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Mapping the spatial distribution of underutilised crop species under climate change using the MaxEnt model: A case of KwaZulu-Natal, South Africa

H. Mugiyo [a,*], V.G.P. Chimonyo [a,b], R. Kunz [c], M. Sibanda [d], L. Nhamo [a,e], C. Ramakgahlele Masemola [a,f], A.T. Modi [a], T. Mabhaudhi [a,g]

[a] Centre for Transformative Agricultural and Food Systems, School of Agricultural, Earth & Environmental Sciences, University of KwaZulu-Natal, P/Bag X01, Scottsville, Pietermaritzburg 3209, South Africa
[b] International Maize and Wheat Improvement Centre (CIMMYT)-Zimbabwe, P. O Box MP 163, Mt Pleasant, Harare, Zimbabwe
[c] Centre for Water Resources Research, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, P/Bag X01, Scottsville, South Africa
[d] Department of Geography, Environmental Studies & Tourism, Faculty of Arts, University of the Western Cape, Bellville, South Africa
[e] Water Research Commission of South Africa, 4 Daventry Street, Lynnwood Manor, Pretoria 0081, South Africa
[f] Precision Agriculture Group, Council for Scientific and Industrial Research (CSIR), Pretoria, South Africa
[g] International Water Management Institute (IWMI-GH) – West Africa Regional Office, Accra, Ghana

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A B S T R A C T

Knowing the spatial and temporal suitability of neglected and underutilised crop species (NUS) is important for fitting them into marginal production areas and cropping systems under climate change. The current study used climate change scenarios to map the future distribution of selected NUS, namely, sorghum (*Sorghum bicolor*), cowpea (*Vigna unguiculata*), amaranth (*Amaranthus*) and taro (*Colocasia esculenta*) in the KwaZulu-Natal (KZN) province, South Africa. The future distribution of NUS was simulated using a maximum entropy (MaxEnt) model using regional circulation models (RCMs) from the CORDEX archive, each driven by a different global circulation model (GCM), for the years 2030 to 2070. The study showed an increase of 0.1–11.8% under highly suitable (S1), moderately suitable (S2), and marginally suitable (S3) for sorghum, cowpea, and amaranth growing areas from 2030 to 2070 across all RCPs. In contrast, the total highly suitable area for taro production is projected to decrease by 0.3–9.78% across all RCPs. The jack-knife tests of the MaxEnt model performed efficiently, with areas under the curve being more significant than 0.8. The study identified annual precipitation, length of the growing period, and minimum and maximum temperature as variables contributing significantly to model predictions. The developed maps indicate possible changes in the future suitability of NUS within the KZN province. Understanding the future distribution of NUS is useful for developing transformative climate change adaptation strategies that consider future crop distribution. It is recommended to develop regionally differentiated climate-smart agriculture production guidelines matched to spatial and temporal variability in crop suitability.

Practical implications

Climate change undermines resource-poor farmers' ability to respond to risk (Tom et al., 2018). Also, climate change will affect species and ecosystem distribution, reducing or increasing crop suitability. The maps developed show suitability zones for selected neglected and underutilised crop species (NUS) in KwaZulu-Natal.

The projected increase in areas suitable for NUS production (i.e., S1-S3) under climate change suggests a positive change in ecology for the selected crops. The increased suitability also could inform how farmers could redesign and diversify their farming enterprise in response to climate risk. For instance, the possible co-occurrence of one or more NUS in a delineated zone could promote crop diversification. Crop diversification is particularly beneficial in areas where maize monoculture is dominant, given that the productivity of maize is projected to decline under climate

* Corresponding author.
E-mail addresses: mugiyoh@gmail.com (H. Mugiyo), v.chimonyo@cgiar.org (V.G.P. Chimonyo), kunzr@ukzn.ac.za (R. Kunz), msibanda@uwc.ac.za (M. Sibanda), luxonn@wrc.org.za (L. Nhamo), modiat@ukzn.ac.za (A.T. Modi), mabhaudhi@ukzn.ac.za (T. Mabhaudhi).

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change. The inclusion of sorghum in areas previously mapped as a livestock region could see the promotion of crop-livestock systems. Sustainable intensification by promoting a mixed cropping system with greater agrobiodiversity supports SDG 15. However, information relating to the type of diversification, either temporal or spatial, will have to be generated together with actors in the agriculture value chain.

This research proposes a method that can be used to improve the targeting of NUS as climate-smart crops, ultimately allowing their inclusion in strategic (long term) and operational (short to medium term) crop systems management. It is important to note that the maps are not decision-ready until various issues around the uncertainty of GCM data and its downscaling are clarified. More importantly, ground truthing is needed to validate the zoned areas for NUS before decision-makers use the maps. However, the method presents a proof of concept for informing the mapping of crop suitability of lesser-known crops. Therefore, the methods presented in this study can aid in the preliminary understanding of what (NUS) grows “where” and “when”.

By delineating the suitability zones, research can better motivate the inclusion of NUS as part of a climate adaptation strategy. Furthermore, agronomists can use the maps to better understand current and future resource limitations across each area and crop. When interpreted by an agronomist, the maps can help to target the appropriate agronomic strategy suited for the farmer context (Andersson-Sköld et al., 2015; Gopichandran et al., 2016).

Data availability

Data will be made available on request.

Introduction

The Intergovernmental Panel on Climate Change (IPCC) projects a global temperature increase by 2050 of 1.2 °C and 2.2 °C under low and high emissions conditions, respectively (IPCC, 2018). In South Africa, the impacts of climate change have rapidly escalated; by 2080, temperatures in the coastal regions of the country are projected to increase by 1.5 °C and between 3 and 6 °C over the western, central and northern parts of South Africa (Chersich and Wright, 2019). Several consequences, including shifting agroecological zones, weather extremes (drought, floods and temperatures), and significant rainfall variability, affect crop production regardless of adaptability (Akinola et al., 2020). In rural farming communities in marginal areas, climate variability and change are already impacting food and nutrition security, and the extent varies across localities. Moreover, poverty, youth unemployment, and inequality within these communities remain high, with little to no access to climate services and inherently low adaptive capacity. However, African regional governments, including South Africa, continue to promote agriculture as a plausible solution to reduce food and nutrition insecurity, poverty, youth unemployment and inequality (NPC, 2013). There is a need to focus on innovative agricultural technologies adapted to changing climate and create sustainable rural development opportunities. It is within this context that several researchers are advocating for mainstreaming of neglected and underutilised crop species (NUS) into agricultural and food systems under climate change (Mabhaudhi et al., 2017a,b; Chibarabada et al., 2020; Chimonyo et al., 2016a; Hadebe et al., 2017; Nyathi et al., 2018).

Neglected and underutilised crop species (NUS) are defined as crops that were once popular (in and out of their centres of diversity) but have become neglected by users and researchers despite their relevance in diversity (Mabhaudhi et al., 2017a,b). They form an important part of agrobiodiversity and are naturally adapted to marginal areas. Akinola et al. (2020) could contribute to food and nutrition insecurity in marginal communities under climate change (Mabhaudhi et al., 2019). Several researchers have reported the benefits of NUS and highlighted high nutritional value, adaptation to marginal soils, and tolerance to drought and heat stresses (Chimonyo et al., 2016a; Hadebe et al., 2017; Nyathi et al., 2018; Chibarabada et al., 2020). In addition, they have low water use, which means they do not threaten water resources (Mabhaudhi et al., 2019). It is reasonable to assume that NUS display traits from natural selection that make them adaptable to harsh agro-ecologies. Moreover, NUS have been reported to offer ecologically viable options for increasing agriculture production and productivity at present or in the future (Chivenge et al., 2015). Despite their reported adaptability to marginal environments and climate change, there is a lack of studies focusing on climate change impacts on NUS’ temporal and spatial distribution. This limits the ability of policy and decision-makers to include them in adaptation options for smallholder farmers (Olayinka Atoyebi et al., 2017).

Spatial modelling and analysis techniques can aid in understanding the distribution of NUS (Pecchi et al., 2019). Species distribution models (SDM) involve collating species occurrence data, relating these occurrences to terrain and climate variables, and generating maps that predict past, present, or future species distributions (Shabani and Kotey, 2016; Akpoti et al., 2020). They relate environmental variables to species occurrence records to gain insight into ecological or evolutionary drivers and help predict agro-ecology suitability across large scales (Kramer-Schadt et al., 2013). These models include climatic-envelop models (Heumann et al., 2013), statistical models, such as generalised linear models (GLM), generalised additive models (GAM) (Austin, 2007), and machine-learning algorithms such as a genetic algorithm for rule-set production (GARP) and maximum entropy (MaxEnt) (Phillips et al., 2006). The latter model, MaxEnt, has become a popular tool for predicting species distributions in environmental research (Su et al., 2021). The model can cope well with sparse, irregularly sampled data and minor location errors (Phillips et al., 2006). The MaxEnt model has been successfully used by Kogo et al. (2019) to identify suitable areas for maize production in Kenya. Similarly, with limited training data, Akpoti et al. (2020) mapped land suitability for rice production in Benin and Togo. Bunn et al. (2019) mapped recommendation domains to scale-out climate change adaptation strategies in cocoa production in Ghana.

This study applied the MaxEnt model to assess climate change impacts on the geographic distribution of suitable production areas for selected NUS with limited empirical data on occurrence. The study assessed the application of presence-only data to evaluate the current and future crop suitability of sorghum (*Sorghum bicolor*), cowpea (*Vigna unguiculata*), and amaranth (*Amaranthus*) and taro (*Colocasia esculenta*). This study considered sorghum as an NUS in sub-Saharan Africa “in terms of ‘extent’ (socio-economic) and ‘where’ (geographical)” (see Hadebe et al., 2017). In addition, it is also considered an NUS because, relative to its potential, the production is low, and utilisation in sub-Saharan Africa is still regarded as low (Taylor, 2003; Macauley, 2015). The application of MaxEnt, a machine-learning algorithm-based model designed to estimate the likelihood of occurrence based on presence-only data, has great potential for use, mainly where extensive land use information is often difficult to obtain. The study is the first step toward understanding the present and future NUS suitability.

Methodology

Study area

This study was carried out in the KwaZulu-Natal (KZN) province in South Africa. The province covers 94 361 km^2, of which 65 000 km^2 is considered suitable for farming. This study classified farming land as either arable (cropland and fallows) or land under permanent crops, pastures, and hayfields. The province has a dual agricultural economy consisting of commercial and subsistence farms (Tibesigwa et al., 2017). KwaZulu-Natal is characterised by summer rainfall, and most of its rain is received in the austral summer period, between October and March

(Kruger and Nxumalo, 2017). The mean annual rainfall ranges from 650 mm in the eastern Grasslands to 1400 mm in the east of Coastal Bushveld, and the Central Bushveld receives 900 mm (Walker and Schulze, 2006; Ghile and Schulze, 2008). Across space and time, rainfall in the province is unevenly distributed (Lobell et al., 2008; Dai, 2011; Ziervogel et al., 2014) and is the dominating factor determining crop suitability (Walker and Schulze, 2006).

MaxEnt model description

MaxEnt (Phillips et al., 2006) is a general-purpose machine learning model based on a precise and straightforward mathematical formulation (Reddy et al., 2015; Akpoti et al., 2020). It is also described as a presence-only model that uses predictor datasets to distinguish species occurrence patterns (Merow et al., 2013). The model utilises categorical and continuous datasets (Merow et al., 2013; Heumann et al., 2013). Although a fundamental assumption of MaxEnt is that regions have been systematically sampled across most existing land, the MaxEnt model is usually built from occurrence records that are spatially biased towards better-surveyed areas (Akpoti et al., 2020). The model offers both a user-friendly graphical user interface and command-line functions. MaxEnt is among the most preferred niche-based geographic species distribution modelling methods and performs exceptionally well with small datasets (Phillips et al., 2006; Kramer-Schadt et al., 2013). The model also provides useful model assessment tools such as i) jack-knife environmental parameter contributions, ii) species-environment curves (with and without other ecological parameters) and iii) Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC) as a metric of model performance (Phillips et al., 2006; Merow et al., 2013). This study used MaxEnt Version 3.4.4 (https://www.cs.princeton.edu/~schapire/maxent) to model the distribution of the four NUS (sorghum, cowpea, amaranth and taro) in KZN.

Species occurrence data

The species occurrence data points were gathered from field surveys conducted in KZN between October and November 2019. During the survey and for each crop (sorghum, cowpea, taro, amaranth), we collected 60 GPS locations, making 240 data points, and the points were randomly selected in a linear pattern (Fig. 1). These data points were randomly collected within 20 m of farmer's fields where the crops were seen to be established.

Predictor variables

In the current study, the MaxEnt model was adopted to simulate the planting area of the selected NUS by combining a set of known geo-coordinates with layers of environmental variables under KZN's current and future environmental conditions. The datasets used in this study were divided into i) continuous surfaces of bioclimatic variables (e.g., climate and topography) and ii) categorical (or discrete) surface variables (e.g., known locations of NUS growing areas). Four climatic, six soil physical and chemical properties, two topographic and two socioeconomic variables were used (Table 1). Social and economic factors, such as the distance along with the road network and distance to metro cities, can significantly affect crop profitability, influencing crop choice to be grown on a farm. These social-economic factors affect farmers' crop preference because some crops like taro are heavy to transport to the markets. In this regard, some farmers who reside far away from metro towns where markets are situated might not grow these crops on large hectarages because of the cost of transporting them to the markets.

In this study, historical and future climatic data were mined from

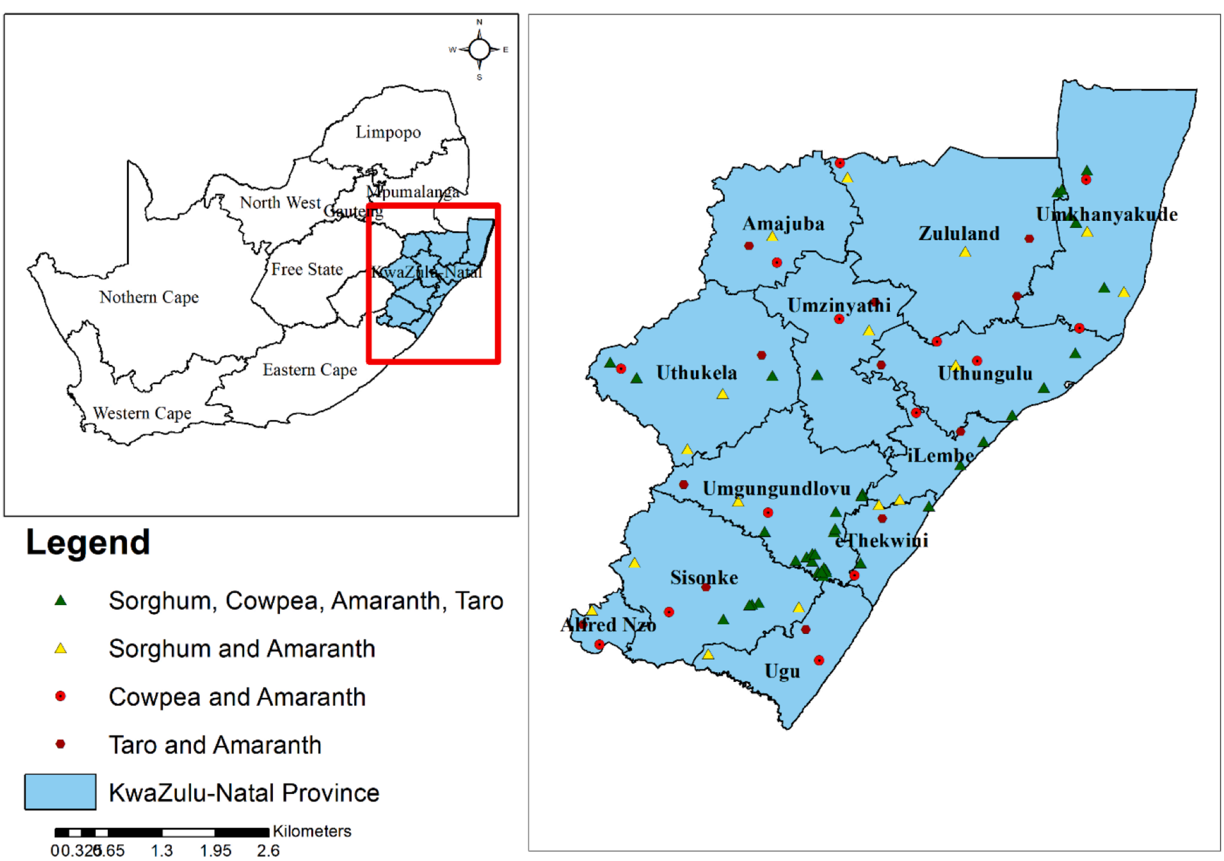

Fig. 1. Map of South Africa and the location of KwaZulu Natal province. Also, the presence data for sorghum, cowpea amaranth and taro in KwaZulu-Natal in South Africa is shown.

Table 1
Input variables used to predict land suitability of NUS in KwaZulu-Natal with MaxEnt, including the original data source and native spatial resolution.

Variable	Name	Source	Resolution
Climate			
Seasonal precipitation (mm)	Seasonal precipitation	https://cordex.org/domains/region-5-africa/	25 km
Minimum temperature (°C)	Minimum temperature	https://cordex.org/domains/region-5-africa/	1 km
Maximum temperature (°C)	Maximum temperature	https://cordex.org/domains/region-5-africa/	1 km
Length of the growing period (days)	LGP	Schulze (2008)	1 km
Soil physical and chemical properties			
Available soil water capacity untilwilting point (volumetric fraction)	WWP	SoilGrids250m	250 m
Soil pH	PH	AfSoilGrids250m	250 m
Soil depth (mm)	DEPTH	AfSoilGrids250m	250 m
Soil texture fraction: clay (%)	CLAY	AfSoilGrids250m	250 m
Soil texture fraction: silt (%)	SILT	AfSoilGrids250m	250 m
Soil texture fraction: sand (%)	SAND	AfSoilGrids250m	250 m
Topography			
Elevation (m a.s.l)	DEM	earthexplorer.usgs.gov	30 m
Slope (%)	SLOPE	earthexplorer.usgs.gov	30 m
Socioeconomic factors			
The distance along with the road network (km)	EUCDIST	Derived in ArcGIS	2 km
Distance to metro cities (km)	ACCESS	Derived in ArcGIS	1 km

high-resolution regional climate projections from the newly performed Coordinated Output for Regional Evaluations (CORE) embedded in the Coordinated Regional Climate Downscaling Experiment (CORDEX) framework (Ciarlo et al., 2020). The CORDEX dataset is provided to conduct climate change impact assessment at the regional and local scales and to understand patterns of projected future climate (Coppola et al., 2020). Three climatic parameters, namely, minimum temperature, maximum air temperature and precipitation with a spatial resolution of 0.25° by 0.25° at the ground level, were selected from the Copernicus Climate Change Service (C3S) (2017). We selected five different Earth System /Regional Climate Model (ESM/RCM) combinations at a spatial resolution of 0.22°. The five climate scenarios where MPI-ESM- LR/REMO2015, HadGEM2-ES/REMO2015, NorESM1-M/REMO2015, HadGEM2-ES/RegCM4-7, and NorESM1-M/RegCM4-7 (Thrasher et al., 2012; Teichmann et al., 2021). Each climate projection includes daily maximum temperature, minimum temperature, and precipitation from 1950 through 2100. Musie et al. (2020) and Vautard et al. (2021) provided more details about the CORDEX method used to generate the datasets.

The elevation and categorical soil type datasets were resampled to 0.25° by 0.25° resolutions using the bilinear interpolation method (Du et al., 2013) (Table 1). Social and economic factors, such as the distance between the main road, road network and distance to metro cities, can significantly affect crop profitability, influencing farmer crop choices. For instance, farmers residing far away from a good road network and markets might be less inclined to grow taro, a tuber crop that is bulky and heavy, owing to the high transportation cost. Finally, South Africa environmental data in GCS-WGS-1984 were obtained from the above global raster data overlaid by the administrative boundary maps of KwaZulu- Natal in ESRI shape format in ArcGIS. All raster files were converted into ‘asc’ format based on the requirements of the Maxent model (Phillips et al., 2006).

A multicollinearity test was undertaken using R- Package ’virtual species’ (version 4.0.4) McLeod, (2011), and Pearson correlation coefficient (r) was selected as an absolute value to filter out correlated variables. The correlation coefficient threshold of 0.7 was chosen to minimise multicollinearity and screen highly correlated environmental predictors. The test was done on both current and future databases.

Future scenario

The Representative Concentration Pathways (RCPs), published in the IPCC’s Fifth Assessment Report (AR5), represent greenhouse gas concentration trajectories that may determine possible future climates (Wei et al., 2018). Datasets of 21 models under Coupled Model Inter-Comparison Project Phase 5 (CMIP5) were generated by downscaling coarser-resolution GCMs. Martynov et al. (2013) indicated that the measure of the global mean temperature response to an increase in CO_2.

The future projections of the CORDEX datasets are available for three representative concentration pathways (RCPs2.6, 4.5 and 8.5), covering the entire range in radiative forcing (Haile et al., 2020). RCP 2.6 assumes that global annual greenhouse gas emissions will peak between 2010 and 2020 and substantially decline. This RCP projects a rise in global mean temperature of 0.4 to 1.7 °C by the end of the century, relative to 1850 (Thrasher et al., 2012; Teichmann et al., 2021). According to IPCC (2018), the RCP 4.5 is an intermediate scenario, and the emissions are projected to around 2040, then decline. The RCP 4.5 is more likely to result in a global temperature rise between 2 and 3 °C, by 2100, with a mean sea level rise 35 % higher than RCP 2.6 (Rodrigues et al., 2015). For RCP 8.5, emissions continue to rise throughout the 21st century, and the global mean temperature is projected to rise by 2.6 to 4.8 °C (Hijmans et al., 2005; Reddy et al., 2015). In this study, we averaged three RCPs to estimate the distribution and suitability of sorghum, cowpea, taro, and amaranth for two periods (2050 and 2070) across KZN.

Model setting and evaluation

The MaxEnt model partitioned the crop presence data using a random 50/50 % split for training and calibration. The following default settings were used: random test percentage = 25; regularization multiplier = 1; the maximum number of background points = 10 000 (Phillips et al., 2006). Ten replicates were simulated and used to calculate the mean relative occurrence or suitability probabilities. The MaxEnt model assumes that species are equally likely to be anywhere on the landscape by default. As such, a 10th percentile training presence logistic threshold was used. This then assumes that 10 % of occurrence records of NUS in the least suitable habitat occur in KZN agro-ecosystems. In this study, we used the area under the receiver operating characteristic (ROC) curve (AUC), a commonly used threshold independent metric, to evaluate the fit of the MaxEnt model to the true presence and absence data (Heumann et al., 2013; van Proosdij et al., 2016). If AUC $\leq$ 0.5, it indicates a random prediction, while AUC $>$ 0.5 indicate a better model prediction (Jiménez-Valverde, 2012; Senay and Worner, 2019). This study used an AUC threshold of 0.7 (or above) to identify good discriminatory power results (van Proosdij et al., 2016; Somodi et al., 2017). The relative suitability probability of $>$ 0.5 was used, which denotes a 50 % chance of NUS being present in suitable production areas of KZN.

Analysis of model outputs

The MaxEnt model outputs a map of occurrence probabilities and tables of model selection (e.g., variable contribution to the model) and the AUC for the training and validation datasets. The mean and the 95th percentile of the 1000 runs conducted for habitat suitability were mapped. Variable contributions and AUC were displayed as jack-knife plots. The contributions for each variable were determined by randomly permuting the values of a variable at each species occurrence point and measuring the resulting decrease in training (AUC). The continuous probability maps were then converted into binary maps (suitable vs unsuitable) based on the probabilities being equal and that the model was correctly classified as i) suitable and ii) unsuitable area (i. e., sensitivity = specificity). The simulated MaxEnt model outputs were then reclassified in ArcGIS using the natural breaks (Jenks) classification method. Change detection was undertaken using an overlay analysis to find spatial shifts from present to projected future suitability. Suitable crop production areas were reclassified as highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and unsuitable (N1), as described in Table 2.

Results

Current vs future crop production areas

The current and future suitability maps of sorghum predicted by the MaxEnt model are shown in Fig. 2. Under current conditions, land deemed suitable for sorghum production followed the west to east suitability trend, mainly due to rainfall distribution. From Fig. 2, areas classified as highly suitable (S1) are located in the western and central parts of the province, whilst the north-eastern was considered largely unsuitable (N1). Highly suitable and unsuitable areas occupy approximately 13.4 and 14.5 % of the province's total land area.

The cowpea distribution for present conditions had a similar trend to sorghum (Fig. 3). Areas classified under S1 and S2 were in the western part of the province, whilst the north-eastern region was largely S3 and N1. Currently, highly suitable and unsuitable areas are estimated to occupy approximately 13.1 and 17.5 % of the total land in the province, respectively. The current distribution maps for amaranth showed that the crop could be produced throughout the province. Like sorghum and cowpea, suitability followed the west to east trend, with areas in the west being more suitable than the east. The taro spread remained spatially sparse in all scenarios in the KZN province (Fig. 5). Suitable land was concentrated in the province's southwest, northwest, and central parts (Fig. 6).

Change detection under RCPs 2.6, 4.5 and 8.5

The spatial and quantitative changes in land area for each suitability category under RCPs 2.6, 4.5 and 8.5 relatives to present growing conditions for each crop are shown in Figs. 2 to 5. The results showed a significant difference between the present suitable habitats and those predicted in the 2050s across all RCPs, with substantial changes occurring under RCP 4.5 and 8.5. In particular, the area deemed moderately suitable for production continues to increase insignificantly for sorghum, cowpea and amaranth (Figs. 2–4). Simulations indicate a decrease in unsuitable areas (N1) of 35.3–39.9 %, 46.5–47.5 % and 10.6–15.4 % for sorghum, cowpea and amaranth, respectively. Contrary to this, the results showed an increase (15.6–18.0 %) in unsuitable areas for taro (Table 3). The change in highly suitable areas increased by 3.6–11.8 %, 3.5–0.8 % and 0.1–2.9 % for sorghum, cowpea and amaranth, respectively, yet decreased by 15.5–8.2 % for taro across all scenarios (Table 3).

Table 2
Suitability assessment for sorghum, cowpea, amaranth and taro cultivation in KwaZulu-Natal (FAO, 2007).

Class of Suitability	Suitability index (SI)	Description of class
Highly suitable (S1)	> 0.8	Optimal conditions for crop cultivation
Moderately suitable (S2)	0.6–0.79	Minor limitations that could reduce crop productivity
Marginally suitable (S3)	0.2–0.59	Land with major limitations that may significantly reduce crop production
Unsuitable (N1)	< 0.19	Lands with severe limitations that are not favourable for crop cultivation

Suitable land for sorghum, cowpea and amaranth production will increase in the 2070s (Fig. 7). However, in the 2070s and across all RCPs, the highly suitable growing area for taro is projected to decrease by 4.59–9.78 % in S1 (Table 4). The moderately suitable and unsuitable areas for taro are projected to increase in the 2070s by 13.68–16.69 and 38.86–40.75 %, respectively (Table 4).

MaxEnt evaluation under current and future growing conditions

The jack-knife plots from the MaxEnt model were used to determine the contribution of all 14 environmental variables (Figs. 8 and 9) to the final maps produced. The AUC varied across all crops; however, the highest contributions were obtained from climatic variables where AUC > 0.8. Different biophysical parameters influenced the suitability of each crop and geographical range. The plots revealed that the climatic variables minimum and maximum air temperature, length of growing period and seasonal precipitation made a relatively higher contribution to sorghum, cowpea and taro (Figs. 8 and 9) suitability. More specifically, rainfall-related factors had the most significant influence on the potential suitability. For edaphic factors, lower AUC values were obtained for soil depth, pH, and slope.

The receiver operating characteristic curves (ROCs) are shown in Fig. 10, together with the final AUCs of 0.93 (sorghum), 0.89 (cowpea), 0.91 (amaranth) and 0.84 (taro). These values represented the average of the replicate runs and were above 0.8, thus indicating that MaxEnt can satisfactorily estimate land suitability for NUS in KZN.

Discussion

This study was the first to explore the impacts of climate change on areas deemed potentially suitable for sorghum, cowpea, amaranth and taro production in KZN. The MaxEnt model identified the most critical biophysical predictors of suitability for each crop. Our analysis of model parameterisation showed two things: (1) that the accuracy of the suitability models increased when maximum temperature and seasonal precipitation were included in the modelling, (2) that the suitability of the studied NUS was affected more by maximum temperature and seasonal precipitation, and (3) socioeconomic factors did not increase the accuracy of the models. The observed results suggest that the reliability of models increases with the inclusion of crop growth indices as they are more related to the observed spatial and temporal distribution of the selected NUS, which provides more confidence in the application of the model for climate impact studies. The finding that precipitation-based factors are most important for the suitability of NUS is in line with other studies that identified rainfall as the critical determinant of marginal production systems (Chemura et al., 2020).

Contrary to finding on precipitation and temperature, the low relevance of socioeconomic factors included in the model could be attributed to the sampling structure used in the study. The study adopted a random sampling approach where the sighting of the investigated NUS did not follow the same trend as major roads. In light of our findings, further investigations are needed to identify the effects of socioeconomic variables and land-use changes on NUS cultivation to ensure sustainable production and mitigate future food insecurity. Transport affects farmers' crop produce; NUS must be transported from farms to the market. Usually, poor transportation in rural areas has resulted in low productivity, low income, a fall in the standard of living of smallholder farmers, and a high poverty rate in KZN. Distance to markets and reliable transport systems are essential in distributing agricultural products. It, therefore, helps to facilitate market access for NUS products and reduces

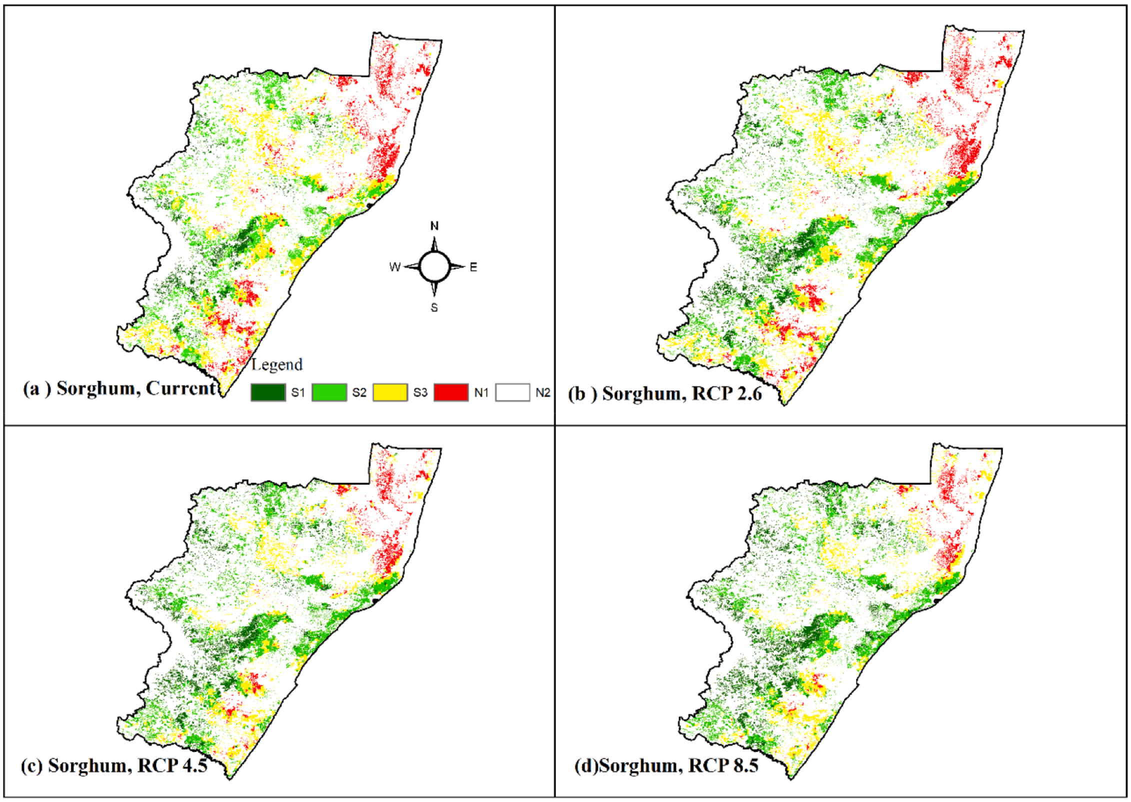

Fig. 2. Land areas deemed potentially suitable for sorghum production undercurrent (a) and three future environmental conditions for the 2050s, based on RCPs 2.6 (b), 4.5 (c) and 8.5 (d). The maps were developed from the continuous probability maps based on the threshold optimisation method (sensitivity = specificity).

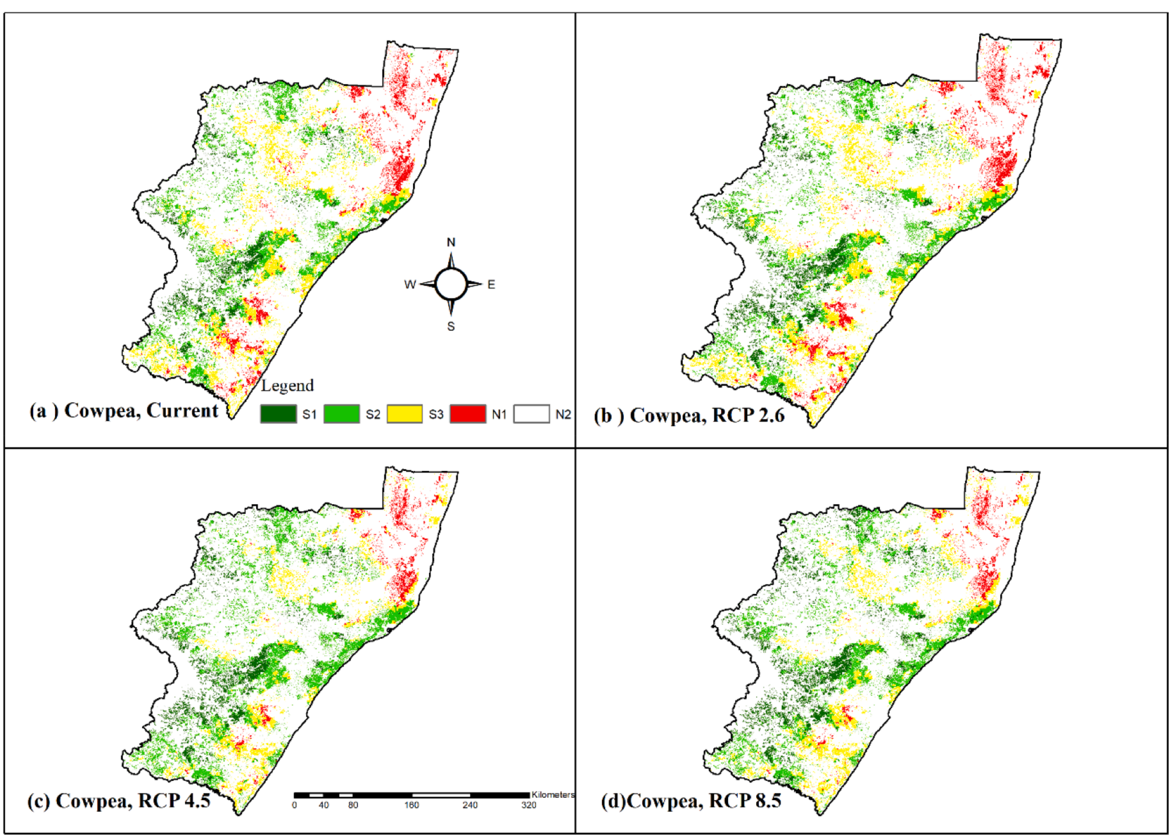

Fig. 3. The current and future suitable zones for cowpea, (a) current (b) RCP2.6, (b) RCP 4.5 and (d) RCP 8.5 in 2050s. The maps are discretised from the continuous probability maps based on the threshold optimisation method (sensitivity = specificity).

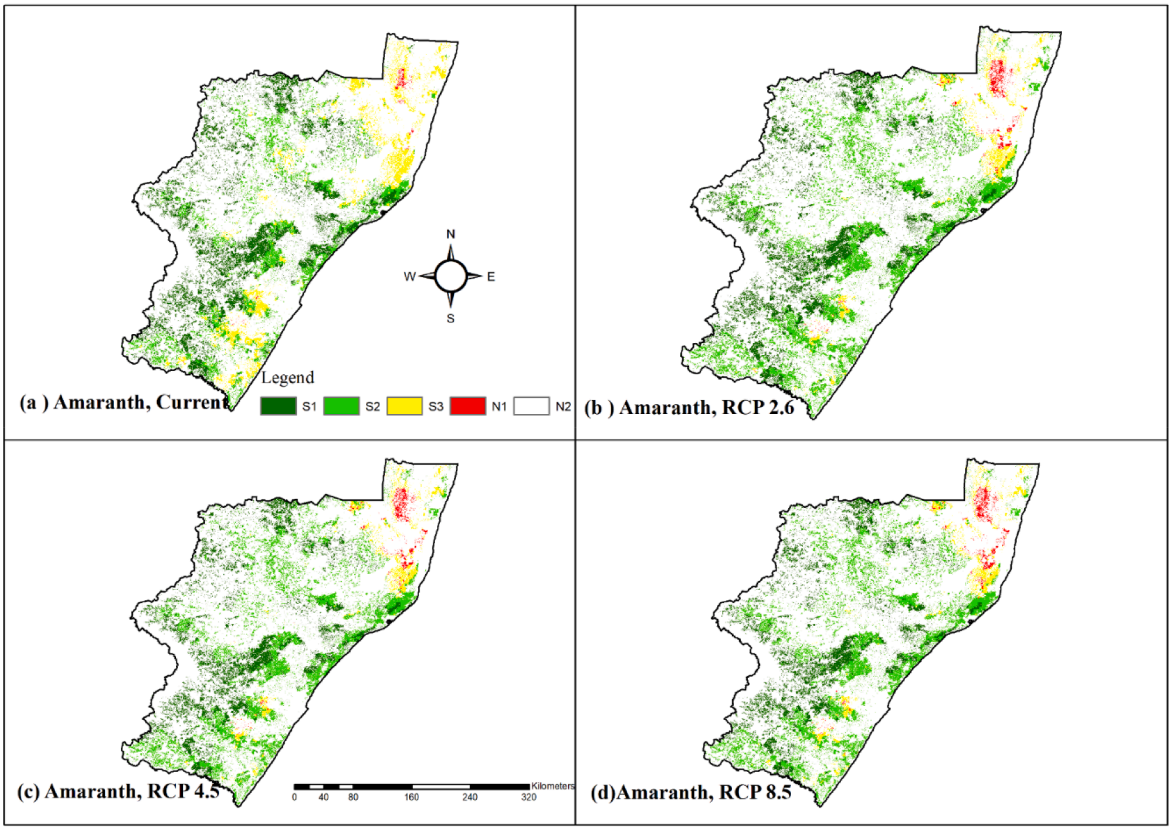

Fig. 4. The current and future suitable zones for amaranth, (a) current, (b) RCP 2.6, (c) RCP 4.5, and (d) RCP 8.5 in the 2050s. The maps are discretised from the continuous probability maps based on the threshold optimisation method (sensitivity = specificity).

spoilage of farm products.

The results indicated that suitable land for sorghum and cowpea followed the same pattern, while amaranth is highly suitable in s KwaZulu-Natal. In contrast, taro's suitability was mainly confined to higher rainfall areas in the province. The similarity in suitable land for sorghum and cowpea could be because these crops have similar water and temperature requirements and growing cycle lengths (Neely et al., 2018). Sorghum and cowpea are tropical crops requiring moderately high temperatures and water. Chimonyo et al. (2016a,b) and Neely et al. (2018) noted that sorghum and cowpea need 450–650 mm of rainfall and are often found in the same cropping system (i.e., monocrop or intercrop). The observed similarities in suitability would suggest that these crops could be recommended, in tandem, in areas earmarked for agroecological intensification. The general suitability of amaranth to present and future climatic conditions could be attributed to its short growing cycle and adaptability to broader temperature ranges. Moreover, it requires less water over the growing season (Bello and Walker, 2017). Short-duration crops have long been suggested to increase farmers' resilience to drought and its mitigation. The observed suitability of sorghum, cowpea and amaranth supports claims on the potential benefits of NUS enhancing climate resilience in marginalised land. However, to further guide sustainable climate resilience in these farming systems, climate services should integrate crop suitability assessments into short (1–5 years), medium (decadal) and long term (30 years) climate impact analysis within agricultural planning.

The study revealed that taro would be most affected by future climate as the crop is less suited to the hotter growing conditions. Nevertheless, results also showed that the tested landrace variety was suitable in dry regions receiving less than 500 mm. Then again, Mabhaudhi et al. (2014) estimated that taro requires 2500 mm of water per year, which explains why the crop is best suited to the province's wetter regions, the western region the province. The studied taro landrace is the upland type, not the swamp or wetland type. Mabhaudhi et al. (2014) indicated that the upland taro landrace grown in the greater KZN region possesses drought avoidance mechanisms. During the dry spell, upland taro regulates water loss through stomatal closure and adjustments in canopy size (Mabhaudhi et al., 2014). Results suggest taro may be out of place for drought adaptation because of its high-water demand, and SA is becoming more water-stressed. Then again, climate projections indicate an increase in floods within the region. In this regard, taro can be grown to mitigate flood losses in other cropping systems. In S1 to S3, it would be necessary to continue supporting and improving climate-smart crop production techniques. However, marginalised smallholder farmers have experienced several challenges when adopting NUS in their farming practices. There is a generation gap among them regarding recipes prepared; to a certain extent, the current generation does not accept NUS. There is a need for concretising end-users about the importance of NUS. In several parts of South Africa, markets of NUS are not well organised (Massawe et al., 2016). Therefore, our results indicate areas where the investigated crops can be introduced as an adaptative management strategy.

There is an increase in suitability for all crops in the Drakensberg area (central region along the western border of KZN). The Drakensberg is a mountain range that experiences relatively high summer rainfall (>700 mm) and has fertile soil foothills (Vinet and Zhedanov, 2011). Lawrence et al. (2012) indicated that for RCP 8.5, the CORDEX projects an increase in minimum and maximum temperature within the central region of South Africa. Based on these projections, the Drakensberg area will become more suitable for producing crops such as sorghum and amaranth (Nyathi et al., 2018). The added suitability for sorghum and amaranth production in this area will increase farmer crop choices. However, this suggests that crops currently occupying these areas will become less suitable. Shifts in crop suitability would indicate a need to re-evaluate the distribution, diversity and suitability of existing crops

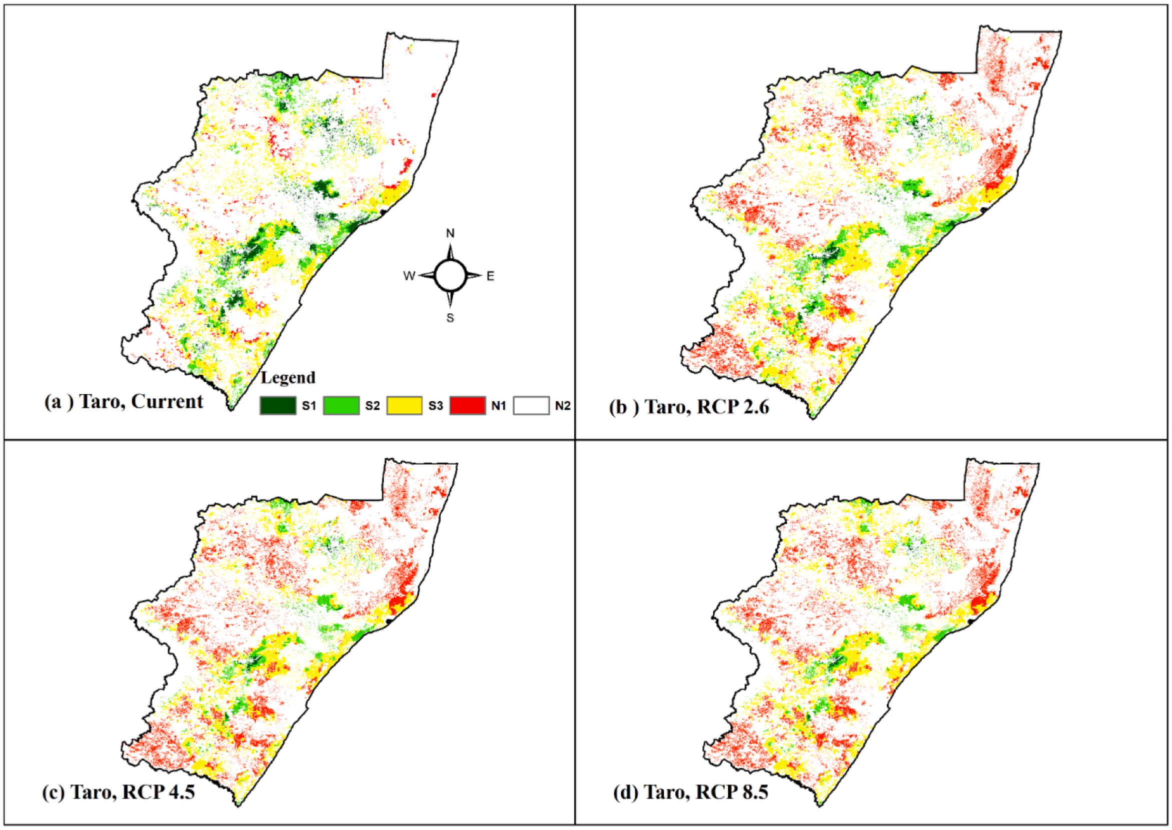

Fig. 5. The current and future suitable zones for taro, (a) current, (b) RCP 2.6, (c) RCP 4.5, and (d) RCP 8.5 in the 2050s. The maps are discretised from the continuous probability maps based on the threshold optimisation method (sensitivity = specificity).

within areas where the current suitability of crops is projected to increase at different Representative Concentration Pathways (RCPs).

Representative Concentration Pathways represent different emissions, concentrations and radiative forcing projections leading to a large range of global warming levels, from continued warming rising above 4 °C by the year 2100 to limiting warming well below 2 °C as called for in the Paris Agreement (IPCC, 2018). In this study, we used three RCPs, very high (RCP8.5), medium (RCP 4.5) and very low (RCP2.6) future concentrations and tried to explore crop suitability options at the different magnitude of pathways. The three scenarios were selected based on the expected differences in radiation forcing for the future climate (Teichmann et al., 2021; Vautard et al., 2021). In addition, the use of GCMs for future climate projections is subject to some uncertainties arising from distinct sources such as different emission/concentration scenarios, parameterization and structure of the GCMs, and boundary and initial conditions. Climate sensitivity is an important source of model uncertainty over large parts of the globe, not just near-surface temperature (Martynov et al., 2013; Teichmann et al., 2021). In GCMs, it is often measured in terms of the equilibrium (or "effective") climate sensitivity (ECS), the global mean near-surface air temperature response to a doubling of CO_2 after equilibrium is reached, or as a GCM's transient climate response (TCR), the change in global mean temperature at the time CO_2 reaches double its initial concentration while increasing at 1 % per year (Zhao et al., 2005; Kattsov et al., 2013). Furthermore, climate models often cannot represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided, which gives a false impression of confidence to users of climate change information (Teichmann et al., 2021). Nissan et al. (2019) suggest focusing on decision-relevant timescales, an increased role for model evaluation and expert judgment, and integrating climate variability into climate change services.

Study limitations

Like most modelling studies on the effects of climate change on crop production, this study also has some limitations. The analysis assumes no improvements in drought and heat tolerance of crops through plant breeding efforts, which would affect their future distribution. Secondly, during data collection, we have not considered the influence of farming systems such as irrigation or dryland farming in KZN because the visual selection of occurrence location points may cause substantial bias in sample selection (Araújo and Peterson, 2012; Merow et al., 2013). A systematic random sampling technique is recommended to capture the dynamics of farming systems in KZN. In addition, this study assumed that future land use and farming systems remain constant, which is an unlikely situation. The approach taken in this study assumes all four crops can grow anywhere, regardless of current land use. Therefore, changes in land use should be considered in future research to improve the results further. In addition, more ground truthing is required to verify the area under NUS in KZN. Despite these limitations, the current study results still hold value and significance in informing planning. It is important to note that the maps need to be ground-truthed after assessing the sensitivity of the predicted crop suitability to uncertainty and spread of the input climate data in KZN. The spatially averaged outputs might not capture seasonal variability such as rainfall intensity, frequency, length of dry and wet spells (Dosio et al., 2019). One of the goals for future work is to investigate and compare the physical mechanisms underlying rainfall variability and changes in rainfall character in observations and the models.

There has been little work on crop suitability in Africa using regional climate models (RCMs); however, the CORDEX project provides an effective source of regional climate model data for crop suitability (Teichmann et al., 2021). Rather than convection parameterizations, global model uncertainty still makes up the largest part of the

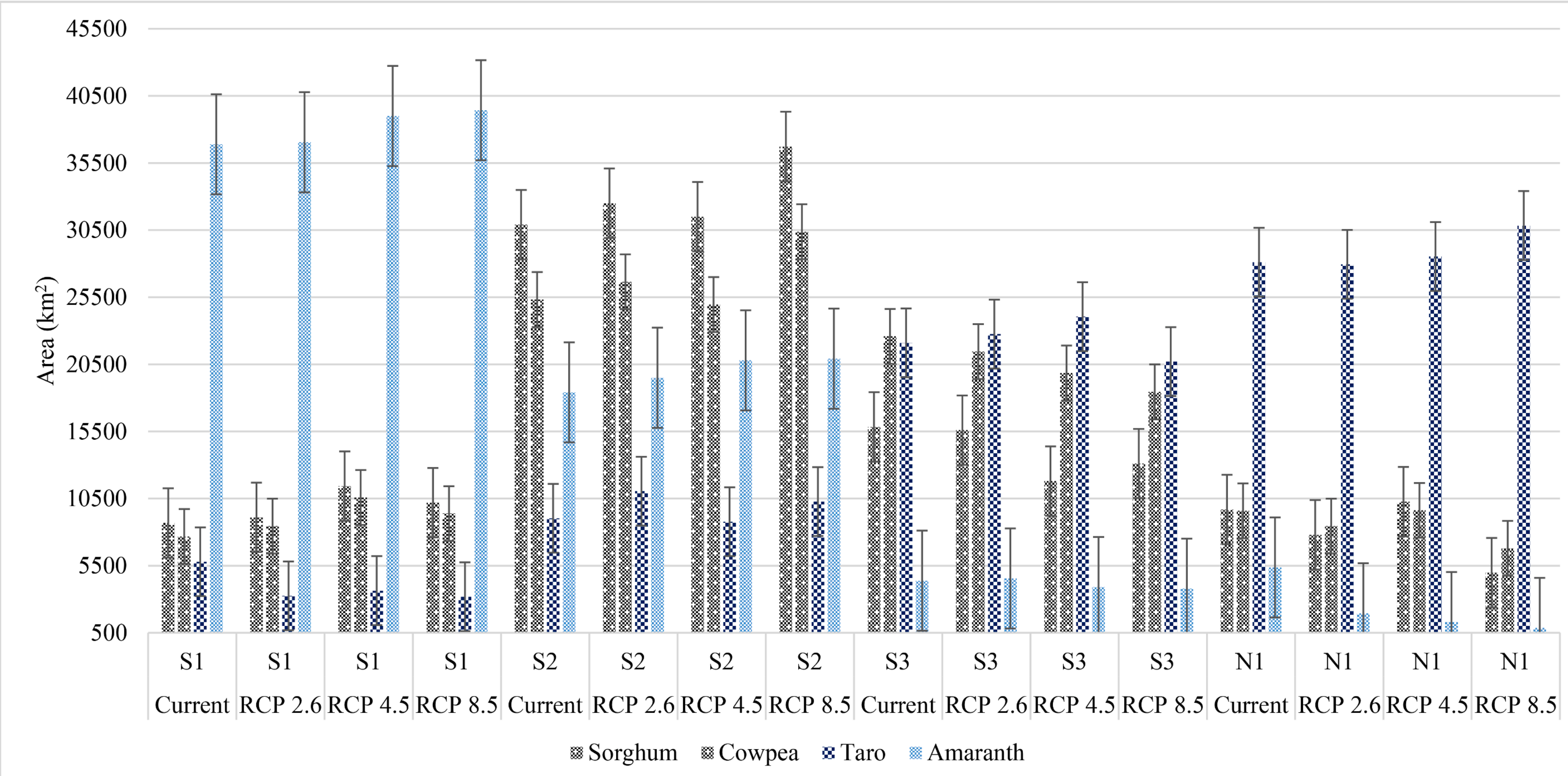

Fig. 6. Changes in land suitability for sorghum, cowpea, taro and amaranth production under RCPs 2.6, 4.5 and 8.5 in the 2050s, relative to present conditions.

Table 3
Changes in land suitability for sorghum, cowpea, amaranth and taro production under RCPs 2.6, 4.5 and 8.5 in the 2050s, relative to present conditions.

Scenario	Suitability Index	Sorghum	Change of area as a %	Cowpea	Change of area as a %	Taro	Change of area as a %	Amaranth	Change of area as a %
Current	**S1**	**8579**		**7678**		**5789**		**36,890**	
RCP 2.6	S1	8884	3.6	7945	3.5	4892	−15.5	36,902	0.0
RCP 4.5	S1	9594	11.8	8505	10.8	4326	−25.3	37,560	1.8
RCP 8.5	S1	9320	8.6	8469	10.3	3580	−38.2	37,946	2.9
Current	**S2**	**27,902**		**28,250**		**9007**		**18,402**	
RCP 2.6	S2	28,905	3.5	28,882	2.2	8568	−4.9	19,800	7.6
RCP 4.5	S2	29,002	3.8	29,931	6.0	8542	−5.2	20,098	9.2
RCP 8.5	S2	30,987	10.7	30,508	8.0	8023	−10.9	20,059	9.0
Current	**S3**	**19,003**		**19,502**		**22,101**		**4338**	
RCP 2.6	S3	18,201	−4.2	19,045	−2.3	23,209	5.0	4206	−3.0
RCP 4.5	S3	17,203	−9.5	17,525	−10.1	23,800	7.7	3841	−11.5
RCP 8.5	S3	14,992	−21.1	17,064	−12.5	24,499	10.9	3699	−14.7
Current	**N1**	**9516**		**9570**		**28,103**		**5370**	
RCP 2.6	N1	9010	−39.9	9128	−46.5	28,331	15.6	4092	10.6
RCP 4.5	N1	9201	−38.6	9039	−47.0	28,332	15.6	3501	−5.4
RCP 8.5	N1	9701	−35.3	8959	−47.5	28,898	18.0	3296	−10.9

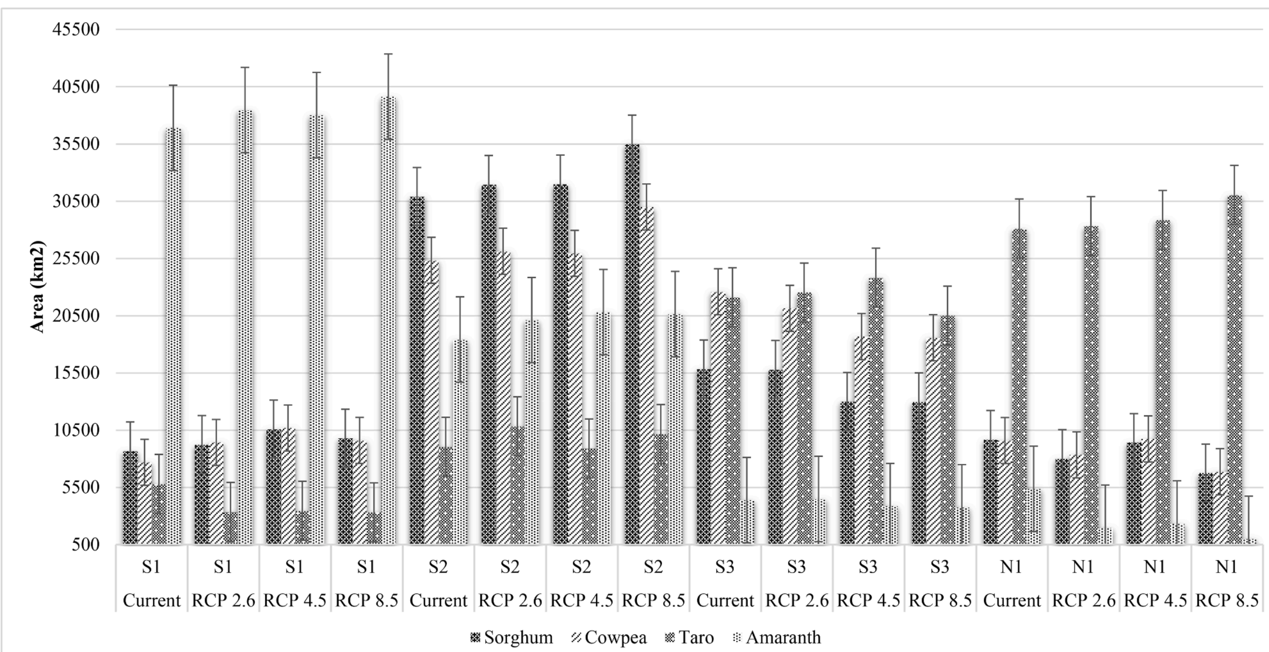

Fig. 7. Changes in land suitability for sorghum, cowpea, taro and amaranth production suitability under RCPs 2.6, 4.5 and 8.5 in the 2070s.

uncertainty in future climate. Using RCMs helps to explore key sources of uncertainty further because they may respond differently to climate forcings than their driving GCM, particularly for precipitation (Chapman et al., 2020; Gao et al., 2021). This work did not evaluate uncertainty from global climate, and there is a need for improved information on sensitivities of RCMs on NUS suitability to give better predictions and make better use of the new generation of explicit-convection models. Explicit convection might have more impact if suitability included a more comprehensive treatment of extremes (Vautard et al., 2021).

The study used a range of RCMs from the CORDEX archive, each driven by a different GCM, to map areas suitable for NUS. It is important to note that the maps are not decision-ready until a host of issues around uncertainty in the results are clarified, such as assessing the sensitivity of the predicted crop suitability to uncertainty and the spread of the input climate data. While the results of our study suggest a good agreement between simulated occurrences and observed occurrences of the crop species, the classification algorithm and the RCMs conditioned by GCM projections introduce some uncertainty to the outputs. Such uncertainty has implications for how the results can be used. In our case, the results are exploratory and can be used for further research on developing NUS production guidelines and breeding varieties suitable for projected environments. The CORDEX datasets are a promising input for crop suitability and climate change impact studies in developing countries such as South Africa, where the required bias correction data are scarce (Teichmann et al., 2021). The model may not identify a novel agro-climatic zone emerging under future conditions. It could be worthwhile to use an ensemble of GCMs to understand the size of the uncertainty (Chapman et al., 2020; Teichmann et al., 2021; Vautard et al., 2021). The uncertainties associated with the modelling process, from

Table 4
Changes in land suitability for sorghum, cowpea, amaranth and taro suitability under RCPs 2.6, 4.5 and 8.5 in the 2070s, relative to present conditions.

Scenario	Suitability Index	Sorghum Area km^2	Change of area as a %	Cowpea Area km^2	Change of area as a %	Taro Area km^2	% Change for taro	Amaranth Area km^2	Change of area as a %
Current	**S1**	**8579**		**7678**		**5789**		**36,890**	
RCP 2.6	S1	8615	0.42	7952	3.57	5396	−6.79	37,942	2.85
RCP 4.5	S1	8617	0.44	8081	5.25	5523	−4.59	37,890	2.71
RCP 8.5	S1	8622	0.50	8158	6.25	5223	−9.78	37,841	2.58
Current	**S2**	**27,902**		**28,250**		**9007**		**18,402**	
RCP 2.6	S2	28,206	1.08	28,395	0.51	7775	−13.68	19,833	7.78
RCP 4.5	S2	28,391	1.73	28,567	1.12	7628	−15.31	19,800	7.60
RCP 8.5	S2	28,439	1.90	28,745	1.75	7504	−16.69	20,044	8.92
Current	**S3**	**19,003**		**19,502**		**22,101**		**4338**	
RCP 2.6	S3	18,700	−1.59	18,922	−2.97	21,028	−4.86	4033	−7.03
RCP 4.5	S3	18,416	−3.09	18,450	−5.39	21,049	−4.76	3901	−10.07
RCP 8.5	S3	18,177	−4.35	18,167	−6.85	21,884	−0.98	3809	−12.19
Current	**N1**	**9516**		**9570**		**28,103**		**5370**	
RCP 2.6	N1	9479	−47.85	9730	−46.44	30,801	40.75	3192	−16.20
RCP 4.5	N1	9576	−47.32	9902	−45.49	30,800	40.74	3409	−10.50
RCP 8.5	N1	9762	−46.29	9930	−45.34	30,389	38.86	3306	−13.21

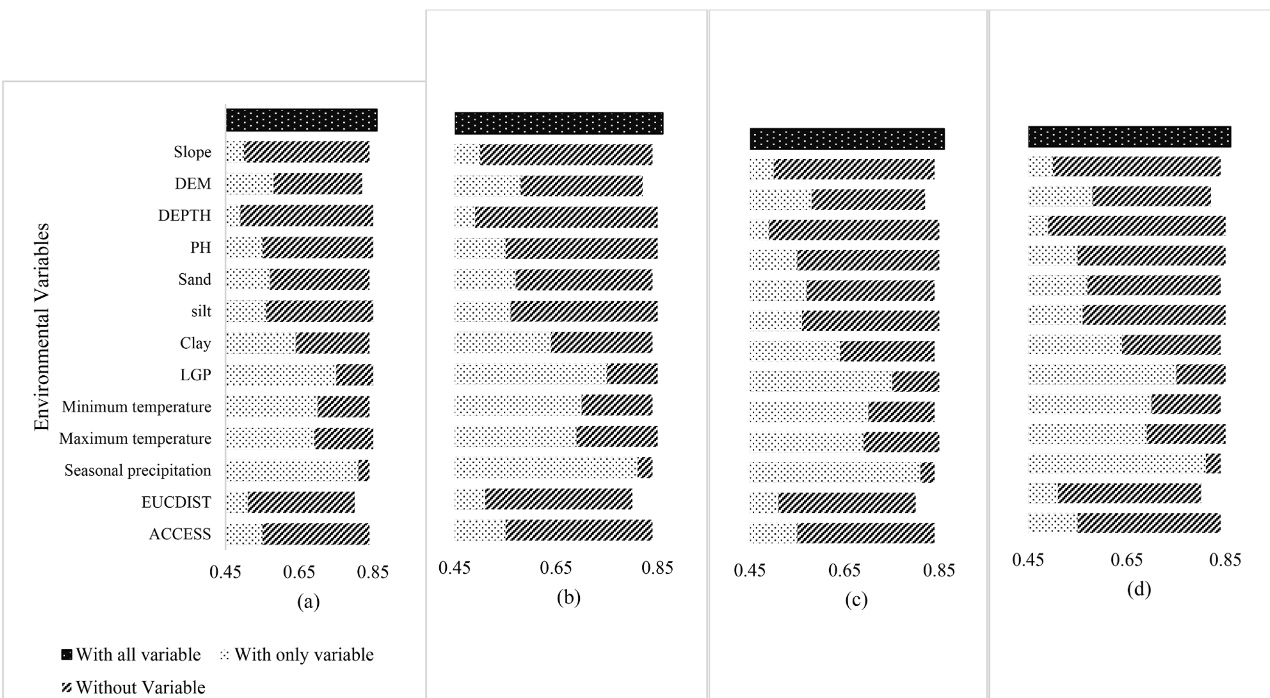

Fig. 8. Jack-knife plots evaluating the relative importance in MaxEnt of environmental variables for (a) sorghum, (b) cowpea, (c) taro and (d) amaranth under present growing conditions. The stripped black bars (without variable) show the performance lost when the variable is removed. In contrast, the dotted black bars (with only one variable) indicate the performance when using a variable in isolation. The boxed dark black bar (with all variables) indicates the model performance when using all variables.

the driving climate to impacts, need to be quantified because RCMs are not equal when it comes to their performance in a localised study area. In future, analysis and intercomparison of the individual RCMs and their ensemble will help us to better understand how the RCMs perform in areas with complex topography, such as Drakensburg in KwaZulu-Natal. Hence, to select the appropriate RCMs for a specific location, evaluating the performance of multiple available RCMs is necessary.

Conclusion

This study is the first step toward a better understanding of present and future suitability for NUS production. The study used a range of RCMs from the CORDEX archive, each driven by a different GCM, to map areas suitable for NUS. The results showed that MaxEnt could predict NUS' present and future suitability across a heterogeneous province like KZN. These results suggest that the same analytic framework could be adopted across South Africa and the region. The analysis predicted that the potential distribution of the selected NUS' current and future

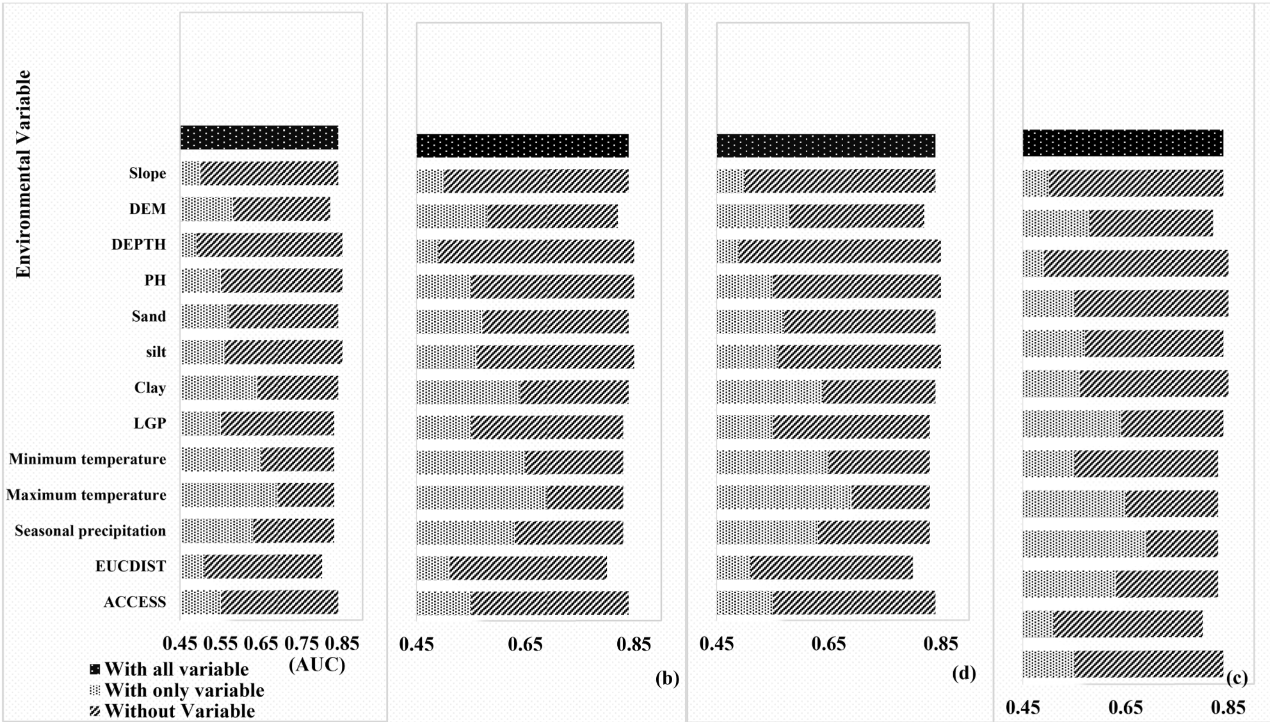

Fig. 9. Jack-knife plots evaluating the relative importance in MaxEnt of environmental variables for (a) sorghum, (b) cowpea, (c) taro and (d) amaranth under future (the 2050s) growing conditions.

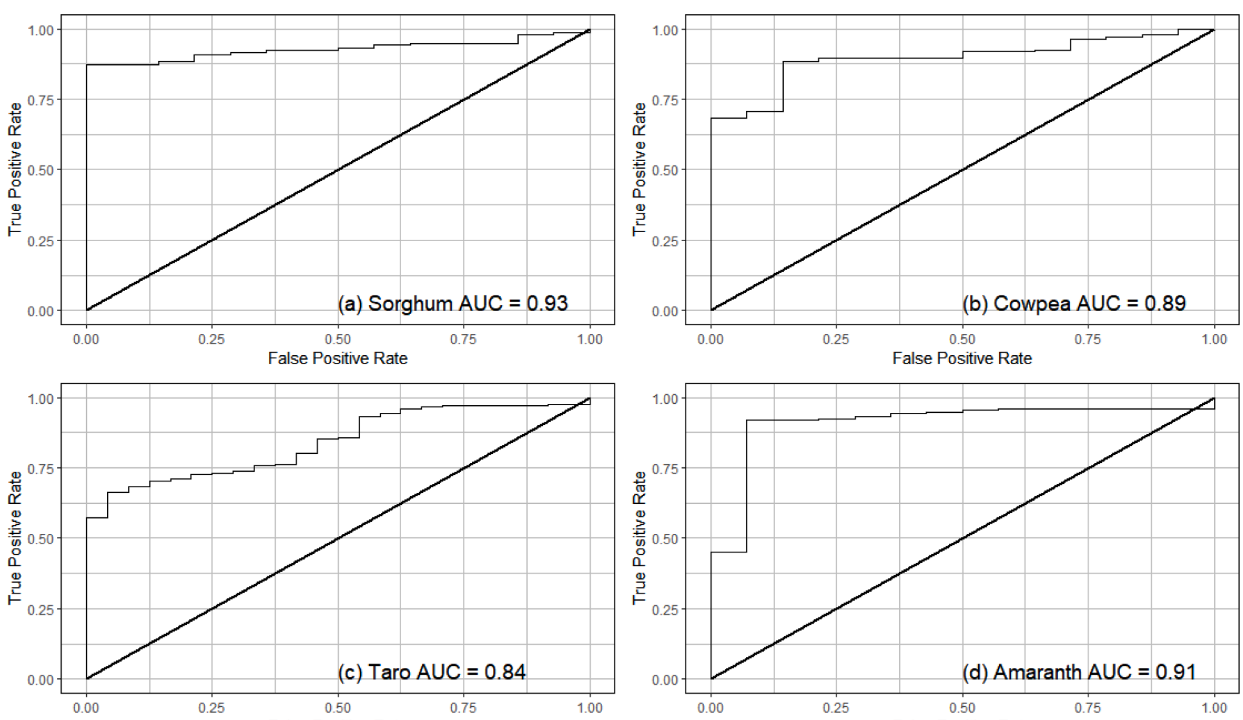

Fig. 10. The receiver operating characteristic (ROC) curve for (a) sorghum, (b) cowpea, (c) taro and (d) amaranth for present period.

growing areas was based more on environmental than socioeconomic factors. Climatic variables related to rainfall (length of growing and seasonal rainfall) and minimum and maximum air temperature significantly contributed to the model performance and crop suitability. The study provides insight into the zoning of areas suitable for producing NUS. However, there is a need to address issues of data uncertainty and model sensitivity. As such, the developed maps show one scenario of possible changes in the future suitability of NUS within the KZN province. The study should be used as a proof of concept to demonstrate an approach to delineate sustainable crop production areas under climate change.

CRediT authorship contribution statement

H. Mugiyo: Conceptualization, Methodology, Validation, Investigation, Formal analysis, Data curation, Writing – original draft, Visualization. **V.G.P. Chimonyo:** Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **R. Kunz:** Methodology, Validation, Formal analysis, Investigation, Supervision. **M. Sibanda:** Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft. **L. Nhamo:** Methodology, Formal analysis, Investigation, Writing – review & editing. **C. Ramakgahlele Masemola:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **A.T. Modi:** Writing – review & editing. **T. Mabhaudhi:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. All authors have read and agreed to the published version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2022.100330.

References

Akinola, R., Pereira, L.M., Mabhaudhi, T., de Bruin, F.M., Rusch, L., 2020. A review of indigenous food crops in Africa and the implications for more sustainable and healthy food systems. Sustain. 12 (8), 1–30. https://doi.org/10.3390/SU12083493.

Akpoti, K., Kabo-bah, A.T., Dossou-Yovo, E.R., Groen, T.A., Zwart, S.J., 2020. Mapping suitability for rice production in inland valley landscapes in Benin and Togo using environmental niche modeling. Sci. Total Environ. 709, 136165 https://doi.org/10.1016/j.scitotenv.2019.136165.

Andersson-Sköld, Y., Thorsson, S., Rayner, D., Lindberg, F., Janhäll, S., et al., 2015. An integrated method for assessing climate-related risks and adaptation alternatives in urban areas. Clim. Risk Manag. 7, 31–50. https://doi.org/10.1016/j.crm.2015.01.003.

Araújo, M.B., Peterson, A.T., 2012. Uses and misuses of bioblamtic envelope modeling. Ecology 93 (7), 1527–1539. https://doi.org/10.2307/23225219.

Austin, M., 2007. Species distribution models and ecological theory: A critical assessment and some possible new approaches. Ecol. Modell. 200 (1–2), 1–19. https://doi.org/10.1016/j.ecolmodel.2006.07.005.

Bello, Z.A., Walker, S., 2017. Evaluating AquaCrop model for simulating production of amaranthus (Amaranthus cruentus) a leafy vegetable, under irrigation and rainfed conditions. Agric. For. Meteorol. 247 (February), 300–310. https://doi.org/10.1016/j.agrformet.2017.08.003.

Bunn, C., Läderach, P., Quaye, A., Muilerman, S., Noponen, M.R.A., et al., 2019. Recommendation domains to scale out climate change adaptation in cocoa production in Ghana. Clim. Serv. 16 (January) https://doi.org/10.1016/j.cliser.2019.100123.

Chapman, S., Birch, C.E., Pope, E., Sallu, S., Bradshaw, C., et al., 2020. Impact of climate change on crop suitability in sub-Saharan Africa in parameterized and convection-permitting regional climate models. Environ. Res. Lett. 15 (9) https://doi.org/10.1088/1748-9326/ab9daf.

Chemura, A., Schauberger, B., Gornott, C., 2020. Impacts of climate change on agro-climatic suitability of major food crops in Ghana. PLoS One 15 (6). https://doi.org/10.1371/journal.pone.0229881.

Chersich, M.F., Wright, C.Y., 2019. Climate change adaptation in South Africa: a case study on the role of the health sector. Glob. Health 15 (1). https://doi.org/10.1186/s12992-019-0466-x.

Chibarabada, T.P., Modi, A.T., Mabhaudhi, T., 2020. Calibration and evaluation of aquacrop for groundnut (Arachis hypogaea) under water deficit conditions. Agric. For. Meteorol. 281 (November 2019), 107850 https://doi.org/10.1016/j.agrformet.2019.107850.

Chimonyo, V.G.P., Modi, A.T., Mabhaudhi, T., 2016a. Assessment of sorghum–cowpea intercrop system under water-limited conditions using a decision support tool. Water SA 42 (2), 316–327. https://doi.org/10.4314/wsa.v42i2.15.

Chimonyo, V.G.P., Modi, A.T., Mabhaudhi, T., 2016b. Simulating yield and water use of a sorghum–cowpea intercrop using APSIM. Agric. Water Manag. 177, 317–328. https://doi.org/10.1016/j.agwat.2016.08.021.

Chivenge, P., Mabhaudhi, T., Modi, A.T., Mafongoya, P., 2015. The potential role of neglected and underutilised crop species as future crops under water scarce conditions in Sub-Saharan Africa. Int. J. Environ. Res. Public Health 12 (6), 5685–5711. https://doi.org/10.3390/ijerph120605685.

Ciarlo, J.M., E. Coppola, A. Fantini, F. Giorgi, and X. Gao. 2020. A new spatially distributed Added Value Index for Regional Climate Models : the EURO-CORDEX and the CORDEX-CORE highest resolution ensembles.

Coppola, E., A. Fantini, F. Giorgi, X. Gao, Y. Tong, et al. 2020. A new spatially distributed Added Value Index for Regional Climate Models : An example of an added value. (May): 4–8.

Dai, A., 2011. Drought under global warming: A review. Wiley Interdiscip. Rev. Clim. Chang. 2 (1), 45–65. https://doi.org/10.1002/wcc.81.

Dosio, A., Jones, R.G., Jack, C., Lennard, C., Nikulin, G., et al., 2019. What can we know about future precipitation in Africa? Robustness, significance and added value of projections from a large ensemble of regional climate models. Clim. Dyn. 53 (9–10), 5833–5858. https://doi.org/10.1007/s00382-019-04900-3.

Du, L., Tian, Q., Yu, T., Meng, Q., Jancso, T., et al., 2013. A comprehensive drought monitoring method integrating MODIS and TRMM data. Int. J. Appl. Earth Obs. Geoinf. 23 (1), 245–253. https://doi.org/10.1016/j.jag.2012.09.010.

FAO, 2007. The FAO Guidelines for Land Evaluation. L. Use, L. Cover Soil Sci. II, 1–9. In this issue. https://www.eolss.net/Sample-Chapters/C12/E1-05-02-03.pdf.

Gao, Y., Zhang, A., Yue, Y., Wang, J., Su, P., 2021. Predicting shifts in land suitability for maize cultivation worldwide due to climate change: A modeling approach. Land 10 (3), 1–31. https://doi.org/10.3390/land10030295.

Ghile, Y.B., Schulze, R.E., 2008. Development of a framework for an integrated time-varying agrohydrological forecast system for Southern Africa: Initial results for seasonal forecasts. Water SA 34 (3), 315–322. https://doi.org/10.4314/wsa.v34i3.180624.

Gopichandran, R., Asolekar S.R., Jani O., Kumar D., Hiremath A.M. 2016. Green energy and climate change. An integrated approach to environmental management. p. 127–150.

Hadebe, S.T., Modi, A.T., Mabhaudhi, T., 2017. Drought tolerance and water use of cereal crops: A focus on sorghum as a food security crop in Sub-Saharan Africa. J. Agron. Crop Sci. 203 (3), 177–191. https://doi.org/10.1111/jac.12191.

Haile, G.G., Tang, Q., Hosseini-Moghari, S.M., Liu, X., Gebremicael, T.G., et al., 2020. Projected impacts of climate change on drought patterns over East Africa. Earth's Futur. 8 (7) https://doi.org/10.1029/2020EF001502.

Heumann, B.W., Walsh, S.J., Verdery, A.M., McDaniel, P.M., Rindfuss, R.R., 2013. Land Suitability Modeling Using a Geographic Socio-Environmental Niche-Based Approach: A Case Study from Northeastern Thailand. Ann. Assoc. Am. Geogr. 103 (4), 764–784. https://doi.org/10.1080/00045608.2012.702479.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated global terrestrial climate surfaces. Int J Clim. 25 https://doi.org/10.1002/joc.1276.

IPCC, (Intergovernmental Panel on Climate Change). 2018. Summary for Policymakers approved: IPCC Special Report on Global Warming of 1.5°C.

Jiménez-Valverde, A., 2012. Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species distribution modelling. Glob. Ecol. Biogeogr. https://doi.org/10.1111/j.1466-8238.2011.00683.x.

Kattsov, V., R. Federation, C. Reason, S. Africa, A.A. Uk, et al. 2013. Evaluation of climate models. Clim. Chang. 2013 Phys. Sci. Basis Work. Gr. I Contrib. to Fifth Assess. Rep. Intergov. Panel Clim. Chang. 9781107057: 741–866. 10.1017/CBO9781107415324.020.

Kogo, B.K., Kumar, L., Koech, R., Kariyawasam, C.S., 2019. Modelling climate suitability for rainfed maize cultivation in Kenya using a maximum entropy (MAXENT) approach. Agronomy 9 (11). https://doi.org/10.3390/agronomy9110727.

Kramer-Schadt, S., Niedballa, J., Pilgrim, J.D., Schröder, B., Lindenborn, J., et al., 2013. The importance of correcting for sampling bias in MaxEnt species distribution models. Divers. Distrib. 19 (11), 1366–1379. https://doi.org/10.1111/ddi.12096.

Kruger, A.C., Nxumalo, M.P., 2017. Historical rainfall trends in South Africa: 1921–2015. Water SA 43 (2), 285–297. https://doi.org/10.4314/wsa.v43i2.12.

Lawrence, D.M., Oleson, K.W., Flanner, M.G., Fletcher, C.G., Lawrence, P.J., et al., 2012. The CCSM4 land simulation, 1850–2005: Assessment of surface climate and new capabilities. J. Clim. 25 (7), 2240–2260. https://doi.org/10.1175/JCLI-D-11-00103.1.

Lobell, D.B., Burke M.B., Tebaldi C., Mastrandrea M.D., Falcon W.P., et al. 2008. Prioritizing climate change adaptation needs for food security in 2030. Science (80-.). 319(5863): 607–610. 10.1126/science.1152339.

Mabhaudhi, T., Modi, A.T., Beletse, Y.G., 2014. Parameterisation and evaluation of the FAO-AquaCrop model for a South African taro (Colocasia esculenta L. Schott) landrace. Agric. For. Meteorol. 192–193, 132–139. https://doi.org/10.1016/j.agrformet.2014.03.013.

Mabhaudhi, T., Chimonyo, V.G.P., Chibarabada, T.P., Modi, A.T., 2017a. Developing a roadmap for improving neglected and underutilized crops: A case study of South Africa. Front. Plant Sci. 8, 2143. https://doi.org/10.3389/fpls.2017.02143.

Mabhaudhi, T., Chimonyo, V.G.P., Modi, A.T., 2017b. Status of underutilised crops in South Africa: Opportunities for developing research capacity. Sustainability 9 (9), 1569. https://doi.org/10.3390/su9091569.

Mabhaudhi, T., Chimonyo, V.G.P., Hlahla, S., Massawe, F., Mayes, S., et al., 2019. Prospects of orphan crops in climate change. Planta 250 (3), 695–708. https://doi.org/10.1007/s00425-019-03129-y.

Macauley, H. 2015. Cereal crops: rice, maize, millet, sorghum, wheat. Feed. Africa An action plan African Agric. Transform.

Martynov, A., Laprise, R., Sushama, L., Winger, K., Šeparović, L., et al., 2013. Reanalysis-driven climate simulation over CORDEX North America domain using the Canadian Regional Climate Model, version 5: Model performance evaluation. Clim. Dyn. 41 (11–12), 2973–3005. https://doi.org/10.1007/s00382-013-1778-9.

Massawe, F., Mayes, S., Cheng, A., 2016. Crop Diversity: An Unexploited Treasure Trove for Food Security. Trends Plant Sci. 21 (5), 365–368. https://doi.org/10.1016/j.tplants.2016.02.006.

McLeod, A.A.I. 2011. Package 'Kendall .' R Packag.

Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. Ecography (Cop.) 36 (10), 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x.

Musie, M., Sen, S., Srivastava, P., 2020. Application of CORDEX-AFRICA and NEX-GDDP datasets for hydrologic projections under climate change in Lake Ziway sub-basin, Ethiopia. J. Hydrol. Reg. Stud. 31 (August) https://doi.org/10.1016/j.ejrh.2020.100721.

Neely, C.B., Rouquette, F.M., Morgan, C.L., Smith, G.R., Hons, F.M., et al., 2018. Integrating legumes as cover crops and intercrops into grain sorghum production systems. Agron. J. 110 (4), 1363–1378. https://doi.org/10.2134/agronj2017.05.0293.

Nissan, H., Goddard, L., de Perez, E.C., Furlow, J., Baethgen, W., et al., 2019. On the use and misuse of climate change projections in international development. Wiley Interdiscip. Rev. Clim. Chang. 10 (3), 1–16. https://doi.org/10.1002/wcc.579.

NPC, 2013. Regional Agricultural Policy: Country Sammary Agricultural Policy Review Reports. http://www.sadc.int/files/7113/5293/3509/Regional_Agricultural_Policy_Review_Reports_2011.pdf.

Nyathi, M.K., van Halsema, G.E., Annandale, J.G., Struik, P.C., 2018. Calibration and validation of the AquaCrop model for repeatedly harvested leafy vegetables grown under different irrigation regimes. Agric. Water Manage. 208, 107–119. https://doi.org/10.1016/j.agwat.2018.06.012.

Olayinka Atoyebi, J., Osilesi, O., Adebawo, O., Abberton, M., 2017. Evaluation of nutrient parameters of selected African accessions of bambara groundnut (*Vigna subterranea* (L.) Verdc.). Am. J. Food Nutr. 5 (3), 83–89. https://doi.org/10.12691/ajfn-5-3-1.

Pecchi, M., Marchi, M., Burton, V., Giannetti, F., Moriondo, M., et al., 2019. Species distribution modelling to support forest management. A literature review. Ecol. Modell. 411 (September), 108817 https://doi.org/10.1016/j.ecolmodel.2019.108817.

Phillips, S.J., Anderson R.P., Schapire R.E. 2006. Maximum entropy modeling of species geographic distributions. 190: 231–259. 10.1016/j.ecolmodel.2005.03.026.

Reddy, M., Begum H., Sunil N., Rao Pandravada S., Sivaraj N. 2015. Assessing climate suitability for sustainable vegetable roselle (Hibiscus sabdariffa var. sabdariffa L.) cultivation in India using MaxEnt model.

Rodrigues, M.A., Martins, N.E., Balancé, L.F., Broom, L.N., Dias, A.J.S., et al., 2015. Drosophila melanogaster larvae make nutritional choices that minimize developmental time. J. Insect Physiol. 81, 69–80. https://doi.org/10.1016/j.jinsphys.2015.07.002.

Schulze, R.E. 2008. South African Atlas of Climatology and Agrohydrology [electronic resource]. Water Res. Comm. Pretoria, RSA. WRC Rep.: 276.

Senay, S.D., Worner, S.P., 2019. Multi-scenario species distribution modeling. Insects 10 (3), 65. https://doi.org/10.3390/insects10030065.

Shabani, F., Kotey, B., 2016. Future distribution of cotton and wheat in Australia under potential climate change. J. Agric. Sci. 154 (2), 175–185. https://doi.org/10.1017/S0021859615000398.

Somodi, I., Lepesi, N., Botta-Dukát, Z., 2017. Prevalence dependence in model goodness measures with special emphasis on true skill statistics. Ecol. Evol. 7 (3), 863–872. https://doi.org/10.1002/ece3.2654.

Su, P., Zhang, A., Wang, R., Wang, J., Gao, Y., et al., 2021. Prediction of future natural suitable areas for rice under representative concentration pathways (Rcps). Sustainability 13 (3), 1–20. https://doi.org/10.3390/su13031580.

Taylor, J.R.N. 2003. Overview: Importance of Sorghum in Africa. Afripro, Workshop on the Proteins of Sorghum and Millets: Enhancing Nutritional and Functional Properties for Africa. p. 1–21.

Teichmann, C., Jacob, D., Remedio, A.R., Remke, T., Buntemeyer, L., et al., 2021. Assessing mean climate change signals in the global CORDEX-CORE ensemble. Clim. Dyn. 57 (5–6), 1269–1292. https://doi.org/10.1007/s00382-020-05494-x.

Thrasher, B., Maurer, E.P., McKellar, C., Duffy, P.B., 2012. Technical Note: Bias correcting climate model simulated daily temperature extremes with quantile mapping. Hydrol. Earth Syst. Sci. 16 (9), 3309–3314. https://doi.org/10.5194/hess-16-3309-2012.

Tibesigwa, B., Visser M., Turpie J. 2017. Climate change and South Africa's commercial farms: an assessment of impacts on specialised horticulture, crop, livestock and mixed farming systems. Environ. Dev. Sustain. 10.1007/s10668-015-9755-6.

Tom, A., Blokland K., Engel A., Speranza C.I., Losch B., et al. 2018. An Africa-Europe Agenda.

van Proosdij, A.S.J., Sosef, M.S.M., Wieringa, J.J., Raes, N., 2016. Minimum required number of specimen records to develop accurate species distribution models. Ecography (Cop.) 39 (6), 542–552. https://doi.org/10.1111/ecog.01509.

Vautard, R., Kadygrov, N., Iles, C., Boberg, F., Buonomo, E., et al., 2021. Evaluation of the large EURO-CORDEX regional climate model ensemble. J. Geophys. Res. Atmos. 126 (17), 1–28. https://doi.org/10.1029/2019JD032344.

Vinet, L., Zhedanov, A., 2011. A "missing" family of classical orthogonal polynomials. J. Phys. A Math. Theor. 44 (8), 6. https://doi.org/10.1088/1751-8113/44/8/085201.

Walker, N.J., Schulze, R.E., 2006. An assessment of sustainable maize production under different management and climate scenarios for smallholder agro-ecosystems in KwaZulu-Natal, South Africa. Phys. Chem. Earth 31 (15–16), 995–1002. https://doi.org/10.1016/j.pce.2006.08.012.

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

Zhao, Y., Camberlin, P., Richard, Y., 2005. Validation of a coupled GCM and projection of summer rainfall change over South Africa, using a statistical downscaling method. Clim. Res. 28 (2), 109–122. https://doi.org/10.3354/cr028109.

Ziervogel, G., New, M., Archer van Garderen, E., Midgley, G., Taylor, A., et al., 2014. Climate change impacts and adaptation in South Africa. Wiley Interdiscip. Rev. Clim. Chang. 5 (5), 605–620. https://doi.org/10.1002/wcc.295.