THE INFLUENCE OF CLIMATE CHANGE ON THE POTENTIAL DISTRIBUTION OF INVASIVE *GUTENBERGIA CORDIFOLIA* IN NGORONGORO CONSERVATION AREA, TANZANIA

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Abstract. Invasive species are one of the major causes of biodiversity loss around the globe, and due to human activities, their invasions have been accelerating. With the changing climate the behavior, distribution, and harm caused by invasive species have been altered profoundly, leading to increased spread and new invasions. *Gutenbergia cordifolia* is one of the highly invasive and damaging plants in the Ngorongoro Conservation Area (NCA), Tanzania. Understanding the spatial distribution and how climate change will alter the spread of this species is the key to develop effective management strategies. In this study, Sentinel-2 was used to map the spatial distribution of *G. cordifolia*, and the MaxEnt model was used to predict current potential distribution and future potential distribution under climate change scenarios. The overall accuracy of classification was 93.81% and *G. cordifolia* is highly distributed in the western part of the study area and the Ngorongoro crater, similar to the current potential distribution result. The area under the curve (AUC) results for the current potential distribution of *G. cordifolia* was 0.911. The model training result shows that Precipitation in the wettest month is the most important variable for the potential distribution of *G. cordifolia*. The results indicate that the habitat suitability of *G. cordifolia* will potentially change under future climate change scenarios with a profound increase in suitability, allowing the invasion to go further into the Serengeti ecosystem. These results will contribute to efforts towards ecological restoration, biodiversity protection, and maintaining sustainable ecosystem services as climate change intensifies.
Keywords: *bioclimatic variables, remote sensing, Sentinel-2, maximum likelihood, species distribution models*

Introduction

The spread of invasive species across the globe has accelerated in the past millennium (Ricciardi, 2013). International trade and travel have facilitated the movement of many species to new habitats across the world where they transform the natural habitat and cause biodiversity loss (Sabat-Tomala et al., 2022). With the climate changes, the behavior, spread and harm caused by invasive species have been profoundly altered (Runyon et al., 2012). Through greenhouse gas emission the global surface temperature has reached 1.1°C above 1850-1900 in -2020 (IPCC, 2023). Increasingly evidences suggest that Climate change will interact with biological invasion and potentially favor invasive species, leading to more suitable areas and new species invasion (Capdevila-Argüelles and Zilletti, 2008). Therefore, identifying and mapping the distribution of invasive species and predicting the spread of invasive species is crucial for animal and plant protection organizations and managers (Jeschke and Strayer, 2008; Rusňák et al., 2022).

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To manage and evaluate the impact of the spread of invasive species, the first step is to identify their geographical location (Dai et al., 2020). The traditional investigation method in which all data are collected on-site is the most direct method to obtain the distribution of invasive species, but those methods need a lot of time and manpower to complete complex investigations (Sabat-Tomala et al., 2022). Recently the use of remote sense images to detect and map invasive plant species has gained popularity (Hestir et al., 2008). And unlike the traditional methods which are time-consuming and costly, remote sensing enables quick detection and mapping of invasive species in large and inaccessible areas (Sabat-Tomala et al., 2022). Sentinel-2 is one of the commonly used data sources for mapping invasive species (Rajah et al., 2019; Masemola et al., 2020; Arasumani et al., 2021; Lewis et al., 2022; Rebelo et al., 2022). This freely available high-resolution, multi-spectral, sun-synchronous instrument has 13 spectral bands ranging from 400 to 2500 nm and 3 different spatial resolutions of 10 m, 20 m, and 60 m with a temporal resolution of 5 days (ESA, 2015). Duncan et al. (2023), map an invasive herbaceous plant species with Sentinel-2 imagery with a robust non-parametric classifier method and the result indicates the importance of the shortwave infrared and red-edge bands in classifying and discriminating invasive plant species. Another study by Forster et al. (2017), assesses the potential of Sentinel-2 time series in detecting the invasive plant with results showing the possibility of mapping where the higher number of Sentinel-2 images increased the model performance. Furthermore, (Rodriguez-Garlito, Paz-Gallardo and Plaza, 2023) developed a new method for detecting invasive plants with Sentinel-2 imagery, which employs Convolutional Neural Network (CNN) architecture and spectral indices and concludes that spectral indices provide useful information for mapping invasive plants. Nevertheless, effective and sustainable management requires a deeper understanding of climate change. Therefore, it is important to anticipate if the species will spread to the new habitat and when the climate changes (Finch et al., 2021).

Species distribution models (SDMs) are commonly used to predict the potential distribution of invasive species. According to Beery et al. (2021), SDMs function to predict the location of the species by using the characteristics of allocation and judge whether the species is present at that location or not in the future. These models can either be mechanistic models which take into account the physiological response of species to environmental factors or correlative models, which estimate habitat suitability by correlating the species occurrence record with environmental variables (Pearson, 2010). Mechanistic models include Biophysical threshold models, life history models, and foraging energetic models (Buckley et al., 2010), they are likely accurate in invasion prediction (Gallien et al., 2010) but rarely used due to their complexity as they require expertise and takes time for gathering enough data (Elith, 2016). On the other hand correlative species distribution models are commonly used due to availability of species occurrence records (Pearson, 2010; Evans et al., 2015). Correlative models include Habitat suitability index (HIS), Non-parametric multiplicative regression, BIOCLIM, One-class support vector machines, Ecological niche factor analysis (ENFA), Maximum entropy (MaxEnt), and Boosted regression trees (BRT) (Elith, 2016). MaxEnt is one of the extensively used models with higher performance (Pearson, 2010; Dutra et al., 2021; Xu et al., 2023). MaxEnt uses environmental characteristics at the locations of species occurrence data within a larger sample of “background” environmental characteristics representing a larger region of interest, to estimate the potential distribution of the species within the larger region.” MaxEnt estimates a

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species probability distribution through the probability distribution of maximum entropy (Phillips et al., 2006), it uses the occurrence data and the background data to estimate the ratio (Elith et al., 2011).

Ngorongoro Conservation Area (NCA) has been reported to have the highest number of invasive species among protected areas in Tanzania, with about 139 invasive alien species, where *Gutenbergia cordifolia* Benth. ex Oliv. is one of the most highly invasive and damaging plants (NCAA, 2019). It has invaded a larger part of the Ngorongoro crater floor and causes a lack of palatable forage species resulting from its allelopathic ability (Ngondya et al., 2016). Ngorongoro conservation area has multiple land uses, recognized as a biosphere reserve under UNESCO's Man and Biosphere program (MNRT, 2019), therefore *G. cordifolia* has a direct impact on tourism, wildlife, livestock, and agriculture sector (NISSAP, 2019). NCA has reported spending about 185 million USD on invasive species in the 2018/19 financial year indicating the magnitude of the problem (NISSAP, 2019). Understanding the spatial distribution and how climate change will alter the spread of invasive species is the key to developing effective preventive, control, and restoration strategies (Finch et al., 2021; Rusňák et al., 2022), considering the transboundary and large-scale impact of invasive species, spatially explicit approaches are required (Gholizadeh et al., 2022).

We aim to map the distribution of invasive species of *G. cordifolia* in the Ngorongoro Conservation Area, Tanzania, and predict the changes with global warming, then analyze the effect of climate changes on the spread of this species and evaluate the impact of its spread on the local ecosystem. We started by mapping the spatial distribution of *G. cordifolia* by using Sentinel 2-imagery, then based on the current climate data the current potential distribution of *G. cordifolia* was predicted, lastly, the future distribution was predicted based on the climate change scenario under Shared Socioeconomic Pathways (SSPSs) in the 2050s and 2070s. Since *G. cordifolia* will likely invade various rangeland inside and outside the protected area (Ngondya et al., 2016), this result will inform the management of NCA and local communities inside and bordering the park on sustainable management and control strategies.

Material and methods

Study site

Ngorongoro Conservation Area (NCA) is located in the northern part of Tanzania, Arusha Region in Ngorongoro Districts sharing part of the Serengeti plains to the north-west and bordering the towns of Arusha and Moshi, and Mount Kilimanjaro to the east (*Fig. 1*). NCA's exact location is Longitude 35° 30' E, Latitude 3° 15' S and covers an area of 8292 km^2 and ranges in altitude from 1020 m to 3587 m above sea level (Eloundou et al., 2012).

The climate of NCA varies from moist and misty in the highlands to temperatures falling up to 2 °C and rising to 35 °C in semi-arid plains, and annual precipitation between November and April which varies from under 500 mm on the arid plains to 1700 mm on the forested slopes in the east which increase with altitude (UNEP and WCMC, 2011). The climate of NCA is characterized by bimodal seasonality with two distinct wet and dry seasons (Mwabumba et al., 2022). The wet season begins from October-December and March - May, whilst the dry season starts from January – February and then June – September (Mwabumba et al., 2020). Ngorongoro Conservation Area is ecologically diverse with numerous vegetation structures

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including forest, woodland, bushland, and grasslands (Niboye, 2010), covering 921.52 km^2, 221.51 km^2, 14890.4 km^2, and 1259488 km^2 respectively (Mwabumba et al., 2020) It is the part of Serengeti ecosystem one of the world's last intact ecosystems known for the great wildebeest migration. Complex landforms include the Ngorongoro crater which is the largest unbroken caldera in the world (UNEP and WCMC, 2011).

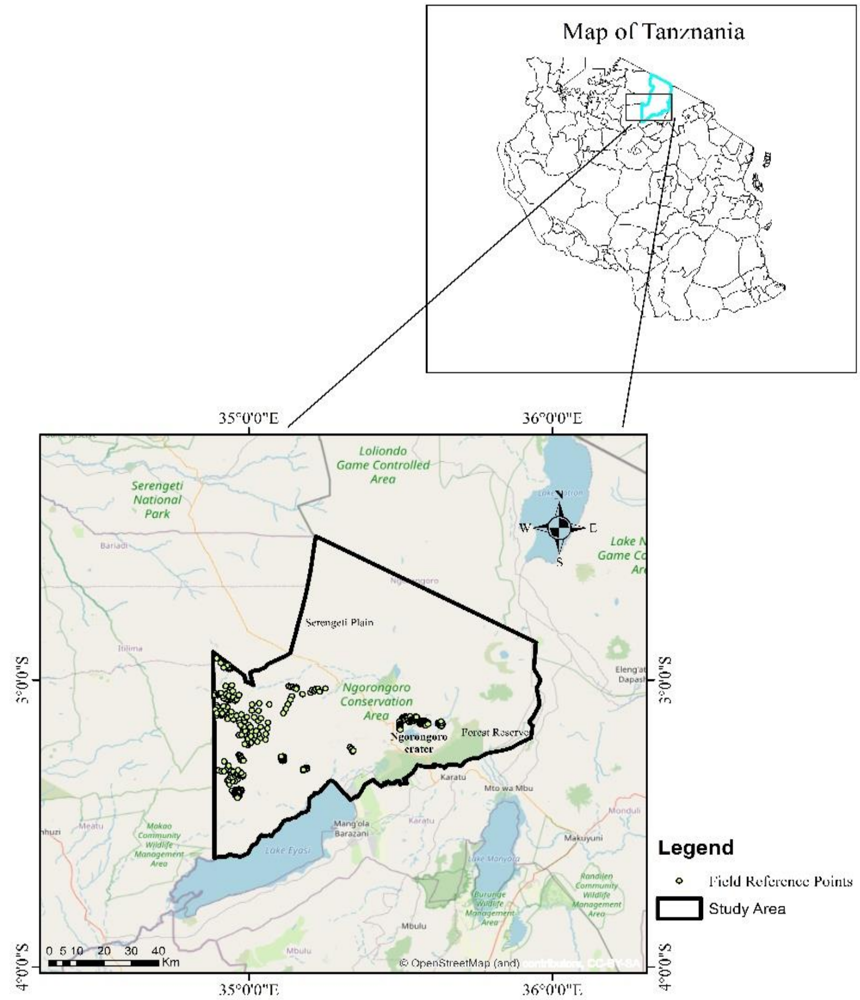

Figure 1. *Location of the study area*

Data acquisition and processing

Sentinel-2 imagery

Sentinel 2 Multispectral Instrument level 2A Images covering the whole study area with less than 7% cloud cover were downloaded from the European Space Agency (ESA) at the Copernicus Data Space Ecosystem, via https://dataspace.copernicus.eu. The acquisition date was on 7 and 9, March 2023 with two images from each date making a total of four images. This timeframe was selected to optimize the spectral differentiation between the invasive *G. cordifolia* and other species in the study area. The Sentinel 2 level 2A data is atmospherically corrected Bottom-Of-Atmosphere

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(BOA) orthoimage product (ESA, 2015). Nonetheless, to improve image quality and ensure higher classification accuracy, we pre-processed the images with Sen2Cor Processor in the Sentinel Application SNAP v9.0. The rest of the pre-processing, including mosaic and mask, was performed in ENVI v5.6 (64-bit) software. All available 13 bands in 10 m, 20 m, and 60 m spatial resolution (Gascon et al., 2017) were resampled to 10 m resolution and stacked into a composite image before mosaicking all downloaded images into a single image and clipping down to cover the study area.

Field measurement

A field survey was conducted in the study area in September 2023 to obtain occurrence records for *G. cordifolia*. Due to the inaccessibility and uneven distribution of *G. cordifolia*, stratified random sampling was used during data collection. Four strata of the highly invaded area were selected where in each site 100 GPS points of *G. cordifolia* were recorded opportunistically, making a total of 400 points. We also randomly collected 20 points for other vegetation identification, and five points at crossroads to be used as checkpoints. In addition to the field data, more reference data were obtained with the help of higher-resolution images from Google Earth Pro. Which was used as a reference image to identify other land cover classes (Ayanu et al., 2015).

Environmental data

To predict the potential distribution of *G. cordifolia* in NCA the environmental variables mainly Temperature and precipitation were used. For predicting the current potential distribution of *G. cordifolia* in the study area 19 Bioclimatic variables (*Table A1*) of 1970-2000 were downloaded from WorldClim (https://www.worldclim.org/data/worldclim21.html) with a spatial resolution of 30 seconds (~1 km^2).

Coupled Model Inter-comparison Project (CMIP) climate projections data was downloaded from https://www.worldclim.org/data/cmip6/cmip6climate.html for predicting the future spread of *G. cordifolia* under different future climatic change scenarios. This study utilizes CMIP6 which is current phase and well adopted climate models used globally in climate change research (Li et al., 2023). There are several models used for climate projection, and the Ec-Earth3-Veg model was used in this study due to its higher climate sensitivity (Döscher et al., 2021). The Intergovernmental Panel on Climate Change (IPCC) assessment report developed a set of emission scenarios known as “Shared Socioeconomic Pathways” (SSPs). For this study, SSP 126 (Low challenges to mitigation and adaptation) and SSP 245 (Medium challenges to mitigation and adaptation) of 30 seconds spatial resolution were used to predict the spreading of *G. cordifolia* in the 2050s (2041-2060) and 2070s (2061-2080). These data are available as a single compacted bioclimatic layer and were processed with RStudio to get the 19 bioclimatic data. To avoid multicollinearity among the variables, the Elastic Net Regression test was used to determine the bio-climatic variables with the highest contribution, and the variables with the least contributions were removed, whereby only 15 bioclimatic variables were used. These environmental variables for predicting current potential distribution and future potential distribution under SSP 126 and SSP 245 in the years 2050s and 2070s were pre-processed in ArcMap v10.8.2 to clip the variables to cover the study area and they were converted to the required MaxEnt software format. In addition, other variables were added to test how they influence the

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distribution of *G. cordifolia* in conjunction with climatic variables. These variables are; soil, road and proximity to the park boundary, which were also processed in ArcMap.

Analyses

Classification

To obtain the distribution of *G. cordifolia*, supervised classification was performed and a Maximum likelihood classifier (MLC) was used in this study. This method is based on Gaussian estimation of the probability density function of each class (Zhang et al., 2008). It is derived from Bayes theorem, which is the probability that each pixel with ω belongs to a certain class,

$$P(i|\omega) = \frac{P(\omega|i)P(i)}{P(\omega)} \quad \text{(Eq.1)}$$

where $P(i|\omega)$ is the likelihood function, $P(i)$ is the probability that class i occurs in the study area and $P(\omega)$ is the probability that ω is observed, given as:

$$P(\omega) = \sum_{i=1}^{M} P(\omega|i)P(i) \quad \text{(Eq.2)}$$

where M is the number of classes (Ahmad and Quegan, 2012). This method has proven to perform well in various invasive species studies (Viana et al., 2010; Thamaga and Dube, 2018). A total of three land cover classes were used during the image classification process (Viana et al., 2010), which are: invasive *G. cordifolia*, other vegetation, and bare soil and low vegetation cover areas.

ENVI v5.6 software was used during classification and an accuracy assessment. The indicator of the error matrix, which provides overall accuracy of the image classification as well as producer accuracy which is the percentage of pixels correctly classified in a given class and account user accuracy that asses the probability for each class being actual on the ground (Cardille et al., 2024), were both calculated and evaluated the accuracy of the classification results. To test the reliability of the result, the Kappa test result is used, which is interpreted as follows: values ≤ 0 indicate no agreement, 0.01–0.20 as none to slight, 0.21–0.40 as fair, 0.41–0.60 as moderate, 0.61–0.80 as substantial, and 0.81–1.00 as almost perfect agreement (McHugh, 2012).

MAXENT modeling

In this study, Maximum Entropy Modeling MaxEnt v3.4.4 was used (http://biodiversityinformatics.amnh.org/open_source/maxent/) for predicting the current potential distribution of *G. cordifolia* and future distribution based on future climatic scenarios. MaxEnt makes the estimates of the ratio $f_1(z)/f(z)$ to calculate the probability of occurrence, from the conditional density of covariates at the presence site $f_1(z)$ and the unconditional density of covariates $f(z)$ (Elith et al., 2011). Presence records collected from the field together with 15 bioclimatic variables were used for SDM. The MaxEnt setting including the Regularization multiplier (RM) and Feature combination (FC) was decided based on the ENMeval result (Xu et al., 2023). This result was derived from the ENMeval package in RStudio v4.3.2. The RM of two was

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used during modeling and the features combination adopted was Linear features, Quadratic features, Threshold features, and Hinge features. The logistic transformation was used in this study, which gives the log of the output: log$(f_1(z)/f(z))$ (Elith et al., 2011). The potential distribution of *G. cordifolia* based on future climate was projected based on future climate change scenarios i.e. SSP 126 and 245, of the year 2050s (2041-2060) and 2070s (2061-2080).

To test the accuracy of the models, the Receiver Operating Characteristics curve (ROC) was used. Within the ROC's curve is a value that summarizes the model performance known as AUC (Area Under the Curve), with several categories in which 0.5~0.6 indicates poor performance, 0.6~0.7 acceptable performance, 0.7~0.8 good performance, 0.8-0.9 excellent performance and 0.9 > is an outstanding model performance (Yang and Berdine, 2017). ArcMap 10.8.2 software was then used to generate final maps with five categories, unsuitable, slightly suitable, moderately suitable, suitable, and highly suitable.

Results

Identification and spatial distribution of Gutenbergia cordifolia

In this study, the maximum likelihood classification method was used to identify the *G. cordifolia* from Sentinel 2 satellite imagery. This is one of the extensively used classification methods with higher classification accuracy (Thamaga and Dube, 2018). The Spectral separability value between *G. cordifolia* and other vegetation indicated a distinct spectral signature which facilitate the mapping process. The overall accuracy of the classification of this study is 95.20% with a Kappa coefficient of 0.88 which indicates the high reliability of the result. The producer and user accuracy for *G. cordifolia* was 85.37% and 100% respectively. For other land classes, bare soil and low vegetation areas had the highest accuracy followed by other vegetation class (*Table 1*).

Table 1. *Confusion matrix result*

Class	Producer accuracy (%)	Account accuracy (%)
Gutenbergia cordifolia	85.37	100.00
Other vegetation	89.03	94.26
Bare soil and low vegetation cover	98.02	95.49

The invasive *G. cordifolia* is spatially distributed in most areas within Ngorongoro (NCA), with the major hotspot areas in the western part of the conservation area and the Ngorongoro Crater (*Fig. 2*). It covers 16% of the total area, equivalent to 1283.90 km^2.

Current potential distribution

Based on the current climatic scenario the current potential distribution of *G. cordifolia* is highly correlated with the spatial distribution result, with suitable areas in the western part of the conservation area as well as in the crater indicating a similar climate (*Fig. 3*). The suitable area accounts for 7% of the total area, whereas moderately suitable, slightly suitable, and unsuitable account for 9%, 9%, and 75% respectively (*Fig. 3*).

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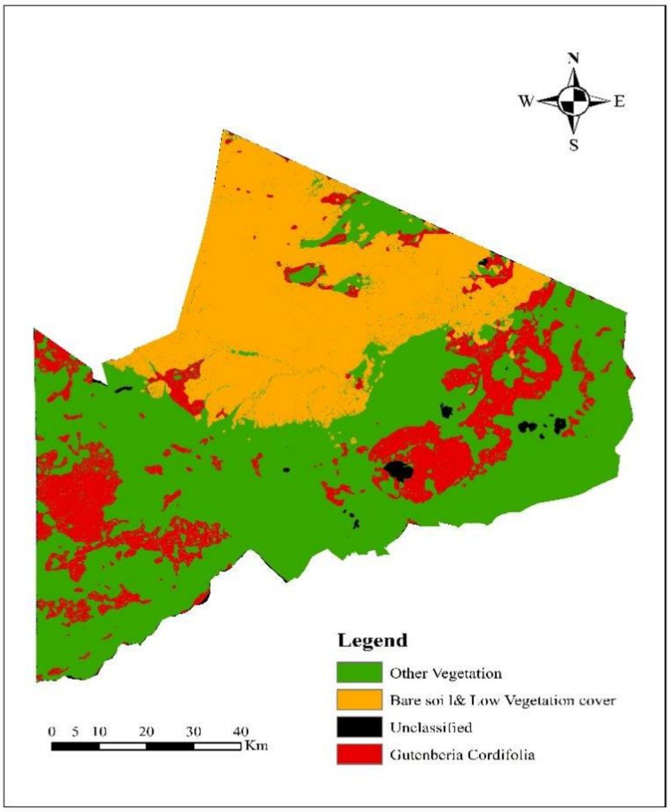

Figure 2. *Spatial distribution of Gutenbergia cordifolia in relation to other land cover classes in the Ngorongoro conservation area*

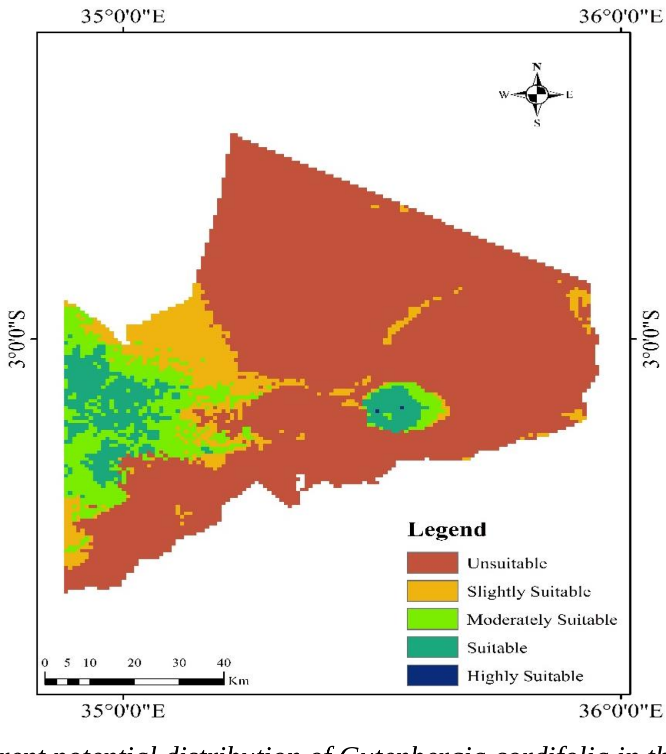

Figure 3. *Current potential distribution of Gutenbergia cordifolia in the Ngorongoro Conservation area*

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The AUC for the best-performed model after 10 repetitions was 0.911 indicating the outstanding performance of the model. The bioclimatic variable with the highest contribution to the potential distribution of *G. cordifolia* when used in isolation was Precipitation of Wettest Month (bio13), and the variable that decreased the gain when omitted is Temperature Seasonality (bio 4) (*Fig. A1*).

Potential distribution under future climate change scenario

This study used climate change scenarios known as SSP to predict the potential future distribution of *G. cordifolia* in NCA. Under future climate change scenarios, SSP 126 and SSP 245 for the 2050s and 2070s the result shows a significant increase in the potential distribution of *G. cordifolia* (*Fig. 4*). The unsuitable area was projected to decrease between 22% to 9% in both climatic scenarios in both year 2050s and 2070s. The slightly suitable area was also projected to have a general increase in the year 2070s but a decrease but 1% under SSP 126 in the year 2050s (*Fig. 5*). The highly suitable areas showed an increasing trend only under SSP 126 while remaining unchanged under SSP 245. Similarly, the suitable areas appear to only increase under SSP 245 in both years. Moderately suitable areas showed an increasing trend throughout the future projection, with a 3% increase under SPP 126 in the 2050s and SSP 245 in the 2070s, while a 2% increase for others. Generally, the potential distribution of *G. cordifolia* under future climate change scenarios has been expanded from the west to the northwest and northern part of the conservation area. Whereas nearly constant suitability has been observed in Ngorongoro Crater except for SSP 126 in the 2070s (*Fig. 4*).

Key environmental variables on the potential distribution of G. cordifolia

When predicting the potential distribution of *G. cordifolia* each environmental variable relatively contributes to the MaxEnt model. The variable with the highest contribution was bio 13 (Precipitation of Wettest Month) with 26.5% followed by bio 18 (Precipitation of Warmest Quarter) with 17.8% (*Table A1*). Furthermore, bio 12 (Annual Precipitation), and bio 19 (Precipitation of Coldest Quarter) are among the highest contributors to the model. Meanwhile, the training result shows that bio13 (Precipitation of Wettest Month) has the highest gain when used in isolation and shows a decrease in maximum gain when omitted, similarly, bio4 (Temperature Seasonality) decreases the most gain when omitted (*Fig. A1*), making them the most important variables in predicting the current potential distribution of *G. cordifolia*. MaxEnt model output also creates a response curve that shows how each environmental variable affects model prediction. *Figure A2* presents the curve of two among the variables with the highest contribution, which illustrate their influence in the potential distribution of *G. cordifolia*.

Change detection analysis in the current and future potential distribution of G. cordifolia

The potential distribution of *G. cordifolia* has been shown to change, from current climate to future climate change scenarios (*Table A2*). Approximately, a total area of 864 km^2 and 831 km^2 in the year 2050s and 2070s respectively under SSP 126 is projected to become suitable habitat for *G. cordifolia* in NCA. Furthermore, an area of 4918 km^2 for SSP 126, and 5229 km^2 for SSP 245 in 2050s, and 5138 km^2 of SSP 126 and 4287 km^2 for SSP 245 in 2070s is projected to remain unsuitable (*Fig. 6*).

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Similarly, the reduction in potential distribution area has been observed highly under SSP 245 in the 2050s (*Fig. 7*).

Distribution of Gutenbergia cordifolia based on additional variables

In addition to climatic variables, this study evaluates the impacts of soil, roads, and proximity to boundary on the distribution of *G. cordifolia* in NCA. The MaxEnt result shows that bioclimatic variables largely contribute to the potential distribution of *G. cordifolia* by 95.2% as compared to road and proximity to the park boundary. When the three variables were added, the model performance improved by 0.005, and there were also small changes in potential distribution areas (*Fig. 8*), of *G. cordifolia* in NCA.

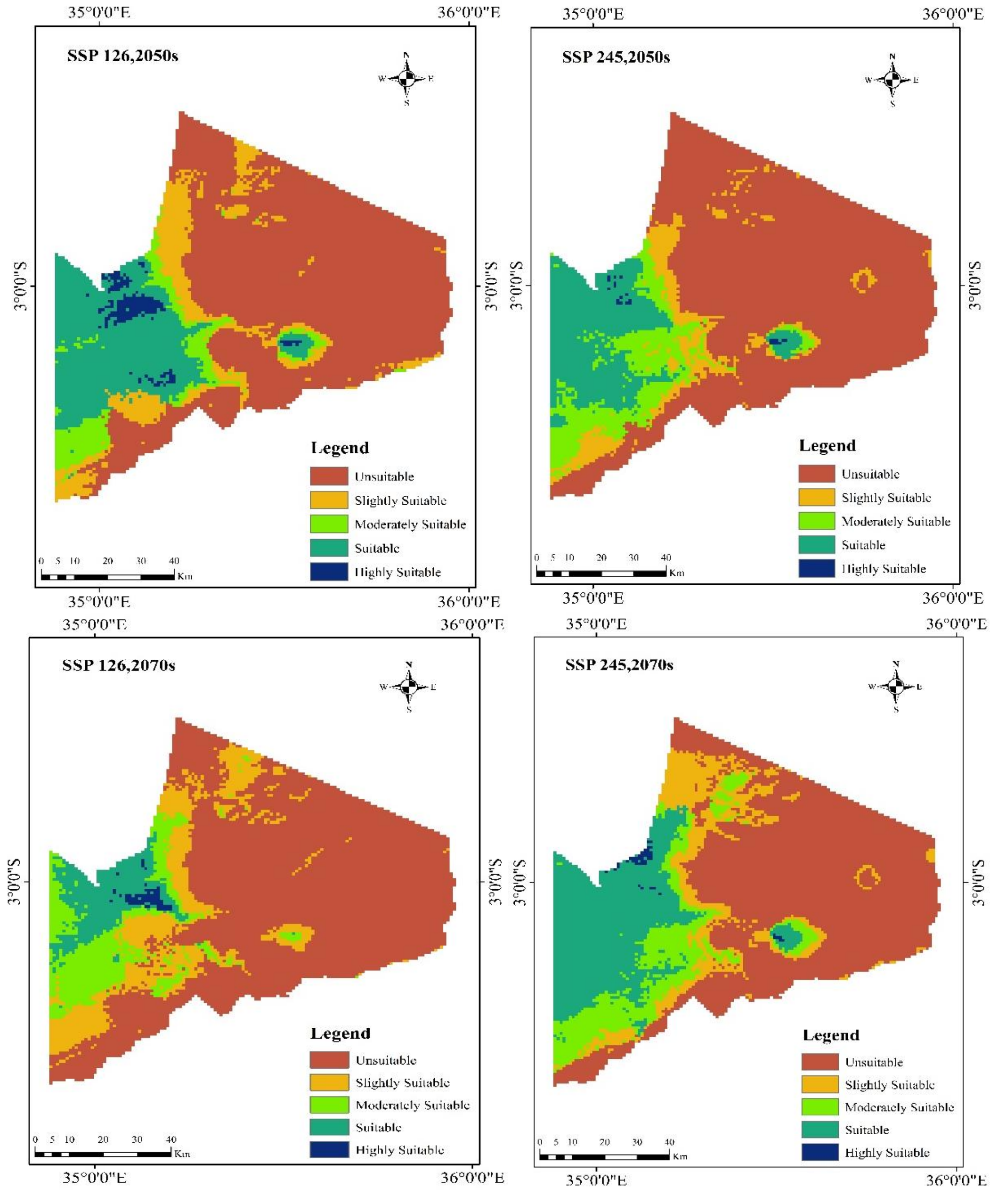

Figure 4. *Potential distribution of Gutenbergia cordifolia in Ngorongoro Conservation Area under climate change scenarios*

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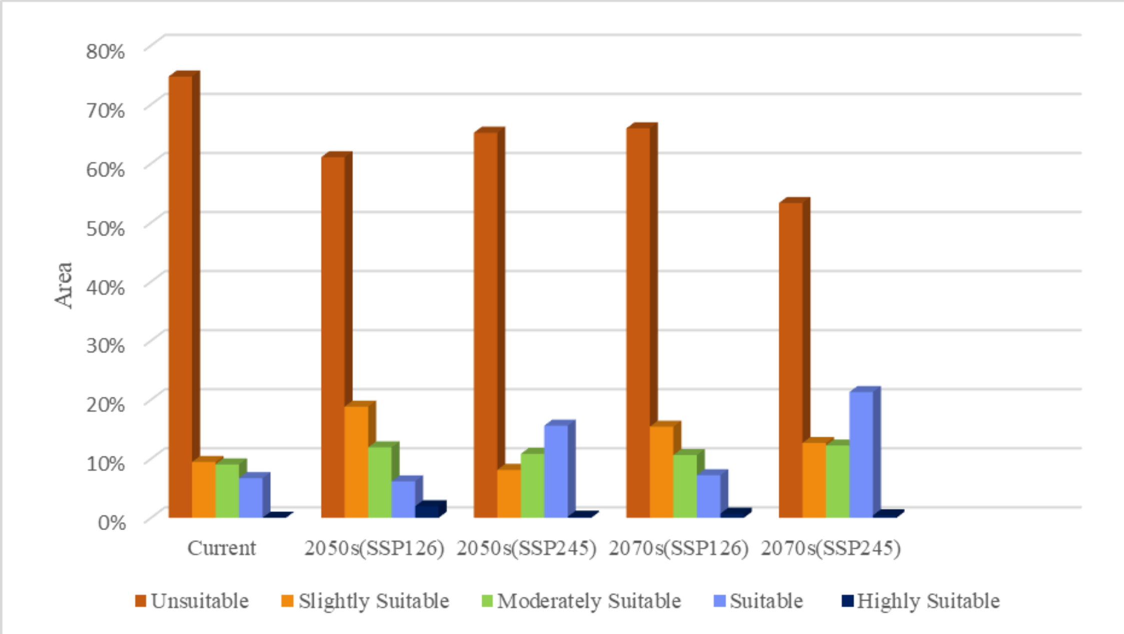

***Figure 5.** Gutenbergia cordifolia potential area suitability in Ngorongoro Conservation area under current climate and future climate change scenarios*

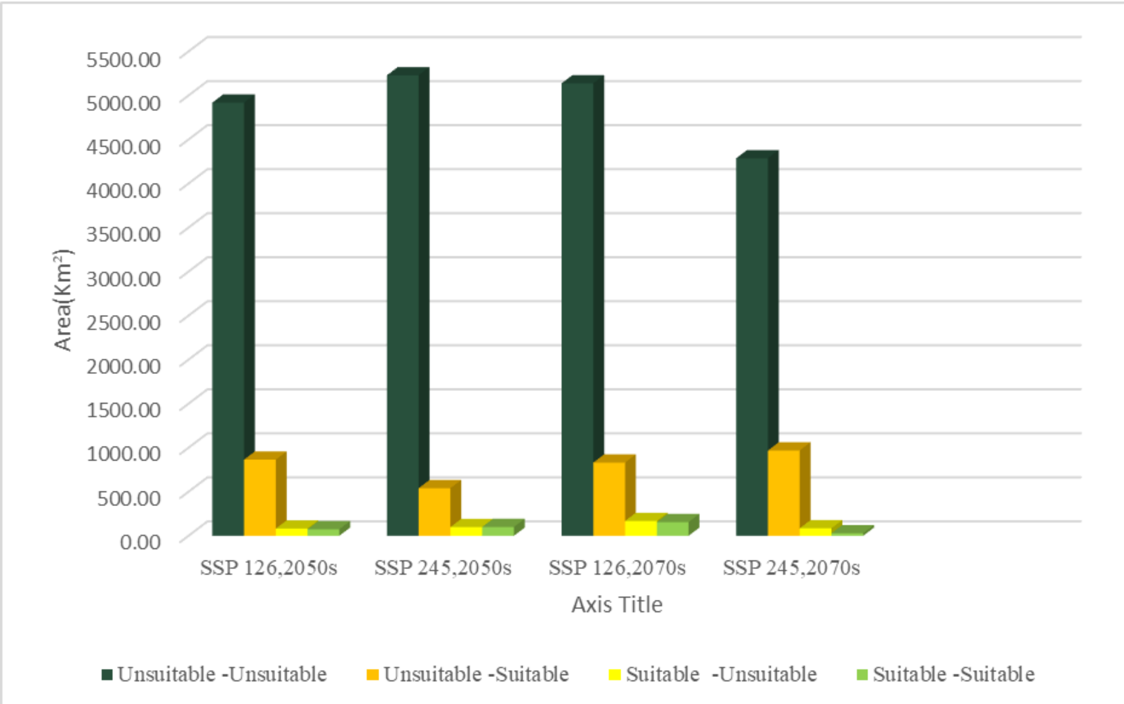

***Figure 6.** Area suitability change of Gutenbergia cordifolia in the Ngorongoro Conservation area under current climate and future climate change scenarios*

Discussion

Invasive species are reported to be the major drivers of biodiversity loss, so identifying their distribution is crucial for sustainable management (Kumar Rai and Singh, 2020).

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Given the ongoing global warming condition (IPCC, 2023), it is important to comprehend the impacts of climate change on the invasion rate. This study uses Sentinel-2 imagery to map the spatial distribution of invasive *Gutenbergia cordifolia* within the Ngorongoro Conservation Area. We then predict its potential distribution under current and future climate change scenarios (SSP 126 and SSP 245) for the 2050s and 2070s. As reported by (Capdevila-Argüelles and Zilletti, 2008), the results indicate that climate change will favor further invasion inside the conservation area.

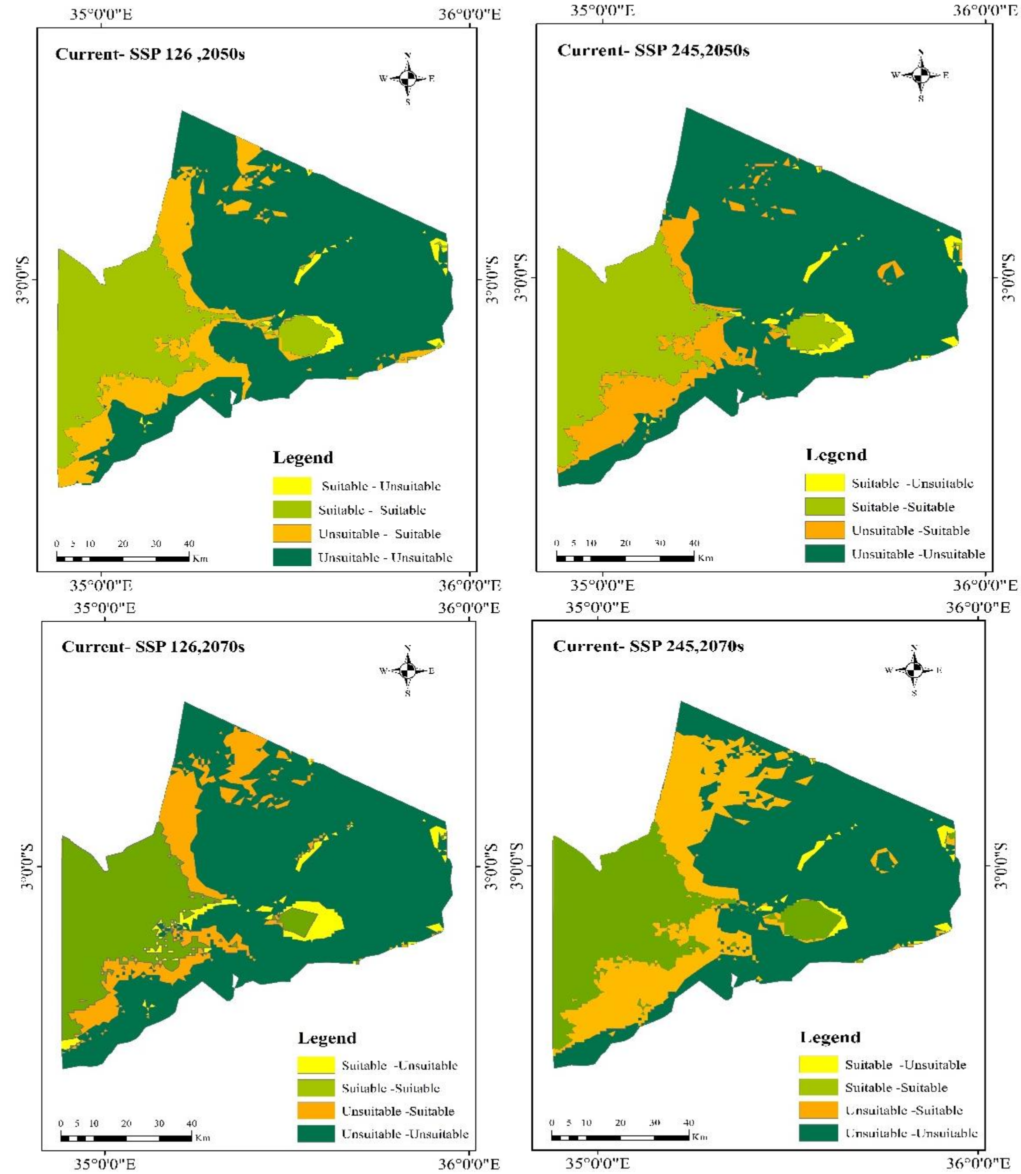

Figure 7. *Change in the potential distribution of Gutenbergia cordifolia between current climate and future climate change scenario in Ngorongoro Conservation Area*

Spatial distribution of Gutenbergia cordifolia in NCA

The classification result shows that *G. cordifolia* covers 16% of the total conservation area. The species is highly distributed in the western part of the study area and the Ngorongoro crater (*Fig. 2*). These findings align with other studies by (Ngondya

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et al., 2016; NISSAP, 2019). Niboye (2010) reported that the main land cover type in NCA is grassland which accounted for 35.3% of the total area. This study shows that *G. cordifolia* has invaded most of the rangelands within the conservation which will compete with palatable species thus posing a threat to wildlife and livestock. Mapping the invasive *G. cordifolia* with sentinel 2 imagery has proven its identification ability, this is likely to be influenced by timing of data acquisition. Other studies on mapping plant species with sentinel 2 have proven its higher performance (Masemola et al., 2020; Lewis et al., 2022; Nkhwanana et al., 2022; Rusňák et al., 2022).

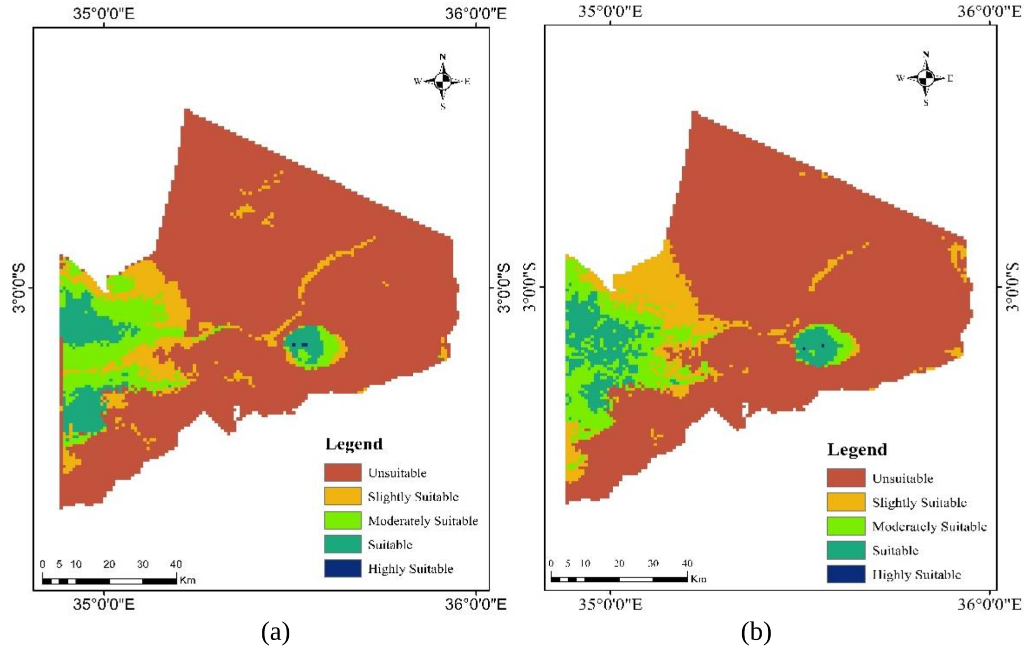

Figure 8. *(a) Distribution of Gutenbergia cordifolia with the road, proximity to the park boundary, soil and bioclimatic variables and (b) distribution of Gutenbergia cordifolia with only bioclimatic variables in Ngorongoro Conservation Area*

Current potential distribution of Gutenbergia cordifolia

Under current climatic variables, this study predicts the habitat suitability of *G. cordifolia* in NCA. The results show that *G. cordifolia* has invaded most of the western part and in the Ngorongoro crater as evidenced by spatial distribution results. The slight differences in spatial distribution could be the result of other environmental factors such as local adaptation or human influence which may result in habitat modification. The environmental variables that highly affect the model prediction for the potential distribution of *G. cordifolia* in NCA are Precipitation of Wettest Month, Precipitation of Warmest Quarter, Annual Precipitation, and Precipitation of Coldest Quarter. Further, the model training result shows that Precipitation of Wettest Month and Temperature Seasonality are the most important variables for the distribution of *G. cordifolia*. The country rainfall anomalies recorded over the past 50 years show an increase in average annual rainfall by 256.5mm higher than long-term total rainfall from 1981-2010 (NCCS, 2021), this indicates that the amount and timing of precipitation influence the habitat suitability of *G. cordifolia* as previously reported by Nyarobi et al. (2022). In addition, the binomial rainfall pattern in the country will cause further invasion in October–December.

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The rainfall of NCA is highly variable due to topographical variation, ranging from 400 to 600 mm/year in the low plains and from 1000 to 1200 mm/year in the eastern forested areas (Mnyawi et al., 2014). Correspondingly, the annual precipitation curve (*Fig. A2*), shows the increase in log contribution between around 400 mm and 700 mm which signifies its contribution to the prediction of *G. cordifolia* habitat suitability. Thus, the current potential distribution areas of *G. cordifolia* are largely in the western parts of NCA (*Fig. 3*), as they experience the aforementioned annual precipitation range. This study also evaluates the impact of soil, road, and proximity to the park boundary together with bioclimatic variables on the distribution of *G. cordifolia* in NCA and the result shows that they have minor contributions to the species distribution. This explains the slight differences in spatial distribution results as some of the unsuitable areas appeared suitable when more variables were incorporated into the model. This finding highlights the importance of the ensemble modeling method for species distribution (Wakie et al., 2014; Ng et al., 2018), nonetheless as previously reported by Finch et al. (2021) climate plays a major role in species distribution.

Climate change impacts on distribution of Gutenbergia cordifolia

Climate change is increasingly intensifying with widespread and substantial impacts on biodiversity and ecosystems including changes in species ranges, seasonal timing, and ecosystem structure (Tang et al., 2022; IPCC, 2023; Xu et al., 2024). Similarly, our results suggest that the habitat suitability of *G. cordifolia* will potentially change under future climate change scenarios (*Fig. 4*). A study by Borges et al. (2022) pointed out that NCA has several land cover types including bare land, forest, grassland, montane heath, shrubland, and water. In this study, the potential suitable habitat for *G. cordifolia* is predicted to be in the grassland areas which indicates that the edible grass for wildlife and livestock will be replaced due to the allelopathic ability of *G. cordifolia* as suggested by Ngondya et al. (2016). This will likely force grazing animals outside the conservation area resulting in ecosystem disruption and human-wildlife conflicts. Furthermore, the invasion has been observed to move towards the areas of Serengeti Plains, indicating that as the climate changes the invasion could go further toward the Serengeti ecosystem which covers Serengeti National Park, Maswa Game Reserve, Grumeti Game Reserve, Ikorongo Game Reserve, and Masai Mara National Reserve. This is similar to the suggestion from Ngondya et al. (2016), as invasion is likely to spread outside the conservation area. The Serengeti Plains is inside the Lake Victoria basin which experiences bimodal rainfall, whereby rainfall projections show an increase in annual rainfall by 18-28% by 2100 (NCCS, 2021). This explains the invasion in the area and confirms our result that rainfall is the most important variable for *G. cordifolia* distribution and indicates that an increase in rainfall will favor further invasion. Additionally, the result shows the decrease in highly suitable areas in the Ngorongoro crater observed under the current climate to zero in the 2050s and slight changes in general suitability in the 2070s. This could be a result of the unique climate of the crater as suggested by Żaba and Gaidzik (2011), which is much drier and locally influenced by differences in height between the floor and highlands of the crater. The reduction in habitat suitability in the crater is consistent with the study by Nyarobi et al. (2022), which showed that *G. cordifolia* cannot tolerate drier climate. The unique observation in the crater under SSP 126 in the 2070s can be the result of rainfall shift and uncertainty, this was previously reported by NCCS (2021), and the suitability located at the eastern part of the crater can be explained by lower soil salinity and the proximity to streams (Żaba and Gaidzik, 2011; Borges et al., 2022). Our study's results

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suggest that climate change is expected to favor the invasion of *G. cordifolia* in NCA. This finding aligns with Ongoma et al. (2018) who reported an increase in annual and seasonal rainfall and an increased likelihood of floods in East Africa, as well as Nyarobi et al. (2022) who showed that *G. cordifolia* is flood tolerant. The results show that the western and Crater parts of NCA seem to maintain nearly constant suitability from the current to future projection of the potential distribution of *G. cordifolia* with expansion in the northern parts of the conservation area (*Fig. 7*). This suggests that *G. cordifolia* is likely invading grassland areas, which are projected to cover 45% of the conservation area by 2035 (Mwabumba et al., 2020), hence management priorities should be allocated to these areas.

Limitations and further work

This study faces a limitation in obtaining cloud-free images, which can affect classification accuracy. In addition the unavailability of higher resolution satellite data for the study area and higher cost for other hyperspectral instruments such as LiDAR and UAV. Further study should be done on the impact of other variables such as terrain and settlements on the distribution of *G. cordifolia* in NCA.

Conclusion

This study maps the spatial distribution of *G. cordifolia* in NCA and with the MaxEnt model the current potential distribution and future potential distribution under climate change scenario was identified. The results show that *G. cordifolia* is highly distributed in the western part of the study area and the Ngorongoro crater. The current distribution of *G. cordifolia* is highly influenced by annual precipitation and precipitation of the coldest quarter. Climate change will potentially favor further invasion of *G. cordifolia* within the conservation area and will likely move outside the conservation area towards the Serengeti plains. This calls for sustainable management strategies and action plans inside the conservation area and communities bordering the area. This study provides the baseline data on the distribution of *G. cordifolia* within the conservation area and how climate change will impact the invasion rate, which can be used by the management toward a conservation plan. Thus, the result contributes to conservation efforts, ecological restoration, biodiversity protection, and sustainable ecosystem services as climate change intensifies.

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APPENDIX

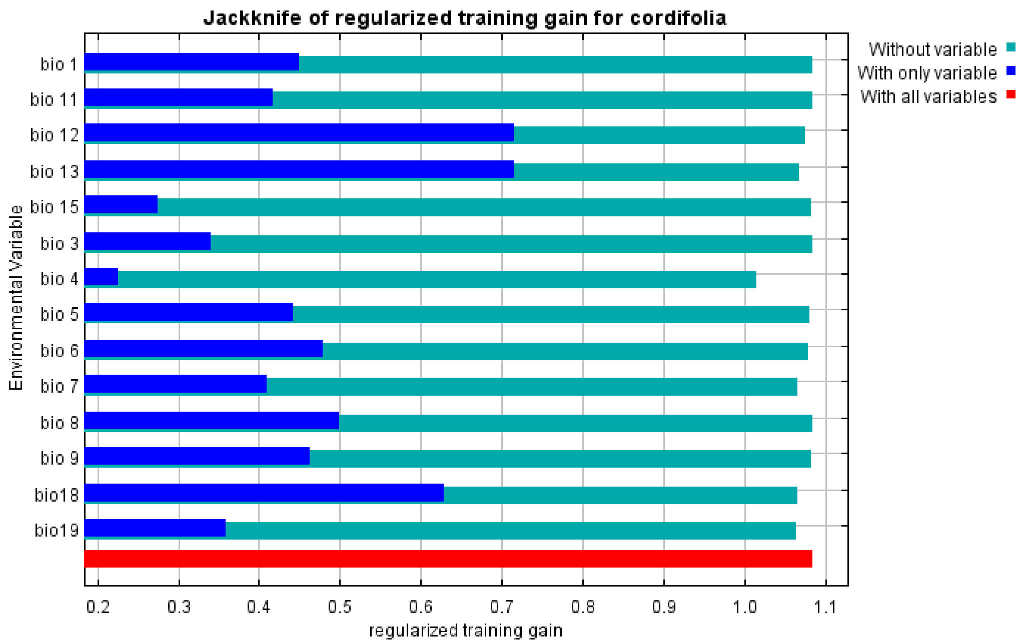

Figure A1. *Jackknife test result of variables importance in the MaxEnt model for Gutenbergia cordifolia potential distribution in Ngorongoro Conservation area*

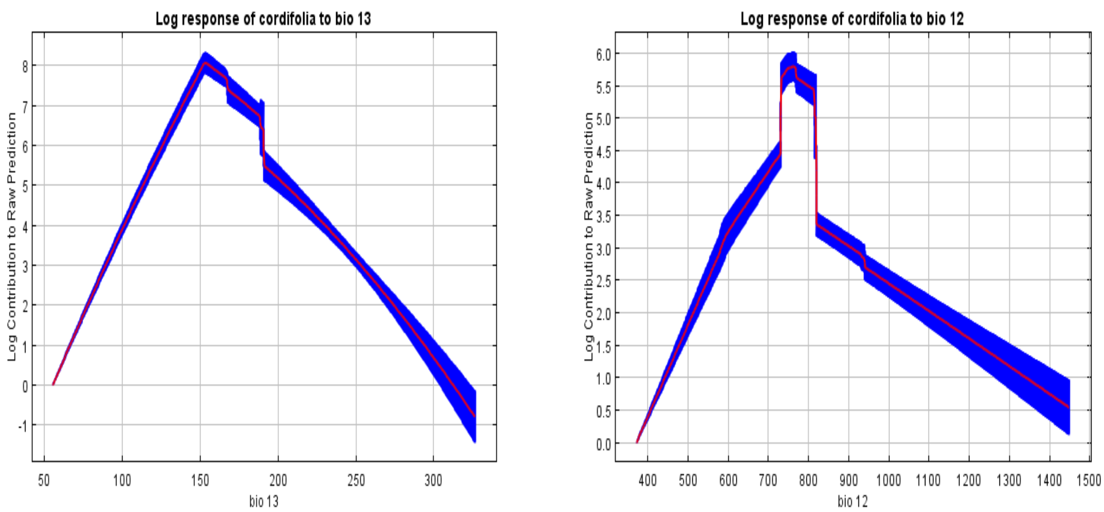

Figure A2. *Response curve of how Precipitation of Wettest Month (bio13) and Annual Precipitation respectively (bio12) affect MaxEnt model prediction for current potential distribution of Gutenbergia cordifolia in Ngorongoro conservation area*

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Table A1. *Key environmental variables and their contribution to the distribution of Gutenbergia cordifolia in the Ngorongoro Conservation area*

Variable	Description	Percentage contribution (%)
BIO13	Precipitation of wettest month	26.5
BIO12	Annual precipitation	16.2
BIO18	Precipitation of warmest quarter	17.8
BIO19	Precipitation of coldest quarter	13.7
BIO6	Precipitation seasonality mean	9
BIO4	Temperature seasonality	7.5
BIO7	Temperature annual range	5.5
BIO9	Temperature of driest quarter	1.5
BIO15	Precipitation seasonality	1.4

Table A2. *Changes in the distribution of Gutenbergia cordifolia in the Ngorongoro conservation area between the current climate and future climate change scenario in km^2*

Change	SSP 126, 2050s	SSP 245, 2050s	SSP 126, 2070s	SSP 245, 2070s
Unsuitable - unsuitable	4918.90	5229.343469	5138.094454	4287.207456
Unsuitable - suitable	864.80	540.87767	831.6107947	968.894828
Suitable - unsuitable	82.01	99.087489	168.6133968	85.262433
Suitable - suitable	74.54	100.27372	155.5535749	28.436735

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