Supplementary information for climatic suitability predictions for the cultivation of macadamia in Malawi using climate change scenarios.

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Supplementary text

Figs. S1 to S2

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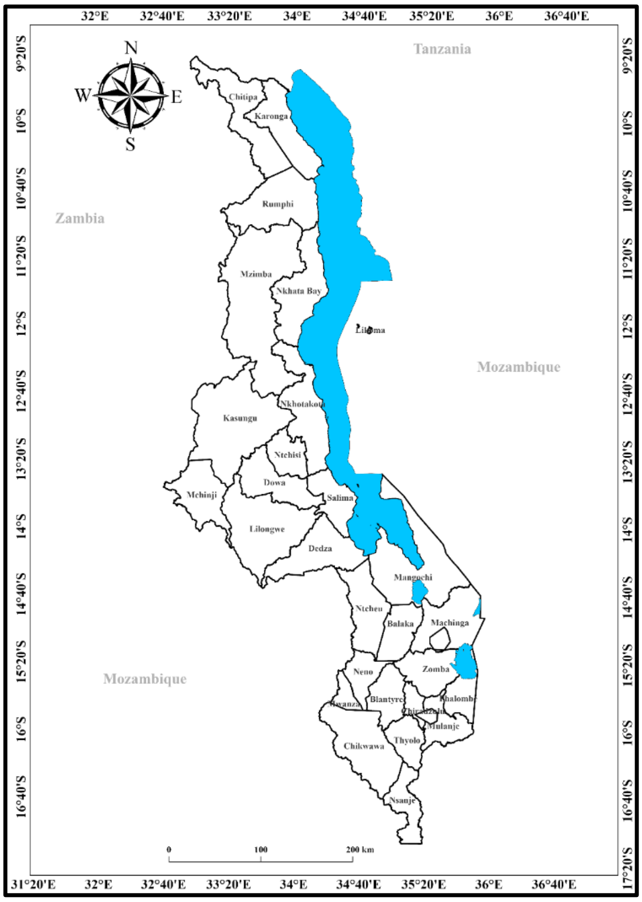

Fig. S1. The geographic location of Malawi.

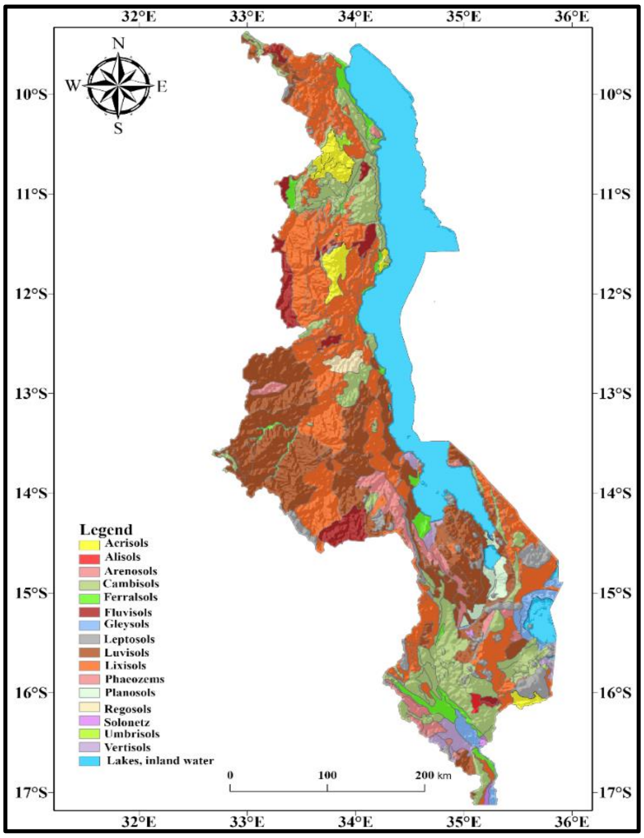

Fig. S2. Soil types in Malawi.

Taxonomy of macadamia

Table S1: Suitable climatic conditions for macadamia production in Malawi.

Description	Category	Adverse	Moderate	Optimal
Minimum temperature of the coldest month.	T_{min}[ºC]	≤1	1–4	5–10
Annual mean temperature.	T_{mean}[ºC]	≤9	10–15	16–30
Maximum temperature of the warmest month.	T_{max}[ºC]	≥36	31–35	25–30
Annual precipitation.	Prec[mm]	0–700 & ≥1750	900–1000 & 1300–1750	1000–1250

Table S2: Bioclimatic variables available in WorldClim.

Covariate	Bioclimatic variable	Unit
Bio1	Annual Mean Temperature	ºC
Bio2	Mean Diurnal Range (Mean of monthly)	ºC
Bio3	Isothermality (BIO2/BIO7) x 100	-
Bio4	Temperature Seasonality (Std. Dev x 100)	-
Bio5	Max Temperature of Warmest Month	ºC
Bio6	Min Temperature of Coldest Month	ºC
Bio7	Temperature Annual Range	ºC
Bio8	Mean Temperature of Wettest Quarter	ºC
Bio9	Mean Temperature of Driest Quarter	ºC
Bio10	Mean Temperature of Warmest Quarter	ºC
Bio11	Mean Temperature of Coldest Quarter	ºC
Bio12	Annual Precipitation	mm
Bio13	Precipitation of Wettest Month	mm
Bio14	Precipitation of Driest Month	mm
Bio15	Precipitation Seasonality (cv x 100)	-
Bio16	Precipitation of Wettest Quarter	mm
Bio17	Precipitation of Driest Quarter	mm
Bio18	Precipitation of Warmest Quarter	mm
Bio19	Precipitation of Coldest Quarter	mm

Table S3. The general circulation model (GCM) used to obtain climatic variables under scenarios RCP 4.5 and RCP 8.5 in 2050.

Country	Modelling centre	GCM	Abbreviation
Australia	Commonwealth Scientific and Industrial Research Organization	ACCESS1-0 AC	AC
China	Beijing Climate Center	BCC-CSM1-1 BC	BC
USA	National Center for Atmospheric Research	CCSM4 CC	CC
France	Centre National de Recherches Météorologiques, Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique	CNRM-CM5 CN	CN
USA	Geophysical Fluid Dynamics Laboratory	GFDL-CM3 GF	GF
USA	NASA/GISS (Goddard Institute for Space Studies)	GISS-E2-R GS	GS
South Korea	National Institute of Meteorological Research, Korea Meteorological Administration	HadGEM2-AO HD	HD
		HadGEM2-CC HG	HG
UK	Met Office Hadley Centre	HadGEM2-ES HE	HE
Russia	Russian Academy of Sciences, Institute of Numerical Mathematics	INMCM4 IN	IN
France	Institut Pierre-Simon Laplace	IPSL-CM5A-LR IP	IP
	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for	MIROC-ESM-CHEM MI	MI
Japan	Environmental Studies, and Japan Agency for Marine-Earth	MIROC-ESM MR	MR
	Science and Technology	MIROC5 MC	MC
Germany	Max Planck Institute for Meteorology	MPI-ESM-LR MP	MP
Japan	Meteorological Research Institute	MRI-CGCM3 MG	MG
Norway	Bjerknes Centre for Climate Research, Norwegian Meteorological Institute	NorESM1-M	NO

Table S4. Characteristics of climate change scenarios by the 2050s (RCPs).

Scenario	Radioactive forcing (W/m^2)	GEI concentration by the year 2100 (ppm CO_2 equivalent)	Temperature change (ºC) by 2100		Greenhouse gas emissions	Agricultural Area	Publication
			Mean	Range			
RCP 2.6	2.6	~490	1.0	0.4–1.6	Very low.	Medium for cropland and pasture.	(Riahi et al., 2007).
RCP 4.5	4.5	~650	1.4	0.9–2.0	Medium-low mitigation (very low baseline).	Very low for both cropland and pasture.	(Fujino et al., 2006).
RCP 6.0	6.0	~850	1.3	0.8–1.8	Medium baseline (high mitigation).	Medium for cropland but very low for pasture.	(Clarke et al., 2007).
RCP 8.5	8.5	~1370	2.0	1.4–2.6	High baseline.	Medium for cropland but very low for pasture.	(Van Vuuren et al., 2007).

Table S5. Algorithms for environmental niche modelling included in the analysis of the suitability of macadamia and the area under the curve (AUC).

Algorithm	**Method**	**Description**	**AUC**
Envelope model	BIOCLIM	It computes the similarity of a location by comparing the fi (xi) at any location to a percentile distribution of the values at known locations of occurrence.	0.74
Multivariate distance	DOMAIN	It computes the Gower distance between environmental variables at any location and those at any of the known locations of occurrence.	0.65
Additive models: Generalized additive models	GAM	Semi-parametric approach to predicting non-linear responses to a suite of a predictor.	-
Regression: Multivariate adaptive regression splines	MARS	It is a non-parametric regression technique that automatically models non-linearity and interactions between variables.	0.93
Stepwise GAM	GAMSTEP	Builds a GAM model in a step-wise fashion.	0.85
Mahalanobis distance	MAHAL	It considers the correlations of the variables in the data set, and it is not dependent on the scale of measurements.	1.00
Maximum entropy	MAXENT	It is a machine-learning method that estimates the species distribution probability by assessing the maximum entropy distribution so that the most spread-out or closest to uniform.	0.87
Boosted regression models: Generalized boosted regression models	GBM	Based on prediction components, where each component consists of a different weighted sum of nonlinear transformations of the predictor variables.	-
Generalized linear models	GLM	Generalizes linear regression by allowing the linear model to be related to the response variable via a link function.	0.88
Support vector machines	SVM	Machine-learning methods that are based on classification (C-svc, nu-svc), novelty detection (one-class-svc), and regression (eps-svr, nu-svr).	0.86
Stepwise boosted regression tree models	GBMSTEP	It is a technique that aims to improve the performance of a single model by fitting many models based on stepwise selection and combining them for prediction.	-
Artificial neural networks	NNET	It is a machine learning approach that employs an adaptive structure, which can be trained with application data to capture complex relationships between input and out variables.	0.77
Random Forest	RF	It is a collection of tree-structured weak learners that comprised identically distributed random vectors where each tree contributes to a prediction.	0.94
Multivariate Adaptive Regression Splines	EARTH	It is a technique that builds enhanced regression models, and it involves a forward and backward automated algorithm for the selection of predictor variables.	-
Stepwise generalized linear models	GLMSTEP	It includes regression models in which the predictive variables are selected by an automated algorithm that involves backward elimination or forward selection.	0.72
Mixed GAM Computation Vehicle	MGCV	It provides functions for generalized additive and generalized additive mixed modelling.	0.74
Maxlike	MAXLIKE	It is a machine-learning method that estimates the species distribution probability by assessing the maximum entropy distribution so that the most spread-out or closest to uniform.	0.77
Ensemble	ENSEMBLE	This is a weighted average of all algorithms used for modelling species distribution.	0.88

Table S6. Summary of news reports about climate change affecting macadamia production worldwide (period 2013-2019).

Organization	Year	Country	Main report
Helvetas	2018	Nepal	Climate change is a challenge in Nepal. Current and projected increases in maximum temperatures and decreases in summer monsoon precipitation may affect macadamia tree growth and yields.
Macadamia Association of Zimbabwe	2020	Zimbabwe	Macadamia nut farmers experience the poorest harvest ever in 2020 owing to the side effects of climate change. Projected reduced rains and heat waves will likely affect macadamia production in the future within the country.
Agricultural Research Council	2016	South Africa	Changing climate is slowly altering the South Africa agricultural landscape, and farmers will need to adjust farming practices. Climate suitability studies show that the northern parts of South Africa are shifting towards the south. The Eastern Cape and KwaZulu-Natal areas could become more suitable for growing nuts, like macadamias, while Limpopo could no longer be suitable for nut production by the year 2090.
Macadamia Conservation Trust	2017	Australia	The MCT in Australia reports that macadamia habitat losses and fragmentation are attributed to climate change and urban footprint. New South Wales will lose about 10 % of its macadamia growing areas due to climate change.
The Standard	2019	Kenya	Kenyan macadamia farmers face poor crop harvests during the 2018-19 growing season due to heavy rains during the flowering phase. Interviews with some smallholder farmers reveal that climate changes will likely continue affecting macadamia yields and hence the need for sustainable technologies for adaptation.
International Pacific Research Center	2014	Hawai‘i	Climate change is a prominent concern among the general public in Hawai‘i and has received significant official attention within the island nation. Hamilton reports that climate change will complicate agricultural planning in Hawai‘i, especially for perennial tree crops such as macadamia and coffee.

Supporting R packages

Datasets were organized using the R packages “data.table” (Dowle & Srinivasan, 2020), “magrittr” (Bache & Wickham, 2016), and “tidyverse” (Hadley Wickham et al., 2019) were utilized. Layers were processed using the packages “sp” (Bivand et al., 2013), “sf” (Pebesma, 2018), “maptools” (Roger et al., 2020), “raster” (Hijmans *et al*., 2020), “rgdal” (Pebesma, 2018), “dismo” (Elith & Franklin, 2017), “rJava” (Urbanek & Urbanek, 2020) and “rgeos” (Bivand et al., 2013). Production of the maps was conducted through the usage of “ggplot2” (Wickham, 2020) and “patchwork” (Pedersen, 2020) packages.

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