Leveraging geo-intelligence to map land suitability for private sector investment in agricultural value chains in Africa: A case study of Malawi

Gladys Mosomtai*[1], Joan Kagwanja[1], Guy Ranaivomanana[1]

[1]Agriculture and Business Enabling Environment, Private Sector Development and Finance Division, United Nations Economic Commission for Africa, Addis Ababa, Ethiopia

*Corresponding author – gladys.mosomti@un.org

Abstract

The Comprehensive African Agricultural Development Programme (CAADP), a continental framework underpinned by the AU Agenda 2063 rallies the African countries to alleviate hunger and poverty by setting aside atleast 10% of their budgetary allocations for agricultural development and attracting private sector investments. Since 2000, private sector investment in land-based activities has significantly increased with contracts in different stages of which 87% of the deals are mainly for large-scale agricultural production. However, the new 'rush for land' in Africa has not spurred the expected economic growth. Most of the existing deals are underutilized due to insufficient prior information about land productivity, water availability, border conflicts with the surrounding communities, and long-term land deal insecurity, among other factors. The African Union endorsed the Guiding Principles on Large Scale Land Based Investment to protect the local communities from exploitation whilst profiting the investors and ensuring that the investments are sustainable and environmentally friendly. However, many countries lack the appropriate tools and information to domesticate these principles to guide their engagement with private investors. In this study, we use Malawi as our case study to demonstrate how African countries can leverage geo-technologies to identify suitable land for private sector investments in agricultural value chains. Firstly, we mapped suitable areas for growing tobacco, maize and groundnuts using a machine-learning modelling framework based on ecological conditions. Secondly, we incorporated a multi-criteria decision analysis model to identify the optimum areas for targeted investment based on socio-economic factors such as access to infrastructure, markets and regions with low population density. The study showed that Malawi has the potential to double the production of maize and increase tobacco and groundnut production by two-thirds. We also noted that tobacco and groundnuts had similar land suitability given that they shared similar ecological conditions, access to roads, grid connection and low population densities in the regions identified as optimum. These regions could benefit from developing agro parks that leverage economies of scale to create multiple value chains. Finally, the methodology adopted in this study can be replicated in other countries given the advancement in data availability through GIS and remote sensing technologies and state of the art modelling frameworks.

Keywords: Land-based investment, Agricultural value chain, Machine learning algorithm, Land suitability, Multi-criteria decision analysis

1. Introduction

The world is at crossroads with a rising population in need of food and conserving the pristine environment while producing the needed food (Global Network Against Food Crisis, 2022). The food crisis is further aggravated by the impacts of climate change and the recent disruption of supply chains due to COVID-19 restrictions and the geopolitical insecurities (Caprile, 2022). The triple effect threat on global food security has exposed the fragility of economies that depend on unsustainable agricultural value chains, challenging the world to redefine the existing structure of the food systems to find sustainable solutions and improve its resilience. This was the core mandate of the UN Food System Summit in 2021 (Von Braun et al., 2021). The Summit not only rallied the world towards finding these solutions but also envisioned that fixing the food crisis was a powerful vehicle to fast-track the progress of achieving all 17 Sustainable Development Goals (Caprile, 2021).

In Africa, Agriculture is the backbone of the economy, with crops such as cocoa, tea, coffee and horticulture contributing significantly to the gross domestic production of most countries. Furthermore, the agricultural value chain employs 65 - 70% of Africans, with 70% being smallholder farmers in rural areas (World Bank, 2013). Ultimately, improving the economic value of agricultural products will ensure that smallholder farmers get better prices for their products and this holds the greatest potential for alleviating poverty and hunger, which is encapsulated in Agenda 2063 of the African Union (AU) and the UN Sustainable Development Goal 1 and 2. However, transforming Africa's food system remains a challenge due to unpredictable weather patterns, pests and diseases, use of rudimental tools for production, high cost of inputs, and dwindling land for agricultural production due to increasing population (World Bank, 2013). Furthermore, agricultural practices lack planning and consistent monitoring tools to guide policy formulations and decision-making on the already limited arable land.

In the last two decades, concerted efforts in developing policies that accelerate Africa's food system transformation has been unprecedented and this has led to several declarations and decisions made at the continental level with impact at national level such as the 2009 AU declaration on land issues and challenges in Africa (AUC, 2009), the 2014 Malabo declaration on accelerated agricultural growth (AUC, 2014a), the 2007 decision on the Abuja summit on food security in Africa among others, among others (AUC, 2007). The greatest milestone made so far is the implementation of the comprehensive African agricultural development programme (CAADP), a continental framework underpinned to Agenda 2063 that rallies the Member States to alleviate hunger and poverty by setting aside atleast 10% of their budgetary allocations for investing in agricultural development and attracting private sector investments (NEPAD, 2009). Notably, private sector investment in land based activities have significantly increased since 2000 with over 40 million ha of land in Africa currently under use with contracts in different stages of which 87% of the deals are mainly for large scale agricultural production (Land Policy Initiative, 2013). Western countries are the predominant investors in many of the African countries with bias towards colonial ties and even though half of the deals are for food crops, the other half are for non-food crops mainly for biofuels.

The new 'rush for land' in Africa however has not spurred the expected economic growth. This is majorly due to conflicts of land with the local communities. The acquisition of community land by private entities has led to disenfranchisement of communities on their rights to access their land and natural resources (Neudert & Voget-kleschin, 2021). As a result, this has led to their loss of livelihoods and widening of poverty margins, especially for women and youths. Furthermore, most of the existing deals are underutilized due to insufficient prior information about the land productivity, water availability, and border conflicts with the surrounding communities, and the long-term land deal insecurity, among other factors (Land Policy

Initiative, 2013). The African Union endorsed the Guiding Principles on Large Scale Land Based Investment (LSLBI) to protect the local communities from exploitation whilst profiting the investors and ensuring that the investments are sustainable and environmentally friendly (AUC, 2014b). However, many countries in Africa lack appropriate tools and information to guide private investments. In particular, the information needed in this regard relates to the location and claims on the available land, agricultural suitability, and infrastructure such as energy, transport, irrigation and market to guide their engagement with private investors in a manner that safeguards environmental services and their rights.

Advancements in geographic information systems (GIS) and remote sensing technology in recent years have led to development of decision support tools adopted by institutions globally to make prudent socio-economic planning, monitoring and developments. In this study, we demonstrate how African countries can leverage these technologies to identify suitable land for private sector investments in agricultural value chains using Malawi as our case study. Firstly, we mapped the suitable areas for growing priority crops for investment based on environmental conditions using a machine learning modelling framework. Secondly, we incorporated a multi-criteria decision analysis model to identify the optimum areas based on access to infrastructure, markets and population density. Ultimately, the aim of this study is to develop a robust methodology that can be replicated in other African countries to enhance their capacity to implement the Guiding Principles on LSLBI and protect the local communities while attracting private sector investments.

2. Study area

Malawi is a landlocked country in South-eastern Africa that borders the following countries, Tanzania in the North, Mozambique in the South and Zambia in the West, with an area covering 118,480 km^2, making it one of the smallest countries in Africa (Government of Malawi, 2017).

The country has a tropical climate with a rainy season that runs from November to April and a dry season from May to October. Malawi has a diverse topography that includes highlands, plateaus, and lowlands, with Lake Malawi, the third-largest lake in Africa, taking up a significant portion of the country's eastern border. The population of Malawi is estimated to be around 19.13 million people, with more than half of the population living below the poverty line (World Bank, 2021).

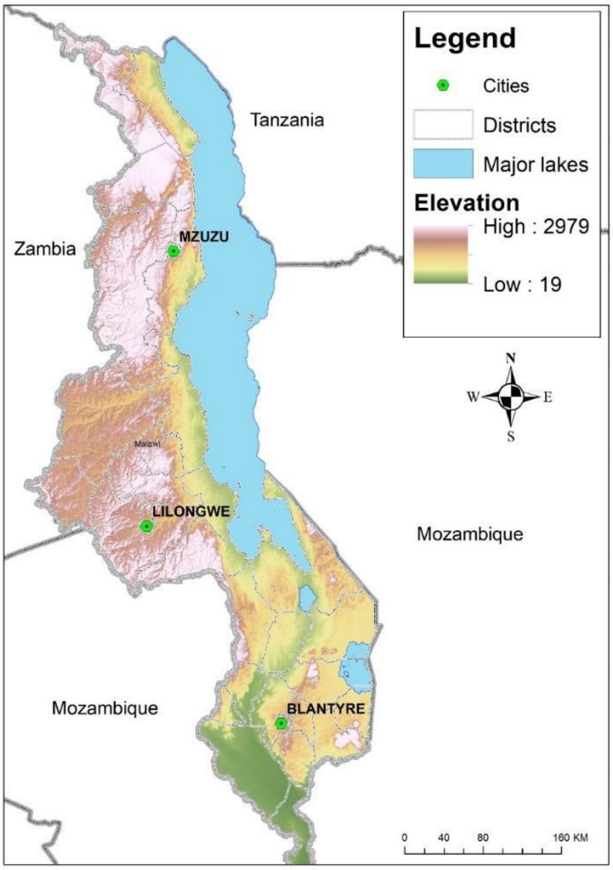

Figure 1: Location map of Malawi.

Agriculture is one of the key economic sectors in Malawi, providing 27% of GDP and 72% of employment, with tobacco being the country's main export crop, followed by tea, sugar, and cotton. However, it severely lacks the investment to revamp dominant poor productivity and production. In 2017, Malawi attracted as low as 1% of Foreign Direct Investment (FDI). FDI into agriculture lags substantially both in the service and industry sectors due to land scarcity and difficulty in allocation for commercial investments. With support from African Land Policy Centre, a tripartite of the African Union Commission (AUC), the United Nations Economic

Commission for Africa (ECA), and the African Development Bank (AfDB), several pieces of legislation were passed in 2016 to formalize land tenure, support inclusive development, and address critical issues in land management but their implementation remains a challenge, limiting their overall potential impact.

3. Materials and methods

3.1. Reference data for maize, tobacco and groundnuts

We had a stakeholder meeting with the Ministry of Agriculture and Land to identify priority value chains for Malawi and specifically those of interest to develop their value chains. Through Malawi Investment Trade Centre, twenty value chains have been identified and three of them are maize, groundnuts and tobacco, which are the focus of this study. To map the suitable areas for growing these crops, reference data containing latitude and longitude were obtained from the Global Biodiversity Information Facility (GBIF) database as well as from the literature review. A total of 83, 186 and 109 GPS points for tobacco, maize and groundnuts were used to predict other suitable regions for growing these crops respectively.

3.2. Environmental layers

Table 1 provides a summary of all the environmental variables used in this study. Several environmental variables were used to define the environmental and geographic space for the three crops of interest. Firstly, current climatic conditions at one kilometre grid resolution from the AfriClim were used (Platts et al., 2015) to define the climatic conditions favourable for growing tobacco, maize and groundnuts. These variables were preferred because they provide high resolution projections for the African continent (Lovett, 2015; Mwalusepo et al., 2015) and contain grids of temperature, rainfall and derived bioclimatic variables (Supplementary Table 1). Secondly, soil data from ISRIC global gridded soil information were used to characterize the soil characteristics favourable for the studied crops (supplementary Table 2). The soil variables used in this study include drainage, soil nutrients, soil organic carbon, soil pH and texture. Finally, land use land cover map from 10m Sentinel 2 for 2021 (Supplementary Table 3) and 30m digital elevation model (DEM) data from the Shuttle Radar Topographic Mission (SRTM) were used to define the topographic gradient and crop extent in which the crops are grown. For value chain analysis, the following variables were used to characterize the socio-economic characteristics of the areas that grow the studied crops; roads, towns, population density and night-time lights from Visible Infrared Imaging Radiometer Suite (VIIRS) and population density grid map from WorldPop.

Table 1: Description of data and their sources used to model crop suitability in the study area

Datasets	**Source**	**Description**	**Type**
Reference data	Harvard Dataverse	Contains lat long for crop occurrence locations for maize, groundnuts, tobacco	Vector
Towns	Digital Chart of the World	Towns	Vector
Roads	Digital Chart of the World	Roads	Vector
Climatic data	WorldClim	1km grids for temperature and precipitation variables representating the present climatic scenario	Raster
Soil data	ISRIC	250m grids for characterizing soil fertility	Raster
Land cover	ESA WorldCover 2021	10m land use land cover map generated from Sentinel 2 for 2021	Raster
Population data	WorldPop	1km population density grids	Raster
Night-time light	Visible Infrared Imaging Radiometer Suite (VIIRS)	1km visible and near-infrared (NIR) band for measuring nocturnal light	Raster

3.3. Crop suitability modelling

To map suitable areas for growing tobacco, maize and groundnuts, we adopted the ecological niche modelling framework (ENM). ENM is a GIS-based tool used to map ecological habitat of species over a geographical and environmental space using sampled reference data. Reference data represent the fundamental niche of the species (Biodiversidad, 2005). This niche in modelling environment is defined by environmental layers and by associating the reference data with environmental layers, other areas with similar environmental characteristics as sampled data are identified and projected over the region of interest (Biodiversidad, 2005). This extrapolation is achieved by making use of algorithms such as Maximum Entropy (MaxEnt), Generalized linear models (GLM), Random Forest, Boosted Regression Trees (BRT) that make use of presence data (Guisan and Zimmermann, 2000). In this study, MaxEnt modelling framework was adopted for mapping tobacco, maize and groundnuts suitability in Malawi (Phillips et al., 2006).

MaxEnt, a popular machine learning algorithm was implemented due to its high predictive accuracy and ease of processing (Phillips and Dudík, 2008). 70% of the reference data was used to train the MaxEnt model whereas the remaining 30% was used to test the model accuracy. Several default settings were adopted while fine tuning the model parameter, however, the regularization parameter was set to 3 to reduce overfitting of the model. The most influential variables with their permutation importance was determined using Jackknife analysis (Merow et al., 2013; Phillips and Dudík, 2008) whereas Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) was used to evaluate the model accuracy (Phillips and Dudík, 2008). AUC which is a threshold independent measure indicates the ability of the model to distinguish between presences from absence of the species of interest (Jiménez-Valverde, 2012). A model of AUC of 0.5 indicates poor performance (it is as good as random) while 1 indicates ideal accuracy (Makori et al., 2017).

To reduce variable collinearity of environmental layers, Variance Inflation Factor (VIF) which quantifies the severity of collinearity using an ordinary least squares regression analysis was used. It provides an index that measures how much of an estimated regression coefficient is increased because of collinearity. A stepwise option was used whereby it drops variables until a threshold of less than 10 is arrived (Abdi et al., 2015; La Sorte and Jetz, 2010; Skarin et al., 2015). Initial model ran was tested on climatic variables only. The second model involved combining all the environmental layers to predict the three crops.

3.4. Multi-criteria decision analysis

A multi-criteria decision analysis (MCDA) was used to identify areas with high potential for private sector investment of the modelled crops based on environmental suitability, access to markets, infrastructures such as roads and electricity whilst maintaining minimal internal displacement of people. MCDA is a decision support tool that aids decision-making when multiple criteria and alternatives exist (Sisman & Aydinoglu, 2020). The following data layers were used to generate value chain analysis maps: suitability layers from MaxEnt model (arable land), population density, on-grid population (night-time lights), towns, and roads. Using the spatial analyst toolbox in ArcGIS, weights were assigned to each variable based on the level of importance, with the highest weights given to the most important variable and vice versa (Table 2). We considered the suitability map to be the most important variable in this study and we assigned the highest weight (0.5). The second most important variable was population density (0.2). Preference was given to regions with low population as the most preferable place to invest as opposed to densely populated areas. Finally, night-time light, which was used to infer the population with electricity, was assigned equal weights with the roads and towns (0.1). A value chain index was generated from the weighted sum of all the variables, showing the most feasible areas for large-scale investment of the model crops to guide private sector investment.

Table 2: Description of datasets used for developing value chain maps and weights assigned for multi-criteria decision analysis model for each crop

Layer	Description	Weights
Suitability map	Probability maps showing suitable areas for growing tobacco, maize and groundnuts based on the modelling framework. The maps were reclassified into five categories with the highest value showing the most suitable areas.	0.5
Population density	The map was reclassified to give a higher value to regions with low population density.	0.2
Night-time light	Reclassified to give regions with high nocturnal reflectance a high value. This regions indicated connection to electricity	0.1
Distance to roads	Euclidean distance map was generated and reclassified to give areas within 10km radius from the main road the highest vale whereas regions 50km away from the road a low value	0.1
Distance to towns	Euclidean distance map was generated and reclassified to give areas within 10km radius from the main towns the highest vale whereas regions 50km away from the towns a low value	0.1

4. Results

4.1. Arable areas for growing tobacco, maize and groundnuts

The overall model accuracy for the studied crops were higher than 0.75 with notable differences existing when only climatic variables were used and when combined with other environmental variables (Table 3). The MaxEnt model with only climatic variables resulted in a higher accuracy than when other variables were added; however, for this study, we adopted the model that incorporates all the environmental characteristics to predict the suitable areas for growing the crops.

Table 3: Accuracy assessment of the model prediction using the mean area under curve (AUC) of the receiver operating curve.

Crop	**bioclim_only**	**bioclim_soil_landuse_elevation**
Groundnuts	0.899	0.805
Maize	0.883	0.782
Tobacco	0.938	0.835

Crop suitability maps for tobacco, maize and groundnuts are presented in Figure 2. The deep colour represents areas highly suitable for growing the crops while the light colour represents the least suitable areas. Generally, the central and part of the northern regions are suitable for growing all the three crops. Tobacco and groundnuts have similar ecological profiles with the following districts being the most suitable for growing them; Kasangu, Mchinji, Lilongwe, Dowa and Ntchisi in the central, Mzimba and part of Rumphi in the north and smaller regions in Blantyre, Mangochi and Ntcheu in the south (Figure 2A and C). For maize, most parts of the country are suitable, however, the degree of suitability varies according to their environmental conditions. The most suitable districts are Blantyre, Chiradzulu, Zomba, Thyolo and part of Ntcheu and Mangochi in the south, Mzimba in the North while Kasungu and the neighbouring districts in the central are within the medium level of suitability for Maize (Figure 2B).

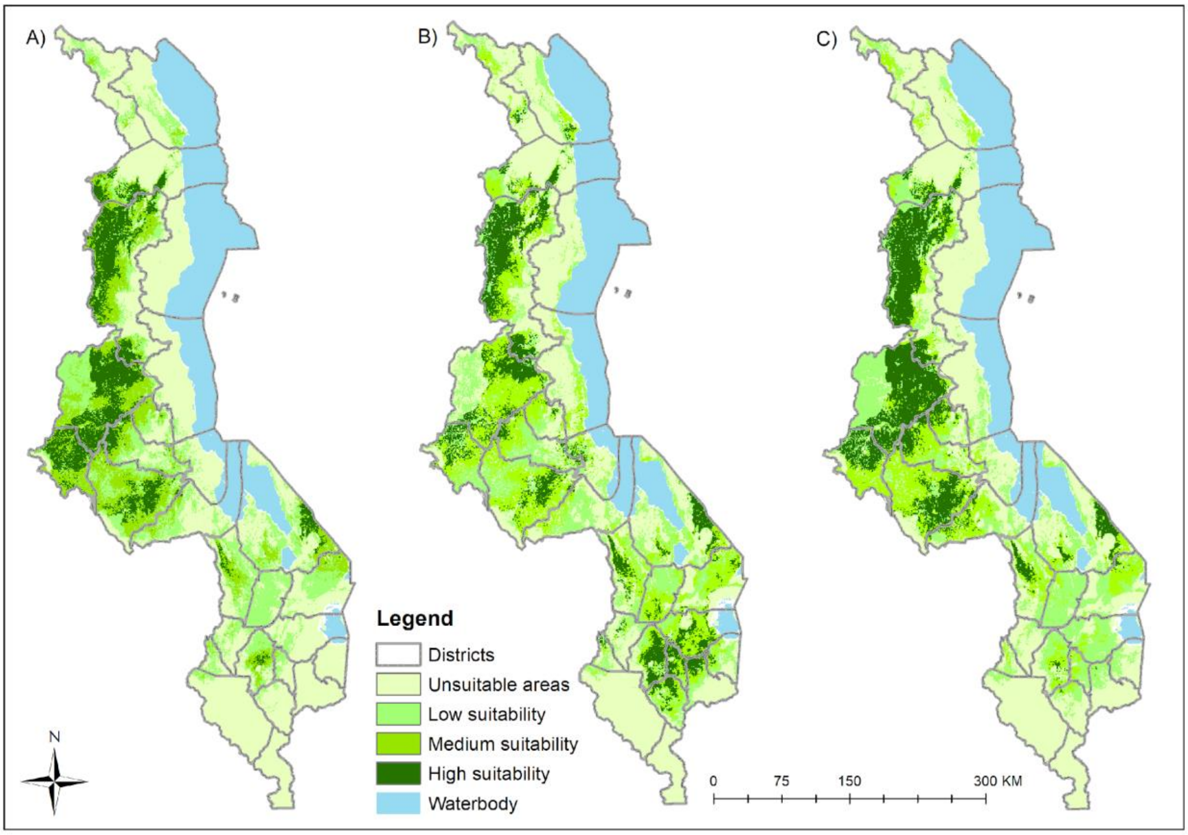

Figure 2: Probability maps showing suitable areas for growing A) tobacco, B) maize and C) groundnuts based on climatic conditions, soil characteristics, elevation and land cover variables

We further calculated the total area (km^2) available for cropping the three value chains in Malawi based on the most environmentally suitable areas and the medium to low suitable areas that do have potential to be improved by infrastructures such as irrigations (Figure 3). Overall, maize had the highest suitable area (27,006 km^2) but also almost an equal area with potential for increased productivity (22,596 km^2). On the other hand, groundnuts slightly had a higher area (23,706 km*2*) than tobacco (20,315 km^2) but both had equal area for potential improvements (15,976 km^2 and 15,143 km^2 respectively). Some of the areas with the highest potential for improvement are found in the following Traditional Authorities (TA), Nsamala, Kalolo, Chimwala, Kawinga, Kabudulu, Mlumbe among others. Key environmental variables that contributed the most in defining the suitable areas in all the models were; land use type, soil texture, elevation and the rainfall driest month (bio14) (Figure 4).

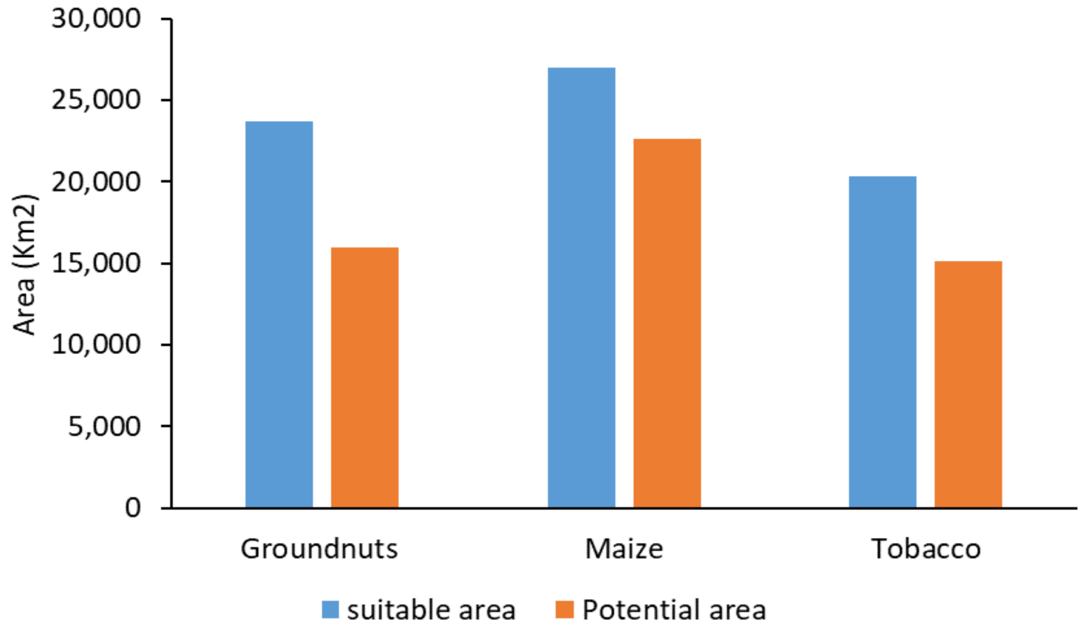

Figure 3: Total area in km^2 with suitable climatic, soil fertility, elevation and land use for growing tobacco, maize and groundnut and areas with medium to low suitability but with potential to improve in Malawi.

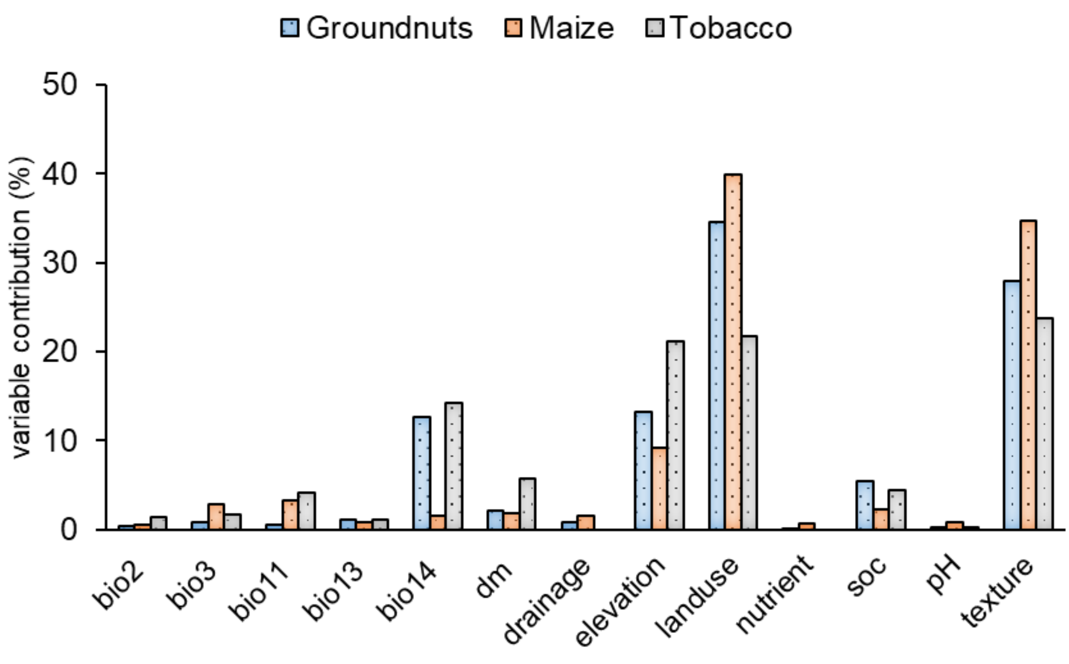

Figure 4: Percentage of contribution of the most important variables in modelling crop suitability

4.2. Value chain suitability

Regions with the most potential for developing the three crops are shown in Figure 5. Tobacco and groundnuts shared similar regions while the maize slightly varied slightly. For Tobacco and groundnuts maximum potential (red colour) is mainly in Mzimba and Rumphi districts in the north specifically in the following TA and sub chief, Mpherembe, Chindi, M'mbelwa, Chikula and Mwahenga while in the central region, the following traditional areas in Kasungu districts have maximum potential, Kasungu boma, Kaomba, and Simlembwa. For maize, the entire country has a high potential for investment however, the optimum regions for investment are in the south in the Blantyre districts specifically in the following TAs, Kapeni, Somba, Chiradzulu, Mpama, Katuli, Chamaliro and Mchinji. For the northern districts, potential regions are similar with the groundnuts and tobacco.

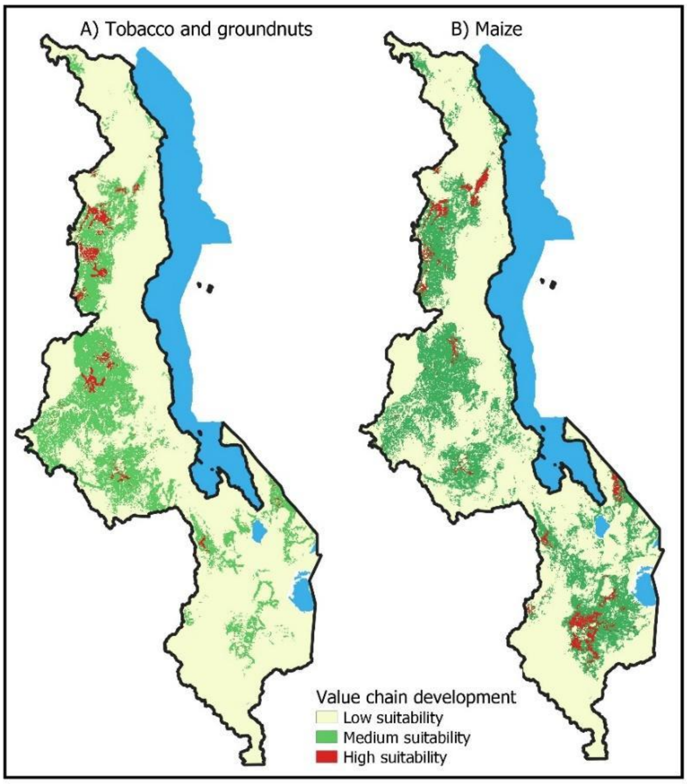

Figure 5: Value chain development maps for maize, tobacco and groundnuts showing the optimum area to invest in Malawi. The red and green colours show regions with most potential for developing the value chains of the crops based on environmental suitability, access to roads, electricity and towns.

5. Discussion

The Government of Malawi is committed to accelerating agricultural transformation through private sector investment as outlined in the National Agriculture Investment Plan. However, the country lacks appropriate tools and information to guide private sector investments and the implementation of the AU Guiding Principles on LSLBI that protect the local communities from exploitation whilst profiting the investors and ensuring that the investments are sustainable and environmentally friendly. In this study we demonstrate how Malawi can leverage cutting-edge technology in geo-intelligence to guide private sector investment in key value chains by identifying regions with suitable land for investment based on environmental conditions, access to markets and infrastructure such as roads and electricity. The study focused on three crops with national importance for value chain development namely, tobacco, maize and groundnuts. Overall, the country has a huge potential for producing the three crops, given its suitable ecological conditions. Furthermore, optimum production and development can be achieved in strategic Traditional Authorities that currently have better access to infrastructure and markets.

The use of ecological niche modelling, also commonly known as species distribution modelling, for mapping crop suitability, pests and disease occurrence, and distribution of invasive and native plant species has gained prominence in the last two decades due to the increasing availability of climatic and environmental datasets and development of statistical and machine learning techniques for data analysis with increasing accuracies in prediction. In this study, the maxent model was able to predict suitable areas for growing the three value chains with high confidence and this will guide the government of Malawi on where to develop these value chains. The central and northern districts generally have suitable ecological conditions for growing all three crops and the southern districts are only suitable for growing maize. We also identified regions with high potential for increased productivity if infrastructures such as irrigation or improving soil fertility can be developed in areas with medium to low suitability. Maize has the highest regions which can produce as much as the maize growing belts doubling the production whereas tobacco and groundnuts share similar ecologies with the same regions for investments.

While developing agricultural value chains, ensuring that the basic condition are met greatly improves the competitive advantage of the priority value chains and in our case, tobacco, maize and groundnuts. The basic conditions include favorable climate for cultivation, soil fertility, and access to farm inputs, labour, capital and access to infrastructures such as roads to facilitate movement of the produce to market. In this study we focused on this primary segment of the value chain and identified regions where optimum production can be achieved. Specific TAs were identified as the priority areas for private sector investments given the establish infrastructure and suitable environmental conditions and this could guide the government of Malawi when attracting foreign investment in these value chains. Notably, the key environmental variables that delianated these suitable areas for growing the crops were elevation gradient, land use type and soil texture. The most important land use type identified by the model was the cropland extent and this was important for limiting the prediction to only arable areas and increasing the accuracy of our model. The elevation alluded to the temperature limit required for growing the crops whereas the soil texture limited the predicted area to areas with favourable soil fertility for the three value chains.

A potential limitation in this study was the weights applied in the multi-criteria decision analysis. The highest weight was assigned to environmentally suitable areas for growing the three value chains whereas the socioeconomic factors were assigned equal weights. The model could further be improved to reflect more on what the government of Malawi deem important while developing the value chains and this could be achieved by involving the major stakeholders in the value chains. Furthermore, this study focused only on one segment of the chain. The maps generated forms the baseline that can further be developed to include other segments of the value chain and ultimately, improving the business environment of the priority crops. We also noted that tobacco and groudnuts had similar value chain maps given that they shared similar ecological conditions, access to roads, grid connection and low population densities in the regions identified as optimum. These regions could benefit from infrastructures such as agroparks that leverage on economy of scale to develop multiple value chains.

Conclusion

Agricultural value chain development in Africa holds the greatest potential for improving the rural economy and achieving the aims of CAADP and Agenda 2063. In this study we developed a methodological framework that can be used to identify optimum areas for private sector investments with the focus of improving the productivity of tobacco, maize and groundnuts value chains. The study showed that Malawi has the potential to double the production of maize and increase tobacco and groundnuts production by two-thirds. Furthermore, the government can give priority to traditional areas with access to infrastructures and market to attract private sector investment in the short term while developing the infrastructure in other suitable areas. Finally, the method used in this study can be replicated in other other member states.

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Appendices

Supplementary table 1: Bioclimatic variables from WorldClim that was used to model climatic condition suitable for growing tobacco, maize and groundnuts in Malawi

Variable	Name
bio1	Mean annual temperature
bio2	Mean diurnal range in temperature
bio3	Isothermality
bio4	Temperature seasonality
bio6	Min temperature coolest month
bio7	Annual temperature range
bio11	Mean temperature coolest quarter
bio12	Mean annual rainfall
bio14	Rainfall driest month
bio15	Rainfall seasonality
dm	Number of dry months
llds	Length of longest dry season
miaq	Moisture index arid quarter
mimq	Moisture index moist quarter
pet	Potential evapotranspiration

Supplementary table 2: Soil variables from ISRIC that was used to model the soil fertility for growing tobacco, maize and groundnuts in Malawi

Variable	Name
drainage	soil drainage
nutrient	soil nutrient
soc	soil organic carbon
pH	soil pH
texture	soil texture

Supplementary table 3: Land use land cover classes of the land use map used in the model. The land cover and types were mapped from 10m Sentinel 2 for 2021

Class	Description
1	Trees cover areas
2	Shrubs cover areas
3	Grassland
4	Cropland
5	Vegetation aquatic or regularly flooded
6	Lichen and mosses / sparse vegetation
7	Bare areas
8	Built up areas
9	Snow and/or ice and
10	Open water