Journal of Scientific Agriculture 2024, 8: 31-37
doi: 10.25081/jsa.2024.v8.8903
https://updatepublishing.com/journal/index.php/jsa

Research Article

ISSN: 2184-0261

Habitat suitability study for green gram production under present and future climatic scenarios in Kibwezi East Kenya

Maluvu Zipporah[1]*, Oludhe Christopher[1], Kisangau Daniel[1,2], Maweu Jacinta Mwende[3]

[1]Department of Earth and Climate Sciences, University of Nairobi, Nairobi, Kenya, [2]Department of Life Sciences, South Eastern Kenya University (SEKU), Kitui, Kenya, [3]Department of Journalism & Communication, University of Nairobi, Nairobi, Kenya

ABSTRACT

The species distribution model was used to predict the suitability of green gram production under the present, RCP 4.5 and 8.5 climate scenarios. An *ensemble* of a species distribution model comprising six models was developed. Validation of these models revealed that all models were robust with the best model being random forest (RF) with Area Under the Curve (AUC) = 0.98 and Deviance = 0.29 while the least was the generalized linear model (GLM) with AUC = 0.87 and Deviance = 0.71. The green gram habitat suitability greatly decreased under RCP 8.5 climate scenario prediction whereby about half of the agricultural land in the Kibwezi East Sub County was highly unsuitable for green gram production. The Habitat suitability predictions showed that Thange ward out of the four wards in the location was the most suitable for green gram production. However, as per the predictions its suitability for green gram production may be affected by climate change under all climate scenarios. Results from this study give decision-makers a foundational understanding of the likely effects of climate change in the 2050s compared to the present scenario on habitat suitability for green gram production and a basis for creating strategies and policies to enhance adaptation and create resilience to its effects.

Received: April 05, 2024
Revised: May 16, 2024
Accepted: May 16, 2024
Published: July 04, 2024

***Corresponding Author:**
Maluvu Zipporah
E-mail: zmaluvu@gmail.com

KEYWORDS: Adaptation, Climate Change, Green gram, Habitat suitability, Kibwezi East Sub-County, Species Distribution Modelling

INTRODUCTION

Green gram is one of the pulse crops that are important for food and income generation in the arid and semiarid lands (ASALs) of Kenya. The crop has been cultivated in these areas for decades. Predicted climate change scenarios in the future may cause adverse effects on the habitat suitability for green gram production in some areas.

Climate change is likely to affect the high potential and low potential agricultural areas making them unsuitable for crop production. Habitat/climate suitability analysis helps to determine areas that are suitable for species survival and find out if they will remain suitable in the future (Halder, 2013). Research on climate suitability is important in adapting to and mitigating the effects of climate change. Green gram is cultivated in more than six million hectares in the warmer locations of the world. It is also adapted to a wide range of agroecological climates and requires low inputs during production (Nair *et al.*, 2012). A study by Mugo *et al.* (2020), found Kenya to be suitable for green gram production whereas Kitui, Makueni and West Pokot Counties were highly suitable for green gram production.

Species distribution models (SDMs) are currently the most commonly used tools for predictions of species habitat suitability (Jarvie & Svenning, 2018). SDMs can have some degree of uncertainties related to inherent variability of natural systems (Gould *et al.*, 2014; Noce *et al.*, 2019). However, ensemble forecasting has been revealed as an effective method of modelling to reduce variability of SDMs. The ensemble forecasting employs more than one model and therefore it combines several sources of uncertainty to improve the accuracy of climate change forecasts (Buisson *et al.*, 2010; Taleshi *et al.*, 2019). SDMs can be combined with Global circulation models and Greenhouse Gas (GHG) emission concentration pathways (RCPs) to quantify projections in climate change studies (Vieilledent *et al.*, 2013; Zhang *et al.*, 2015; Noce *et al.*, 2017). RCPs are dependent trajectories of concentrations of GHGs and other environmental pollutants resulting from human activities (AR5) (IPCC, 2014). The RCP 4.5 stabilizes radiative forcing at 4.5 w/m^2 in the year 2100 when strategies and technologies to reduce GHG emissions are employed. RCP 8.5 is characterized by increasing GHG emissions and high concentration levels in the atmosphere. The increasing emissions present a rising radiative forcing pathway leading to 8.5 w/m^2 in 2100 approximately 1370 ppm equivalent (Noce *et al.*, 2017; del Río *et al.*, 2021).

Studies on green gram production and climate change have been carried out in Kenya (Mugo *et al.*, 2016, 2020).The effects of climate change on habitat suitability have been analyzed from different forms of view (Kufa *et al.*, 2022). To our knowledge, no study has been conducted in Kibwezi East Sub County using ensemble-forecasting models combining standard bioclimatic variables and biogeographic predictors to model habitat suitability of green grams production under present and future climate scenarios.

Therefore, this study analyzed the habitat suitability situation for green gram in Kibwezi East subcounty, Kenya. It was carried under the present (1970-2000) and the future climate scenarios in the 2050s (2041-2060) under RCP 4.5 and RCP 8.5 climate scenarios using the Species Distribution Modelling (del Río *et al.*, 2021). The study combined an ensemble of species distribution models applied to Global circulation models driven by two representative concentration pathways.

MATERIALS AND METHODS

Study Location

This study was carried out in Kibwezi East Sub County in Makueni County, Kenya (Figure 1). Kibwezi East Sub County is approximately 200km south east of Nairobi and lies between longitude 37°58'4.25" E and latitude 2°24'37.89" S. Makueni County is approximately 8,034.7 Km^2 (GoK, 2013). It is divided into six sub-counties namely: Kaiti, Kilome and Mbooni, which are situated in the upper parts of the county while Makueni, Kibwezi East and Kibwezi West are situated in the middle and lower parts of the county. Kibwezi East Sub County has four wards namely; Thange, Mtito Andei, Ivingoni/Nzambani and Masongaleni.

Data Collection

World species presence data for green grams was obtained from the Global Biodiversity Information Facility (GBIF) using *dismo* package in R statistical software (R) (Fick & Hijmans, 2017). Using *raster* package in R, historical/present data from 1970-2000 that was released in 2020 was accessed from the Worldclim version 2 database. A total of 19 standard Worldclim bioclimatic variables were downloaded at a resolution of 30 seconds which

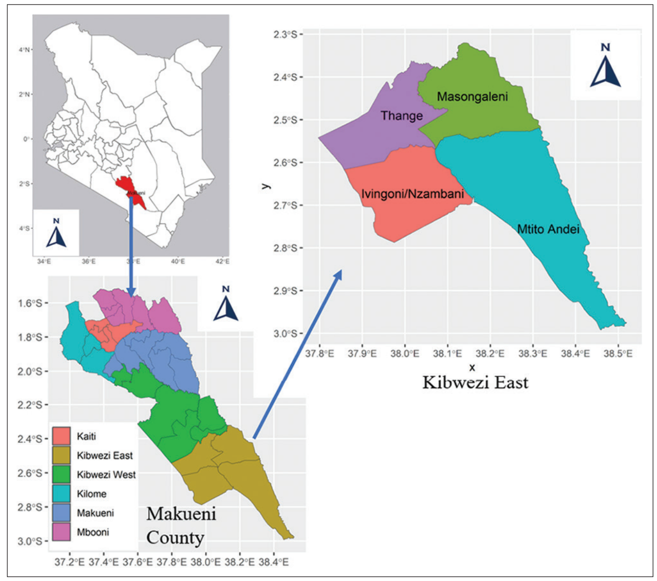

Figure 1: Map of Makueni County. Source: Author (2023)

is about an area of 1km^2 per pixel. More information about the standard bioclimatic variables is found on https://www.worldclim.org/data/bioclim.html. Bioclimatic variables with multicollinearity were identified and removed using *usdm* package in R (Chan *et al.*, 2022). The remaining nine standard bioclimatic variables were used in this study (Table 1).

Future bioclimatic data was downloaded from Worldclim version 2 at a resolution of 30 seconds for the year 2050s, which are the years between 2041 and 2060 using *raster* package in R. This was downloaded from Coupled Model Intercomparison Project Phase 5 (CMIP5) downscaled data for future climate projections for the IPCC5 climate projections and global climate models (GCMs) for two representative concentration pathways (RCPs) i.e., RCP 4.5 and RCP 8.5. The Greenhouse Gas emission pathways provide a time and space dependent trajectory of concentrations of GHGs.

Other data included elevation, soil type and soil pH. Soil type and pH were obtained from (International Soil Reference and Information Centre (ISRIC) at a resolution of 250 m per pixel while elevation was obtained from Worldclim (Fick & Hijmans, 2017) at a resolution of 30 seconds. These were kept constant for the three simulations; current, RCP 4.5 and RCP 8.5 climate scenarios.

Development of green gram habitat suitability model

Using *sdm* package in R, six models namely; generalized linear model (glm), support vector machine (Svm), random forest (rf), boost regression tree (brt), multivariate adaptive regression splines (mars) and maximum entropy (maxent) were trained. The choice of these models was based on previous studies which stated their importance in providing robust predictions (Hastie *et al.*, 2009; Latif *et al.*, 2013). The algorithms were combined into an ensemble. The procedure was carried out using ten bootstrap replicate run types.

Table 1: Standard bioclimatic variables used for model development

Variable	Description
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp)
BIO3	Isothermality (BIO2/BIO7) (×100)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

BIO=Bioclimatic variable

Model Evaluation

The prediction quality of the six models were evaluated using area under the curve of receiver operating characteristic plot (AUC_{ROC}) (Hosmer & Lemeshow, 2013), Pearsons's correlation between predicted and observed species presence-absence data (COR), true skills statistics (TSS) (Allouche *et al.*, 2006) and deviance (Lobo *et al.*, 2008). This was important in evaluating the model specificity and sensitivity. Specificity is the ability of a model to predict absence in a location while sensitivity is the ability of a model to predict presence in a location (Zurell, 2020).

Green Gram Habitat Suitability Predictions

The ensemble of the developed models was used for predicting green gram habitat suitability under present scenario, RCP 4.5 and RCP 8.5 climate scenarios. This was carried out with the assumption that the species are at equilibrium with the environment and that they should also respond dynamically to global change show transient dynamics (Urban *et al.*, 2016; Zurell, 2017). To make predictions for Kibwezi East, bioclimatic datasets from the predicted future data were cropped to scale down to Kibwezi East boundary coordinates accessed from Global Administrative Areas (GADM) version 4.1 (www.gadm.org). Green gram habitat suitability predictions were carried out using *ensemble* function of *sdm* package in R. These predictions were visualized using plots plotted from the predicted results using *ggplot2* package in R. Three final suitability maps were presented under the present scenario, RCP 4.5 and RCP 8.5 climate scenarios as proposed by the IPCC AR5 (Mastrandrea *et al.*, 2011; Noce *et al.*, 2017). Percentage suitability change was computed in R.

RESULTS

Green gram distribution and presence data across the world indicated that the crop is majorly grown in the Asian countries and Australia (Figure 2). The green gram presence data used for modelling covered all global geographic areas suitable for its growth. The use of global green gram presence data increases environmental variability which enhances the reliability of the developed model. Species can only survive in geographic areas where both the abiotic and biotic conditions allow positive plant population growth of that particular species (Zurell, 2020).

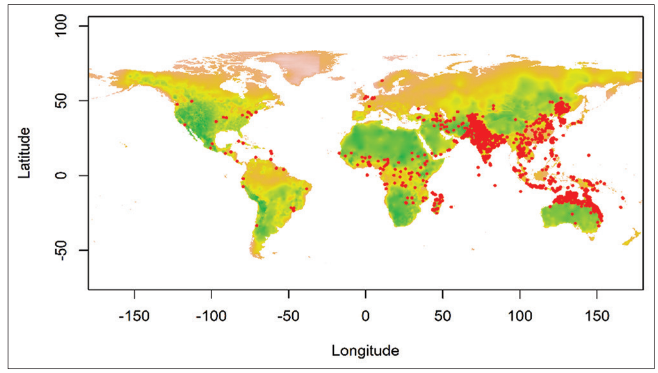

Figure 2: Plot of green gram presence across the world

Relative variable importance averaged over the six models was used to make an ensemble is shown in Figure 3. Out of nine bioclimatic variables, four had the highest contribution to the ensemble (Figure 3). Among these variables, bio9 (Mean Temperature of Driest Quarter) had the highest mean relative variable importance in the development of green gram habitat suitability ensemble model. This bioclimatic variable provides the mean temperature during the driest three months of the year. The second highest mean relative important variable in this study was bio3 (Isothermality) while bio14 (Precipitation of Driest Month) had the lowest mean relative variable importance.

Validation statistics showed that all models that were developed were robust (Table 2). Based on AUC_{ROC} values, the least was 0.87 for glm and highest was 0.98 for rf model. The highest COR values were (0.89) for the rf model while the least value was (0.65) for glm model. Trues Skill Statistic (TSS) values ranged from 0.59 for glm to 0.88 for rf. The Deviance values ranged from 0.29 for rf model to 0.94 for maxent model.

The AUC_{ROC} plots show AUC means for training and testing sets (Figure 4). From these plots, the training and testing AUC values for all models fitted well. The highest values were for the rf model where training set AUC value was 1 and testing AUC value was 0.98. The least values were in glm model with training set AUC value of 0.87 and testing AUC value of 0.87.

Figure 5 shows green gram habitat suitability plot for the present climatic scenario. This figure was plotted from results predicted using the developed ensemble model. The results showed that green gram habitat suitability was high in Ivingoni/Nzambani, Thange and Masongaleni wards. However, the western parts of Ivingoni/Nzambani and Thange wards had medium habitat suitability for green gram. A greater part of Mtito Andei ward had medium green gram habitat suitability with a small section of its southern part having very low habitat suitability.

In the year 2050s under RCP 4.5 climate scenario, the results (Figure 6) revealed loss in habitat suitability compared to present climatic scenario as shown in Figure 5. The habitat suitability for growing green grams in the western parts of Ivingoni/Nzambani and Thange wards greatly reduced from relatively

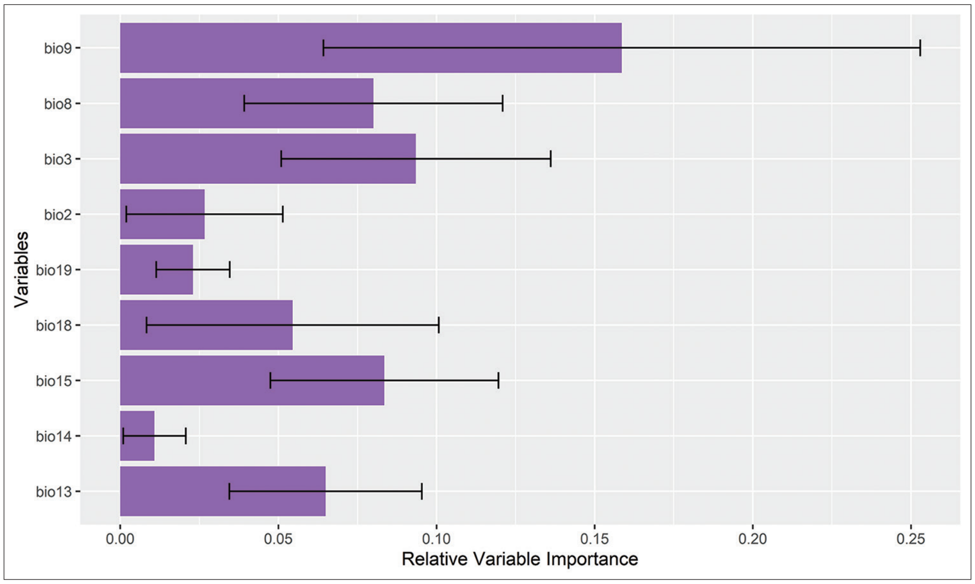

Figure 3: Relative variable importance averaged over six models

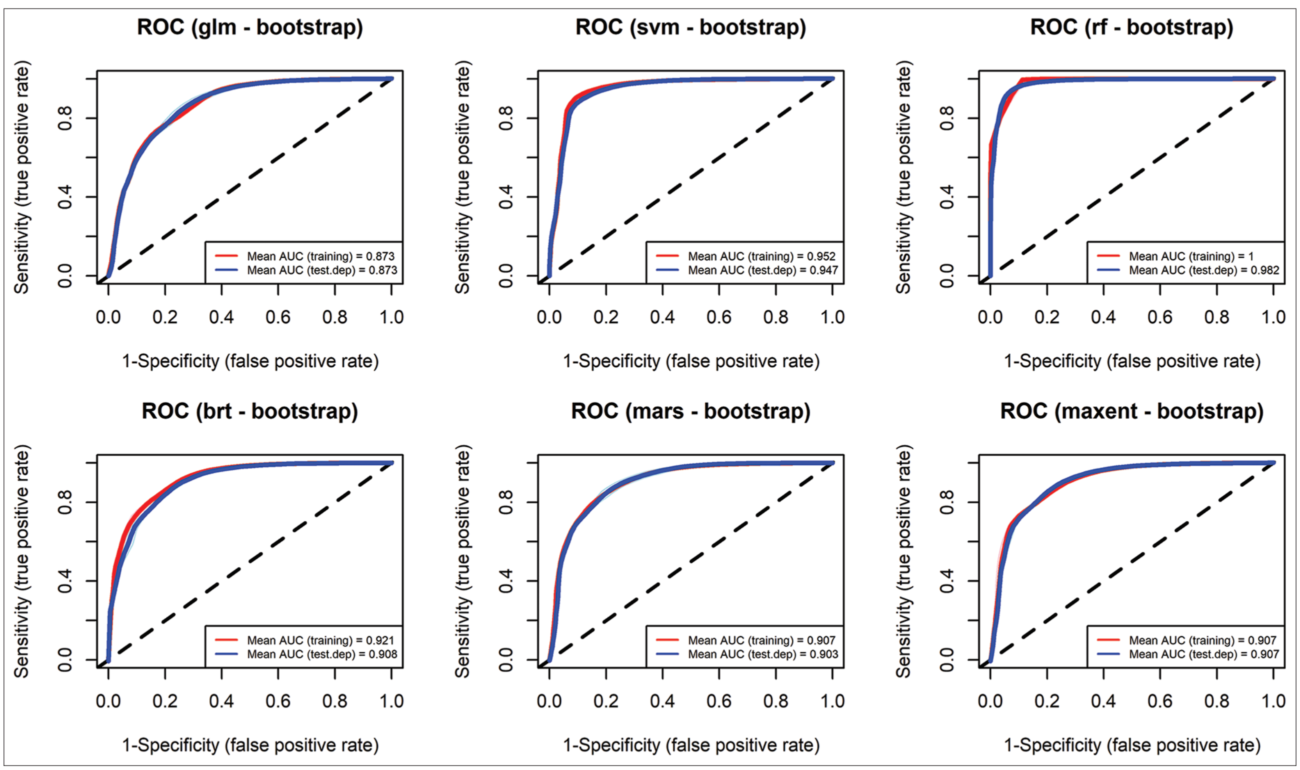

Figure 4: ROC curves with AUC values for training and testing sets

Table 2: Model evaluation Statistics

Models	AUC_{ROC}	COR	TSS	Deviance
GLM	0.87	0.65	0.59	0.71
SVM	0.95	0.81	0.8	0.45
RF	0.98	0.89	0.88	0.29
BRT	0.91	0.71	0.67	0.75
MARS	0.9	0.71	0.66	0.61
MAXENT	0.91	0.7	0.67	0.94

high to medium and low. In Mtito Andei ward, there was loss of suitability making it unsuitable for green gram production. Habitat suitability for green gram production increased from medium to high in the central parts of the study area.

Predicted climate data for the 2050s showed that green gram habitat suitability reduced greatly under RCP 8.5 compared to RCP 4.5 climate scenario (Figure 7). This was evident in Mtito

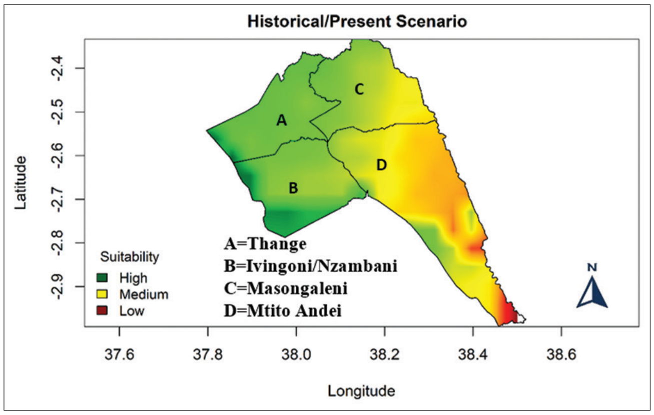

Figure 5: Green gram habitat suitability in Kibwezi East under historical /near present climate scenario

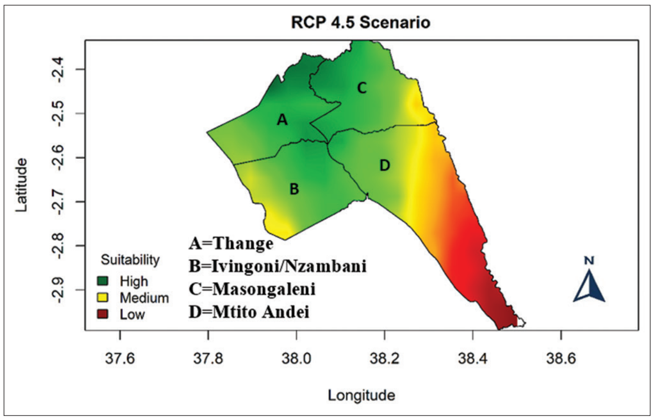

Figure 6: Green gram suitability in Kibwezi East under RCP 4.5 scenario

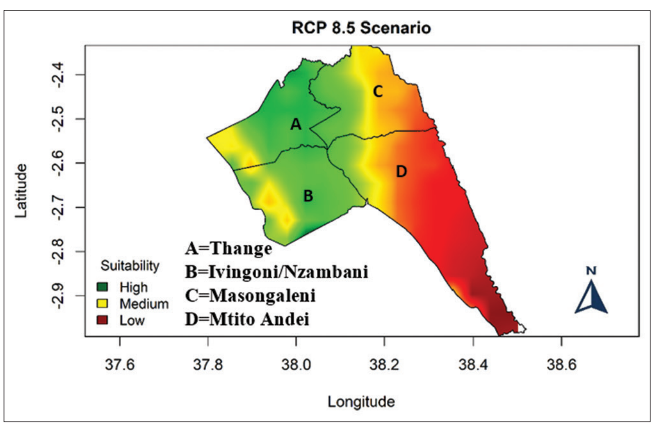

Figure 7: Green gram suitability in Kibwezi East under RCP 8.5 scenario

Andei and the eastern parts of Masongaleni wards. Green gram habitat suitability in the western parts of Ivingoni/Nzambani and Thange wards was predicted to reduce from Medium to low. In (Figure 7), suitability in the central part of the sub county appears to decrease from high to medium. Overall, the predictions in the 2050s under RCP 8.5 climate scenario show that about 50% of the study location will have low habitat suitability for green gram production, about 25% will have medium suitability and the remaining 25% will have high habitat suitability for green gram production.

Table 3 shows the predicted habitat suitability change in percentage. The results show that the habitat suitability will change by 10.24% from the present climatic scenario to RCP 4.5 scenario in the 2050s. However, under the RCP 8.5 climatic scenario the suitability will change by 18.8% from the present scenario.

DISCUSSION

An ensemble of six species distribution models was developed and used to predict future green gram habitat suitability under RCP 4.5 and RCP 8.5 climate scenarios. In model development, variable importance is used to indicate the degree at which that variable affects the response value (Inglis *et al.*, 2022). Among the standard bioclimatic (bio) variables used, bio9 had the highest variable importance averaged across the 6 models while bio14 had the lowest. Therefore, bio9 which contains the mean temperature of driest quarter significantly varied across geographical regions and consequently, it had the highest contribution to the model (Xie & Zhang, 2023). The developed model had 6 out of 9 predictors with high variable importance. This implied that the model was robust. This result on relative variable importance revealed the relative importance of each environmental factor in affecting species distributions (O'Donnell & Ignizio, 2012). Based on this result, it was concluded that the mean temperature during the driest three months of the year (bio9) contributes most to green gram habitat suitability.

Model validation results revealed that all models in the ensemble were robust in predicting green gram habitat suitability. The model validation statistics showed that the least robust model had $AUC_{ROC} = 0.85$. Validity of a model can be effectively measured using its sensitivity and specificity components (Kumar & Indrayan, 2011). This method relies on receiver operating characteristic curve (ROC) and depicts the trade-off between sensitivity and (1-specificity) across a series of points (Gajowniczek *et al.*, 2014). A high AUC_{ROC} value was an indication that the developed model was robust to use in the prediction of habitat suitability (Kumar & Indrayan, 2011). Based on AUC_{ROC} statistics, all models were reliable. The COR statistics is the Pearson's correlation between the predicted and observed species presence-absence data. A model is more robust when the COR values approaches one and less robust when this value approaches zero (Han & Liu, 2017). High COR values indicates that the models fitted the predicted and observed values well (Smith & Santos, 2020). In the developed models, the COR values ranged between 0.65 and 0.89 indicating that the models were robust.

Another metric used for model evaluation is True Skill Statistic (TSS). This is the most effective metric that is employed in validating species distribution models (Yoon & Lee, 2023). Calculation of TSS involves a confusion matrix composed of number of correct and incorrect predictions of species presence-

Table 3: Predicted Percent Habitat suitability change

Base	Predicted	Suitability Change
Present suitability	RCP 4.5	10.24%
Present suitability	RCP 8.5	18.80%

absence data (Allouche *et al.*, 2006). This method accounts for sensitivity, specificity and accuracy and therefore, it is the most practical metric. In this study, the results show that the TSS values ranged between 0.59 and 0.88 and therefore, the models were reliable for habitat suitability prediction. The last metric used to evaluate the models was Deviance. Deviance is a measure of error and therefore, lower values means that the model fits well (Di Mari *et al.*, 2023). In the results, out of the six models, four had Deviance values of more than 0.60. Based on this metric, the individual models did not perform well. It is on this premise that ensemble of models becomes helpful. An ensemble combines all sources of error from the various models and works on it to improve the accuracy of prediction (Buisson *et al.*, 2010; Taleshi *et al.*, 2019). Therefore, based on high accuracy of developed models and the use of the ensemble of the six models to fix uncertainties, the final ensemble model was highly reliable to predict green gram habitat suitability in Kibwezi East and other regions with similar agro climatic conditions. This accuracy is attributed to the use of predictors from wide geographical regions across the world and the application of an ensemble of models.

This research shows that climate change will have a great impact on green gram habitat suitability in Kibwezi East sub-county. Effects of climate change will significantly contribute to green gram habitat suitability loss. The result shows that habitat suitability will reduce by 18.8% in RCP 8.5 and 10.24% in RCP4.5. High habitat suitability loss in RCP 8.5 compared to RCP 8.5 scenario is due to high emissions of greenhouse gas from anthropogenic sources. This leads to increased temperatures in RCP 8.5 climate scenario compared to RCP 4.5 scenario. Green gram habitat suitability will greatly reduce in Mtito Andei and the western part of Ivingoni/Nzambani and Thange.

Habitat suitability models assess the environmental conditions and factors that influence the growth and development of crops. These models can identify areas with the most favorable conditions for crop cultivation. This information is invaluable for farmers in selecting suitable sites for planting, maximizing crop yield potential and minimizing risks associated with environmental constraints and climate change. They also aid in land use planning and management, helping to allocate resources efficiently and sustainably (Dastres *et al.*, 2023).

The models facilitate risk assessment by identifying potential yield-limiting factors and guiding adaptation strategies to adapt to their impacts (James *et al.*, 2017).

Applying habitat suitability models in green gram farming is essential for optimizing production, ensuring sustainability, and building resilience against risks associated with climate change. These models empower farmers with valuable insights into site suitability, crop performance and adaptation strategies, ultimately contributing to improved livelihoods and food security in green gram-producing regions.

CONCLUSION

The results indicated that the habitat suitability for green gram production in Kibwezi East was well described by the selected predictors. Based on the evaluation statistics, all single models were included in the final ensemble forecasting model. The model that was developed will provide information on the current situation in green gram production and prediction on future performance of the crop under the various climate change scenarios and emission trajectories. It is a very important tool for decision making on green gram cropping management systems in the arid and semiarid lands as well as in development of climate change mitigation and adaptation strategies. Climate change effects are experienced differently in different places. The analysis for Kibwezi east Sub County predicts a decline in habitat suitability. This calls for adaptation strategies as well as climate mitigation strategies. Joint efforts by all stakeholders are needed to devise the strategies because green gram is a major crop in this location. The study presents the importance of conducting the analysis at the biogeographic level since the effects of climate change are experienced differently in every area and require engagement and conservation policies at the local level.

ACKNOWLEDGEMENTS

The authors wish to thank the county agriculture officers in Kibwezi East Sub-County who helped in institutional support and administrative assistance throughout the study as well as the respondents in the Sub County who participated in data provision through interviews and focus group discussions. Special thanks to Wilfred Abincha and Dr. Murenga Mwimali for the insights offered in putting this study into perspective.

REFERENCES

Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology, 43*(6), 1223-1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x

Buisson, L., Thuiller, W., Casajus, N., Lek, S., & Grenouillet, G. (2010). Uncertainty in ensemble forecasting of species distribution. *Global Change Biology, 16*(4), 1145-1157. https://doi.org/10.1111/j.1365-2486.2009.02000.x

Chan, J. Y.-L., Leow, S. M. H., Bea, K. T., Cheng, W. K., Phoong, S. W., Hong, Z.-W., & Chen, Y.-L. (2022). Mitigating the multicollinearity problem and its machine learning approach : A review. *Mathematics, 10*(8), 1283. https://doi.org/10.3390/math10081283

Dastres, E., Bijani, F., Naderi, R., Zamani, A., & Edalat, M. (2023). Evaluating the habitat suitability modeling of Aceria alhagi and Alhagi maurorum in their native range using machine learning techniques. *Research Square*. https://doi.org/10.21203/rs.3.rs-2441475/v1

del Río, S., Canas, R., Cano, E., Cano-Ortiz, A., Musarella, C., Pinto-Gomes, A., & Penas, A. (2021). Modelling the impacts of climate change on habitat suitability and vulnerability in deciduous forests in Spain. *Ecological Indicators, 131*, 108202. https://doi.org/10.1016/j.ecolind.2021.108202

Di Mari, R., Ingrassia, S., & Punzo, A. (2023). Local and Overall Deviance

R-Squared Measures for Mixtures of Generalized Linear Models. *Journal of Classification, 40*, 233-266. https://doi.org/10.1007/s00357-023-09432-4

Fick, S. E., & Hijmans R. J. (2017). WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. *International Journal of Climatology, 37*(12), 4302-4315. https://doi.org/10.1002/joc.5086

Freeman, E. A., & Moisen, G. G. (2008). A comparison of the performance of threshold criteria for binary classification in terms of predicted prevalence and kappa. *Ecological Modelling, 217*(1-2), 48-58. https://doi.org/10.1016/j.ecolmodel.2008.05.015

Gajowniczek, K., Ząbkowski, T., & Szupiluk, R. (2014). Estimating the Roc Curve and Its Significance for Classification Models' Assessment. *Quantitative Methods in Economics, XV*(2), 382-391.

GoK. (2013). *Makueni County First County Integrated Development Plan 2013-2017*. Government of Kenya, Nairobi.

Gould, S. F., Nicholas, J. B., Harris, R. M. B., Michael, F. H., Lechner, A. M., Porfirio, L. L., & Mackey, B. G. (2014). A tool for simulating and communicating uncertainty when modelling species distributions under future climates. *Ecology and Evolution, 4*(24), 4798-4811. https://doi.org/10.1002/ece3.1319

Halder, J. (2013). Land Suitability Assessment for Crop Cultivation by Using Remote Sensing and GIS. *Journal of Geography and Geology, 5*(3), 65-74. https://doi.org/10.5539/jgg.v5n3p65

Han, F., & Liu, H. (2017). Statistical analysis of latent generalized correlation matrix estimation in transelliptical distribution. *Bernoulli, 23*(1), 23-57. https://doi.org/10.3150/15-BEJ702

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning. New York, US: Springer. https://doi.org/10.1007/978-0-387-84858-7

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied Logistic Regression. (3rd ed). New York, US: John Wiley & Sons, Inc. https://doi.org/10.1002/9781118548387

Inglis, A., Parnell, A., & Hurley, C. B. (2022). Visualizing Variable Importance and Variable Interaction Effects in Machine Learning Models. *Journal of Computational and Graphical Statistics, 31*(3), 766-778. https://doi.org/10.1080/10618600.2021.2007935

IPCC. (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Retrieved from https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-FrontMatterA_FINAL.pdf

James, W. J., Antle, J. M., Basso, B., Boote, K. J., Conant. F. I., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., & Wheeler, T. R. (2017). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural Systems, 155*, 269-288. https://doi.org/10.1016/j.agsy.2016.09.021

Jarvie, S., & Svenning J.-C. (2018). Using species distribution modelling to determine opportunities for trophic rewilding under future scenarios of climate change. *Philosophical Transactions of the Royal Society B Biological Sciences, 373*(1761), 20170446. https://doi.org/10.1098/rstb.2017.0446

Kufa, C. A., Bekele, A., & Atickem, A. (2022). Impacts of climate change on predicted habitat suitability and distribution of Djaffa Mountains Guereza (*Colobus guereza gallarum*, Neumann 1902) using MaxEnt algorithm in Eastern Ethiopian Highland. *Global Ecology and Conservation, 35*, e02094. https://doi.org/10.1016/j.gecco.2022.e02094

Kumar, R., & Indrayan, A. (2011). Receiver operating characteristic (ROC) curve for medical researchers. *Indian Pediatrics, 48*, 277-287. https://doi.org/10.1007/s13312-011-0055-4

Latif, Q. S., Saab, V. A., Dudley, J. G., & Hollenbeck, J. P. (2013). Ensemble modeling to predict habitat suitability for a large-scale disturbance specialist. *Ecology and Evolution, 3*(13), 4348-4364. https://doi.org/10.1002/ece3.790

Lobo, J. M., Jiménez-Valverde, A., & Real, R. (2008). AUC: A misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography, 17*(2), 145-151. https://doi.org/10.1111/j.1466-8238.2007.00358.x

Mastrandrea, M. D., Mach, K. J., Plattner, G.-K., Edenhofer, O., Stocker, T. F., Field, C. B., Ebi, K. L., & Matschoss, P. R. (2011). The IPCC AR5 guidance note on consistent treatment of uncertainties: A common approach across the working groups. *Climatic Change, 108*(675), https://doi.org/10.1007/s10584-011-0178-6

Mugo, J. W., Kariuki, P. C., & Musembi, D. K. (2016). Identification of Suitable Land for Green Gram Production Using GIS Based Analytical Hierarchy Process in Kitui County, Kenya. *Journal of Remote Sensing & GIS, 5*, 1000170.

Mugo, J. W., Opijah, F. J., Ngaina, J., Karanja, F., & Mburu, M. (2020). Suitability of Green Gram Production in Kenya under Present and Future Climate Scenarios Using Bias-Corrected Cordex RCA4 Models. *Agricultural Sciences, 11*(10), 882-896. https://doi.org/10.4236/as.2020.1110057

Nair, R. M., Schafleitner, R., Kenyon, L., Srinivasan, R., Easdown, W., Ebert, A. W., & Hanson, P. (2012). Genetic improvement of mungbean. *Sabrao Journal of Breeding and Genetics, 44*(2), 177-190.

Noce, S., Caporaso, L., & Santini, M. (2019). Climate change and geographic ranges: The implications for Russian forests. *Frontiers in Ecology and Evolution, 7*, 57. https://doi.org/10.3389/fevo.2019.00057

Noce, S., Collalti, A., & Santini, M. (2017). Likelihood of changes in forest species suitability, distribution, and diversity under future climate: the case of Southern Europe. *Ecology and Evolution, 7*(22), 9358-9375. https://doi.org/10.1002/ece3.3427

O'Donnell, M. S., & Ignizio, D. A. (2012). *Bioclimatic predictors for supporting ecological applications in the conterminous*. United States: U.S. Geological Survey Data Series. Retrieved from https://pubs.usgs.gov/ds/691/ds691.pdf

Smith, A. B., & Santos, M. J. (2020). Testing the ability of species distribution models to infer variable importance. *Ecography*, *43*(12), 1801–1813. https://doi.org/10.1111/ecog.05317

Taleshi, H., Jalali, S. G., Alavi, S. J., Hosseini, S. M., Naimi, B., & Zimmermann, N. E. (2019). Climate change impacts on the distribution and diversity of major tree species in the temperate forests of Northern Iran. *Regional Environmental Change, 19*, 2711-2728. https://doi.org/10.1007/s10113-019-01578-5

Urban, M. C., Bocedi, G., Hendry, A. P., Mihoub, J.-B., Pe'er, G., Singer, A., Bridle, J. R., Crozier, L. G., De Meester, L., Godsoe, W., Gonzalez, A., Hellmann, J. J., Holt, R. D., Huth, A., Johst, K., Krug, C. B., Leadley, P. W., Palmer, S. C. F., Pantel, J. H., Travis, J. M. (2016). Improving the forecast for biodiversity under climate change. *Science, 353*(6304), aad8466. https://doi.org/10.1126/science.aad8466

Vieilledent, G., Cornu, C., Sanchez, A. C., Pock-Tsy, J.-M. L., & Danthu, P. (2013).Vulnerability of baobab species to climate change and effectiveness of the protected area network in Madagascar: Towards new conservation priorities. *Biological Conservation, 166*, 11-22. https://doi.org/10.1016/j.biocon.2013.06.007

Xie, S., & Zhang, J. (2023). TOPSIS-based comprehensive measure of variable importance in predictive modelling. *Expert Systems with Applications, 232*, 120682. https://doi.org/10.1016/j.eswa.2023.120682

Yoon, S., & Lee, W.-H. (2023). Application of true skill statistics as a practical method for quantitatively assessing CLIMEX performance. *Ecological Indicators, 146*, 109830. https://doi.org/10.1016/j.ecolind.2022.109830

Zhang, L., Liu, S., Sun, S., Wang, T., Wang, G., Zhang, X., & Wang, L. (2015). Consensus forecasting of species distributions: The effects of niche model performance and niche properties *Plos One, 10*(3), e0120056. https://doi.org/10.1371/journal.pone.0120056

Zurell, D. (2017). Integrating demography, dispersal and interspecific interactions into bird distribution models. *Journal of Avian Biology, 48*(12), 1505-1516. https://doi.org/10.1111/jav.01225

Zurell, D. (2020). *Introduction to Species Distribution Modelling (SDR) in R*. Retrieved from https://damariszurell.github.io/SDM-Intro