changes (Powers and Jetz 2019). For example, an earlier study showed that human activities such as overgrazing and crop irrigation in riparian areas are threatening the survival of WEPs in Turkana County (Oluoch et al. 2023) and neighboring countries (Bahru et al. 2013; Kidane and Kejela 2021). These additional threats were not assessed in this study but could worsen the negative effects of climatic changes on WEPs.

## Changes in wild edible plants' species richness under the future climate conditions in Turkana County, Kenya

In scarcely sampled areas, species richness can be derived from stacking binary outputs of species distribution models as shown for instance in studying endemic flora for conservation (Hoveka et al. 2020) and wild food plants in southern Africa (Wessels et al. 2021). Our aggregated model outputs suggest stability or gain in the richness of about half of the studied WEPs within our study area. The WEPs could be already existing in conditions comparable to projected future climates in the region. Although other studies have reported climate change in East Africa as serious threat to WEPs (Kidane et al. 2019; Schipper et al. 2020), such studies did not consider wider environmental conditions under which the species existed as achieved in this study. Nonetheless, we are aware that this study did not include other factors that could further limit the potential suitable habitats of the WEPs such as anthropogenic activities on land and dispersal ability of the WEPs to reach new suitable areas under future climates.

### Beyond the abiotic

While we have only considered abiotic factors in the present analysis, there are also biotic and mobility/dispersal factors that influence distribution of species over space and time, as described in the biotic, abiotic, and mobility Venn diagram by Peterson et al. (2011). Interactions among the studied WEPs and competition between the WEPs and other plants over land could also influence the size of potentially suitable habitat and species richness. Additionally, the dispersal rates of different WEPs differ and their efficiency in following the shifting area size of potentially suitable habitats might also vary; hence, we cannot claim occupancy of the predicted potentially suitable pixels in future. Seeds of some WEPs are dispersed by birds such as *Z. mauritiana* (Grice 1996) while others by water like *Hyphaene compressa* (Sullivan et al. 1995; Stave et al. 2006). Dynamics among and within these agents could drive the success of a WEP in colonizing new potentially suitable regions beyond the current habitats. Land use activities, such as overstocking and expansion of agriculture, could also influence the ranges of the WEPs in the future and their richness. Overstocking and overgrazing, for instance, reduce regeneration of WEPs (Oluoch et al. 2023), hence could limit range expansion as well as persistence of the WEPs within their current ranges. It is thus crucial to consider these factors when designing any management and conservation efforts and strategies for WEPs.

## Conclusions

Our results reveal a decline in potentially suitable habitat for half the selected woody WEPs in Turkana County, Kenya, from the current climatic conditions to 2041–2070 and 2071–2100 periods across all three SSPs. Importantly, our models may overestimate the potentially suitable habitat for the WEPs because we did not consider anthropogenic factors that could further negatively influence the habitats and richness of the WEPs. Nonetheless, our findings contribute to improving the understanding of the influence of climate variability on the potential distribution and richness of WEPs in northwestern Kenya. The use of SDMs is criticized for their assumption of state of equilibrium between species and environment which is not always the case as complete sampling of species records is hardly achievable. Further, the models assume that we have included all major predictor variables governing the distribution of a species. Our use of SDMs in predicting potentially suitable habitat of WEPs, however, provides valuable insights for conservation and sustainable management of WEPs for use in improving dietary diversity of local communities. Both mitigation of climate change on a global scale and local management strategies such as controlled livestock farming and improving education and awareness for WEPs could help to better manage and sustainably conserve these valuable resources.

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**Data Availability** Data sets and R codes generated during the current study are available from the corresponding author on reasonable request.

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