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Ecological determinants and risk areas of *Striga hermonthica* infestation in western Kenya under changing climate

Emily Kimathi[1,2] | **Elfatih M. Abdel-Rahman**[1] | **Catherine Lukhoba**[3] | **Asaah Ndambi**[4] | **Bester Tawona Mudereri**[1] | **Saliou Niassy**[1] | **Henri E. Z. Tonnang**[1] | **Tobias Landmann**[1]

[1]International Centre of Insect Physiology and Ecology (*icipe*), Nairobi, Kenya

[2]Faculty of Science and Technology, Department of Earth and Climate Sciences, University of Nairobi, Nairobi, Kenya

[3]Wageningen Livestock Research, Wageningen University and Research, Wageningen, Netherlands

[4]Faculty of Science and Technology, Department of Biology, University of Nairobi, Nairobi, Kenya

Correspondence
Emily Kimathi, International Centre of Insect Physiology and Ecology (*icipe*), P.O. Box 30772, Nairobi 00100, Kenya.
Email: ekimathi@icipe.org

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Abstract

Striga hermonthica (Del.) Benth is a parasitic weed that is damaging major cereal crops in sub-Saharan Africa (SSA). Although *Striga* is recognised as an agricultural scourge, there is limited information available indicating the extent of its growth and spread as impacted by the changing climate in Kenya. This study investigated the impact of current climate conditions and projected future (2050) climate change on the infestation of *Striga hermonthica* in the western Kenya region. Specifically, the study aimed to predict *Striga hermonthica* habitat suitability in five counties in the western Kenya region through using the maximum entropy (MaxEnt) model and bioclimatic, soil, topographic and land use, and land cover (LULC) variables. *Striga hermonthica* geolocations were collected and collated and ecological niche models were developed to determine the habitat suitability. The results showed that approximately 1767 km^2 (10% of the total study area) is currently highly suitable for *Striga hermonthica* occurrence. The future projections showed a range between 2106 km^2 (19% of the total study area) and 2712 km^2 (53% of the total study area) at the minimum carbon (RCP 2.6) and the maximum carbon emission scenarios (RCP 8.5) respectively. Elevation, annual precipitation, LULC, temperature seasonality and soil type were determined to be the most influential ecological predictor variables for *Striga hermonthica* establishment. The study revealed the importance of using climate, soil, topographic and LULC variables when evaluating agricultural production constraints such as *Striga*'s prevalence. The methodology used in this study should be tested in other *Striga* affected areas.

KEYWORDS
agriculture productivity, ecological niche models, food security, maize, maximum entropy, weed infestation

1 | INTRODUCTION

Poverty reduction and food security continue to be the focal points for policies on agriculture and rural development in sub-Saharan Africa (SSA) (AGRA, 2017). Improving agricultural productivity has a great potential for increasing food and nutrition security and simultaneously reducing poverty levels in the region (Diao et al., 2010). Studies have shown that in Africa, there is a large yield gap between the potential optimal crop yield and the current attainable yield (van Ittersum et al., 2016). These yield gaps are caused by biotic and abiotic factors and other multiple sub-optimal crop management strategies like timing, spatial arrangement of crop establishment, fertiliser application, quality of seeds and crop variety. Some of the major biotic and abiotic constraints, include climate change, crop diseases, insect pests, and parasitic weeds like *Striga*. *Striga* is an obligate root hemiparasitic plant from the family Orobanchaceae which attaches to the root system of the host plants, creating a phytotoxic effect (Bellis et al., 2021). The parasitic weed causes harm to the host plant by siphoning water and nutrients, thus causing stunting, chlorosis, wilting and yield reduction (Spallek et al., 2013).

Striga infestation affects approximately 300 million people and over 50 million hectares of smallholder farmlands in Africa, causing approximately 20%–80% yield losses and often total crop failure (AATF, 2006). However, these estimates are likely to be inaccurate and the current extent of *Striga* infestation and magnitude of crop losses is unknown. Globally, *Striga* is the most economically important parasitic weed since it affects staple food crops including maize, millet, sorghum, and rice (Muranaka et al., 2017). Over 35 different species of *Striga* are documented, with approximately 80% of them occurring in the tropical belt of Africa (Mohamed et al., 2001). The two *Striga* species causing massive yield losses across Africa are *Striga hermonthica* (Del.) Benth and *Striga asiatica* (L.) Kuntze. *Striga hermonthica* has a higher prevalence in central, eastern, and western Africa, while *Striga asiatica* is mostly prevalent in southern and central Africa (Rodenburg et al., 2016). In Kenya, *Striga hermonthica* is widespread and endemic in the western region, especially around the Lake Victoria basin. The geographic extent and intensity of *Striga* are projected to increase as the suitable conditions for the parasitic weed's growth are projected to expand with envisaged climatic changes (Mudereri, Dube, et al., 2020). Despite the recognition of the problem and projection, there is inadequate information available to monitor and forecast its occurrence and distribution shift in the face of climate change. Therefore, predicting future changes in distribution would provide information needed for proactive planning for interventions and control.

Introduced plant species tend to have high resilience and adaptability to diverse climatic conditions, thus making them more competitive than native co-occurring plants (Amare, 2016). The geographical distribution of most weeds is largely influenced by climate, which determines the successful invasion of new environments. Increased temperatures thus affect the occurrence and distribution of parasitic weeds (Scott et al., 2020). *Striga* seeds require a certain set of conditions to germinate, including optimal soil moisture and temperature conditions, and signalling compounds, which are exuded by the host roots (Jamil et al., 2011). Considering climate change, increase in *Striga* infestation will result in complicated crop-weed biotic interactions that will necessitate urgent adaptive interventions (Mandumbu et al., 2017). Therefore, our hypothesis assumed that climate change will play an important role in increasing the severity and spread of *Striga* in the future.

Various interventions have been developed to curb the problem of *Striga* infestation in SSA (Jamil et al., 2021). The implementation and upscaling of *Striga* management strategies, however, require knowledge on the spatial extent of *Striga* and its suitable niche sites. The knowledge of the spatial distribution and intensity of *Striga* will enable the farmers to determine where to apply the right integrated *Striga* management (ISM) intervention to control the parasitic weeds. This will in turn create resilient agro-ecological systems, creating a ripple effect that will increase cereal crop yields and the income for farmers, hence improving their livelihoods.

Studies have demonstrated that the spatial distribution of parasitic weeds can be predicted through ecological niche modelling (ENM) approaches using environmental variables as proxies for the prediction (Cotter et al., 2012; Sadda et al., 2021). The ENMs statistically correlate environmental variables with plant or other species observations by assessing the spatial variabilities (Elith et al., 2011). By using advanced ENM machine learning algorithms, such as maximum entropy (MaxEnt), the priority and buffer zones around high incidence areas of *Striga* that require urgent control operations can be identified over larger areas (Sadda et al., 2021). Predictive models of *Striga* occurrence could complement the field efforts and produce information that is more concise regarding areas that require priority attention during interventions (Cotter et al., 2012). In the case of *Striga*, it is possible that some areas might present suitable conditions, but the infestation is not yet established. Therefore, some of the suitable localities that are identified by the ENMs could represent areas where *Striga* is already occurring or could occur in the future.

There are several studies that have specifically used ENM tools to predict and map *Striga* infestation and suitable habitats in Africa (Cotter et al., 2012; Sadda et al., 2021). However, none of the studies has utilised ENMs to predict the spatial distribution and suitability of *Striga hermonthica* in Kenya. Nevertheless, previous studies have used ground-based (Mudereri, Dube, et al., 2020) and satellite-based (Mudereri, Abdel-Rahman, et al., 2021) remotely sensed data to detect the spectral features of *Striga hermonthica* only, as *Striga asiatica* is not detectable owing to its height, which is shorter than the host canopy. Although these studies accurately mapped *Striga* in agro-ecology systems, detection of the *Striga* spectral signature was challenging, particularly as the parasitic weed is attached to the host plant. Furthermore, for accurate *Striga* spectral signature detection, the exercise should be conducted during its flowering stage when it is visible. This is at a late stage for managing *Striga* during the cropping season; hence, a decision-support system is needed that uses geospatial modelling approaches like MaxEnt to inform the farmers about the suitable habitats for the parasitic weed.

The aim of the present study was, therefore, to predict *Striga hermonthica* habitat suitability in western Kenya region through using MaxEnt model and bioclimatic, land use/land cover (LULC), and soil variables. The landscape structure provided by the LULC affords valuable information for predicting the habitat suitability of species, as often the host crops are among the main classes in LULC layers (Mudereri, Kimathi, et al., 2021).

2 | MATERIALS AND METHODS

2.1 | Study area

The study was conducted in five counties in the western region of Kenya (Figure 1) where *Striga* infestation is prevalent

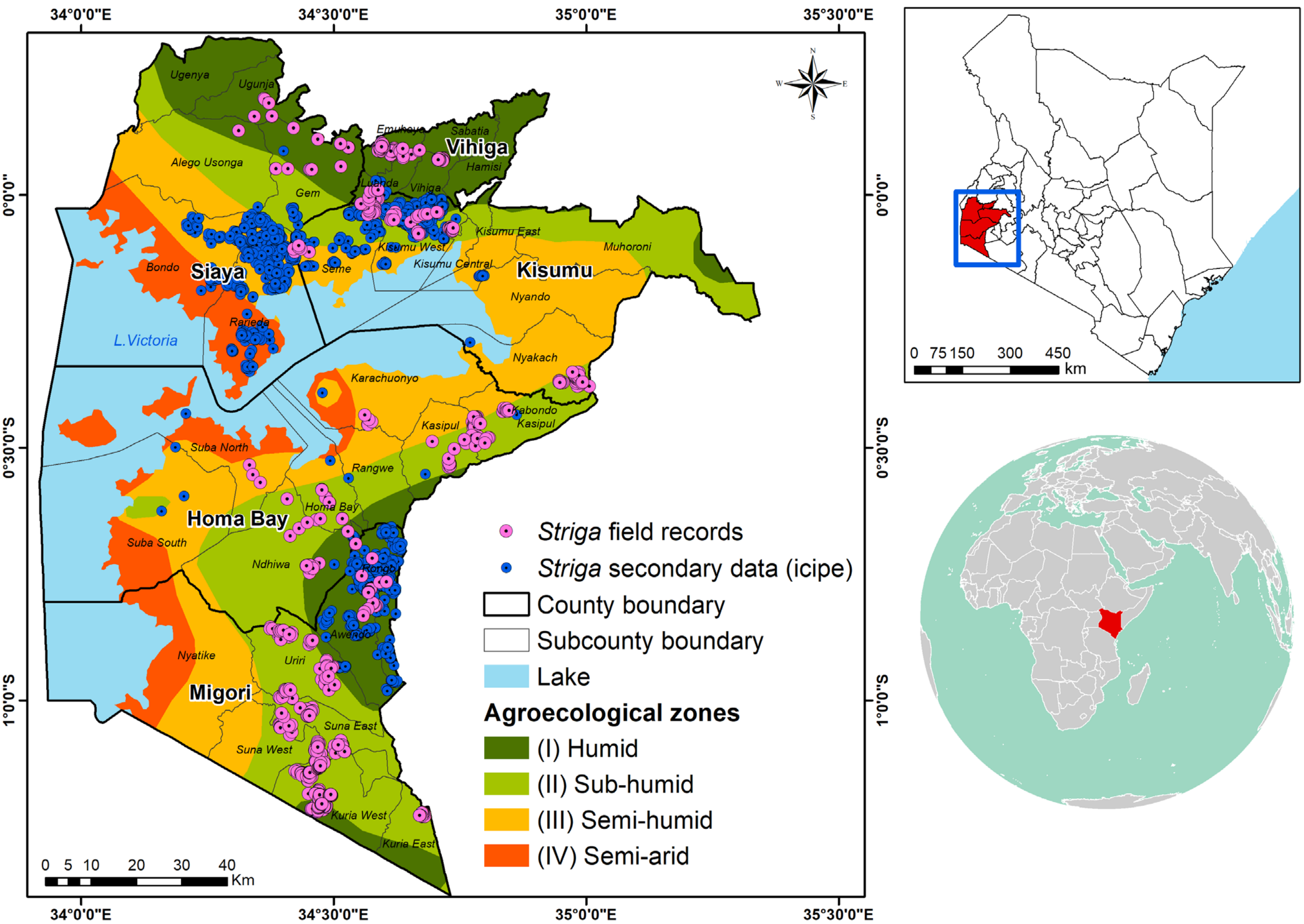


FIGURE 1 Spatial distribution of occurrence records of *Striga* in western Kenya overlaid on the four agro-ecological zones sourced from the United Nations Environmental Programme (UNEP) (https://www.unep.org). The insets indicate the position of the study region in Kenya and the globe. The map was generated using QGIS 3.3 software.

namely: Migori, Homabay, Kisumu, Vihiga and Siaya (Midega et al., 2017). The counties cut across four agro-ecological zones: humid, sub-humid, semi-humid and semi-arid. The average annual rainfall received in western Kenya region ranges between 900 mm and 1988 mm with an annual mean temperature of 24.3–31.7°C (Fick & Hijmans, 2017). The region experiences a bimodal rainfall pattern where it receives long rains between the months of March to May and short rains from October to December (Mugalavai et al., 2008). The region's agro-natural ecology is dominated by dispersed savanna grasslands in combination with deciduous and exotic forest, with subsistence and small-scale farming being the primary agricultural activity. Maize (*Zea mays*) is the major staple and cash crop in the region. It is grown in two seasons (March to August and September to January) of each year. Other crops grown include beans (*Phaseolus vulgaris*), groundnuts (*Arachis hypogaea*), green gram (*Vigna radiata*), cassava (*Manihot esculenta*), mango (*Mangifera indica*), banana (*Musa acuminata*), avocado (*Persea americana*), pawpaw (*Asimina triloba*), and indigenous vegetables.

2.2 | *Striga* occurrence data

A field survey was conducted in the five study counties to collect *Striga hermonthica* occurrence data between December 2018 and January 2019. A purposive sampling approach was adopted during the field survey to target 160 maize fields infested with *Striga hermonthica* in the study area (Figure 1). The *Striga hermonthica* occurrence observations were collected during the flowering season for easier visualisation of the parasitic weed in the maize croplands. A global positioning system (GPS) of ≤ ± 3 m accuracy was used to geotag the maize sampled fields. The sampled fields were spaced at a minimum distance of 1–3 km to ensure a good spatial distribution. In addition, 1000 *Striga hermonthica* infested fields were sourced from the international centre of insect physiology and ecology (*icipe*) database (Midega et al., 2017) as secondary *Striga* occurrence data for evaluating our model's performance. In this regard, a total of 1160 *Striga hermonthica* georeferenced records were used in the present study (Figure 1).

2.3 | Predictor variables

The climatic, edaphic, topographic, and LULC variables used to predict the habitat suitability of *Striga hermonthica* are summarised in Supplementary S1. These climatic, edaphic, and topographic variables were considered for the modelling experiment with previous knowledge of their influence on the habitat suitability of the *Striga* species (Scott et al., 2020). The LULC variable was included to provide information on the distribution of *Striga*, and host crops within the cropland class. The predictor variables were all pre-processed and resampled to a spatial resolution of 250 m to harmonise them to the same spatial resolution. Hence, the *Striga* habitat suitability was predicted as a probability of occurrence within each 250 × 250 m grid cell.

2.3.1 | Climate variables

Climatic variables were sourced from the worldclim global climate data repository (https://worldclim.org) for both current and future (2050) climate scenarios (Supplementary S1). The expected future changes for these climatic variables were projected by using downscaled data, averaged for the climate scenarios for years 2041–2060. Specifically, this study used 2.6 and 8.5 representative concentration pathways (RCP) that were developed during the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report (IPCC, 2014). The 2.6 RCP represents a conservative pathway that projects a decline in carbon dioxide (CO_2) emissions at an approximate rate of 2 Gigatons of CO_2 per year, which will keep the global rise in temperatures below 2°C by 2100 (van Vuuren et al., 2011). On the other hand, the 8.5 RCP represents the worst-case climate scenario, where the CO_2 emissions are projected to steadily rise to a radiative forcing of 8.5 W/m^2, causing the global temperatures to rise above 2°C (Riahi et al., 2011). In general, these pathways were estimated through using the global circulation model (GCM), but for this study the Hadley Centre Global Environment Model Version 2 (HadGEM2-ES) was selected because of its good performance in simulating precipitation and temperature patterns on the African continent (Dike et al., 2015).

2.3.2 | Edaphic variables

Five soil variables, namely sand content, soil organic carbon content, soil nitrogen, soil pH and soil types were sourced from the International Soil Reference and Information Centre (ISRIC) data hub (https://data.isric.org). The dataset consisted of gridded data developed using 28 000 soil ground observations at six soil depth intervals in combination with many covariates to develop prediction models of various soil properties (Hengl et al., 2017). The data are provided at a spatial resolution of 250 m in Africa. These soil parameters were selected for use in this study because they are key in revealing soil fertility, water retention capacity, and texture. Studies have shown that low soil fertility can result in high *Striga* infestation rates (Bellis et al., 2020).

2.3.3 | Land use and land cover (LULC) and digital elevation model (DEM)

In addition to the climatic and soil variables, the study also utilised 20-m LULC prototype data that were developed by the European Space Agency (https://www.esa-landcover-cci.org/). Moreover, a digital elevation model (DEM) was sourced from shuttle radar topographic mission (SRTM) data (https://www.usgs.gov) at a resolution of 30 m. LULC and terrain were anticipated to influence the infestation levels of *Striga* as reported by other studies (Mudereri, Abdel-Rahman, et al., 2020).

2.4 | Collinearity test and variable selection

Usually, the 19 Worldclim climatic variables are highly correlated, meaning that they are mostly redundant. Therefore, it is recommended that a collinearity test should always be performed to explore the collinearity among the predictor variables (Sheppard, 2013). In this regard, a Pearson correlation test was performed to determine the less correlated predictors that would be suitable for model development for predicting *Striga* habitat suitability. The 'virtual species' package (Leroy et al., 2016) in R software (R Core Team, 2020) was used to analyse the correlation among the variables listed in Supplementary (S1). A cluster tree that shows the degree of collinearity among the predictor variables (Leroy et al., 2016) was produced (Figure 2). A correlation coefficient of $|r| > 0.7$ (Dormann et al., 2013) was set as a collinearity indicator. In addition to the evaluation of correlation coefficient, knowledge informed variable selection was also applied to select the predictor variables to improve the robustness of the developed MaxEnt model.

The correlation analysis selected nine bioclimatic variables out of the 19 variables. In total, 16 predictor variables, comprising nine bioclimatic variables (Bio1, Bio2, Bio3, Bio4, Bio5, Bio12, Bio15, Bio17 and Bio18), five soil parameters (soil type, soil pH, sand content, soil nitrogen and soil organic content), one DEM and one LULC were utilised for predicting *Striga* habitat suitability.

2.5 | Maximum entropy (MaxEnt) model development and parameter settings

Striga hermonthica occurrence data were utilised together with the 16 selected predictor variables to develop predictive models for *Striga* habitat suitability in western Kenya. The modelling experiment was conducted by using the MaxEnt algorithm, a machine learning technique, which utilises the principle of maximum entropy to estimate the distribution or probability of species occurrence (Elith et al., 2011). The MaxEnt model incorporates environmental variables and georeferenced presence only occurrence data to develop a model that highlights the habitat suitability where each pixel in the study geographic space represents a probability value of suitability (Phillips et al., 2017). The model was trained using 70% (n = 128) of the presence of *Striga hermonthica* data, while 30% (n = 32) of the data were used for assessing the performance of the model. The 'ENMeval' tool (Muscarella et al., 2014) in R software was used to optimise the parameters for calibrating the MaxEnt model. The tool provides several evaluation metrics that guide in the selection of optimal settings that create a balance between goodness of fit and model complexity.

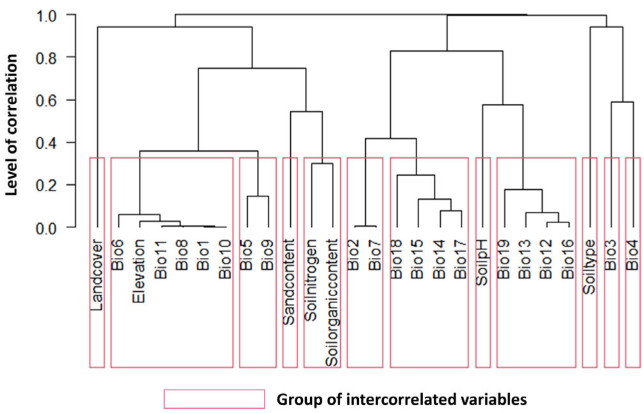


FIGURE 2 Cluster tree indicating the groups of intercorrelated predictor variables. Lower-level lines (towards zero) show high levels of correlation while levels closer to one show low correlation.

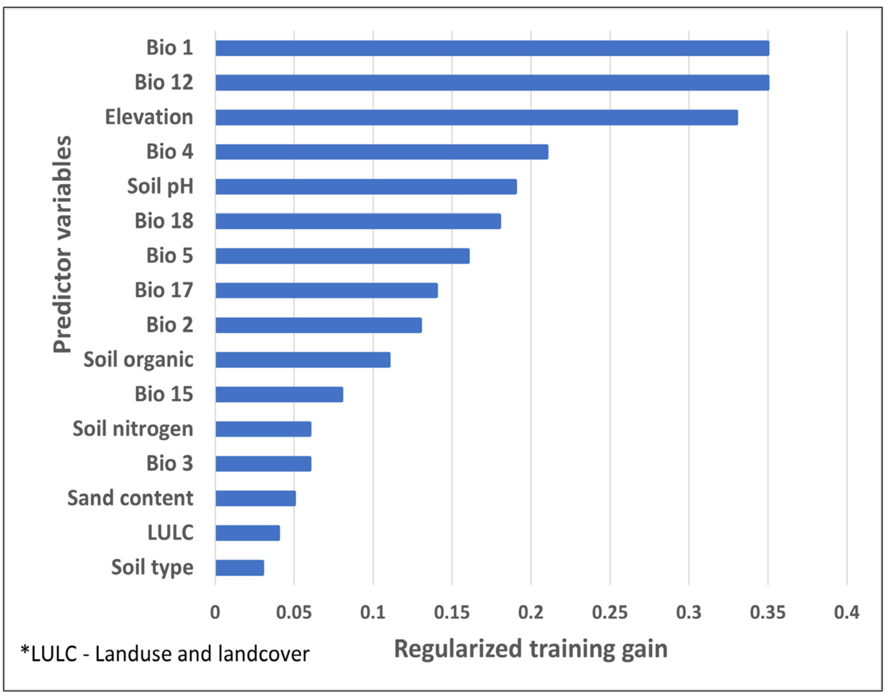
More specifically, linear, quadratic and hinge features were used with a regularisation multiplier of three to fit the MaxEnt model. To control overfitting, the models were replicated five times by using the cross-validation strategy and an ensemble of the five replicates was used to average the final model outputs. The model outputs, which are *Striga hermonthica* suitability scores ranging from 0 (very low) to 1 (optimal), were mapped out through using the QGIS 3.10.9 software (QGIS Development Team, 2019). The *Striga hermonthica* suitability index for each model was classified into five classes: very low (0–0.1), low (0.2–0.3), moderate (0.4–0.5), high (0.6–0.7), and very high (0.8–1) following Mudereri, Kimathi, et al. (2021). The contribution of each predictor variable to the *Striga hermonthica* habitat suitability model was assessed by using the response curves and jack-knife methods. Response curves indicate the influence of each of the predictor variables on the *Striga* habitat suitability predictive models. The curves highlight the relationship between the logistic probability of species presence and predictor variables, creating a better understanding of the ecological niche of the weed. The Jack-knife test of variable importance on the other hand, highlights the gain in the model of individual predictor variables when used in isolation (Phillips et al., 2017).

2.6 | Maximum entropy (MaxEnt) model validation and evaluation

The performance of the *Striga hermonthica* habitat suitability model was evaluated through using the area under the curve (AUC) of the

Variable	% contribution
Elevation	42.1
Bio 12	19.8
LULC	11.9
Bio 4	8.8
Soil type	7.8
Bio 2	2.6
Bio 1	1.7
Bio 3	1.4
Bio 18	1.4
Bio 17	0.9
Soil nitrogen	0.5
Bio 15	0.5
Soil pH	0.2
Bio 5	0.2
Sand content	0.1
Soil organic	0.1

(A)



(B)

FIGURE 3 Relative contribution and importance of predictor variables used in the maximum entropy (MaxEnt) modelling experiment for predicting *Striga hermonthica* habitat suitability in western Kenya as measured by (A) relative contributions for each environmental variable and (B) Jack-knife test of regularised training.

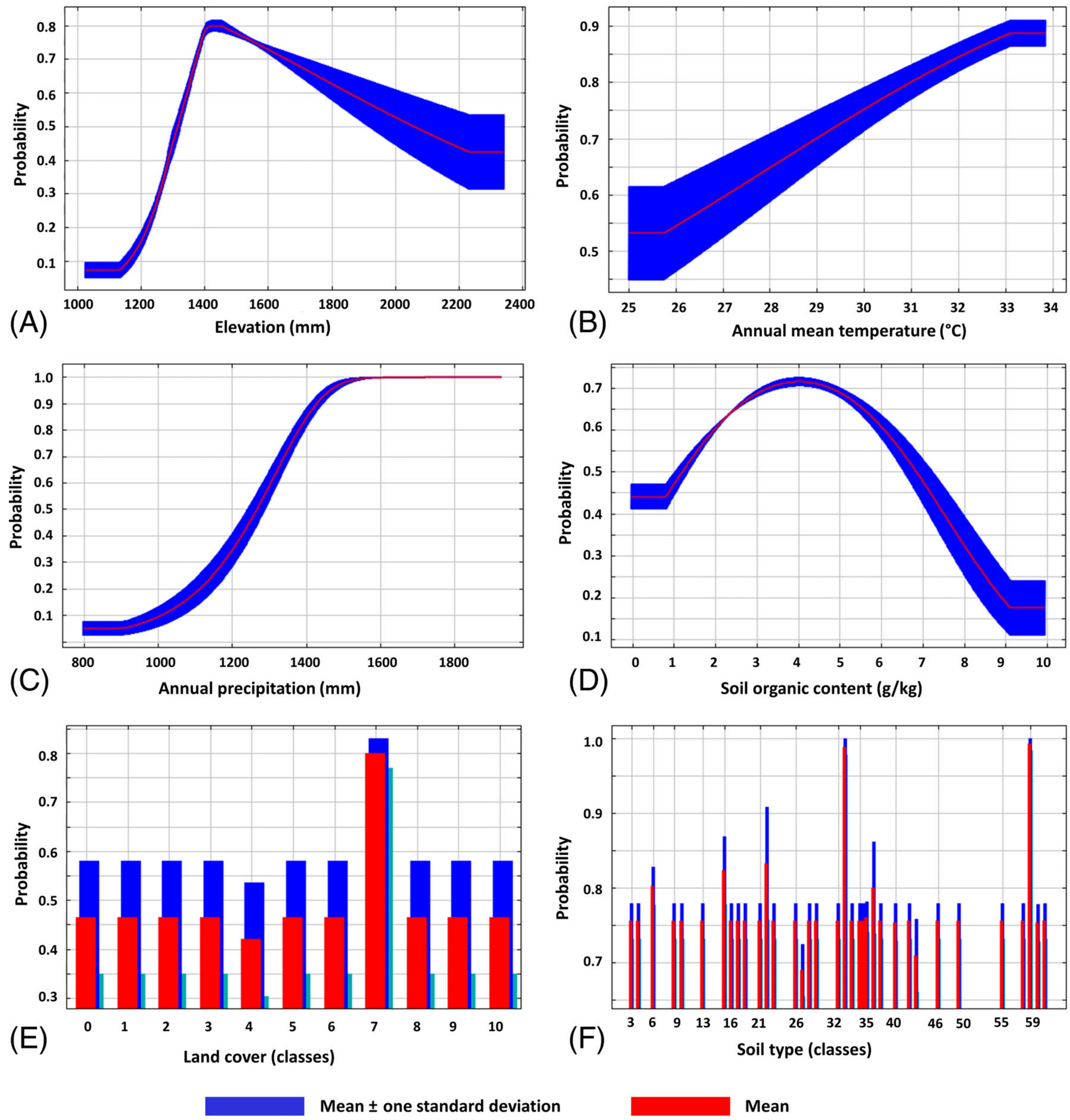


FIGURE 4 Response curves derived from the maximum entropy (MaxEnt) model.

receiver operating characteristic curve (ROC). The AUC indicates the balance between the specificity and sensitivity with values ranging from 0 to 1. The AUC values of >0.5 indicate good performance while values close to 0 indicate poor model performance (Metz, 2006). Additionally, descriptive statistical analysis was used to evaluate the performance of the *Striga hermonthica* predictive model. The 1000 independent set of georeferenced records of *Striga hermonthica* infested farms were overlaid on the MaxEnt model output maps to extract *Striga* habitat suitability scores for model evaluation at the study area level. Specifically, histograms and normal distribution curves were fitted on the extracted *Striga hermonthica* suitability scores to explore the model's performance. Then, the mean, standard deviation and skewness were calculated from the extracted *Striga hermonthica* suitability scores to test the model's accuracy.

3 | RESULTS

3.1 | Contribution of the predictor environmental variables on the maximum entropy (MaxEnt) model performance

The results depicted in Figure 3A show that elevation has the highest percentage contribution to the model. The jack-knife test (Figure 3B) showed that Bio1 (annual mean temperature), Bio12 (annual precipitation) and elevation had the highest gain in the MaxEnt model when used in isolation. These variables therefore provided valuable information on the distribution of *Striga hermonthica* in western Kenya.

Figure 4 indicates the responses of the six most important predictor variables in predicting *Striga hermonthica* occurrence as assessed using the MaxEnt model. The suitable elevation for *Striga hermonthica* suitability ranged from 1000 to 1400 m above sea level. After 1400 m, a sharp decline in *Striga hermonthica* suitability was observed (Figure 4A). The annual mean temperature ranged between 33°C and 34°C (Figure 4B). Figure 4C indicates that the optimal annual precipitation range was 1500–2000 mm. The response curves also demonstrated that the suitable LULC for *Striga hermonthica* was cropland (Figure 4E). Moreover, the model predicted that *Striga hermonthica* thrives in a range of soil types including Eutric planosols, Haplic nitosols, Haplic acrisols, Haplic phaezoems, and Luvic phaeozems (Figure 4F). The optimum range for soil organic content was between 3 and 5 g/kg (Figure 4D).

3.2 | Maximum entropy (MaxEnt) model performance evaluation

The MaxEnt predictive models, which estimated the habitat suitability of *Striga hermonthica* in western Kenya under current and future climate projections, performed highly accurately, as indicated by an average AUC value of 0.8 (Figure 5).

Figure 6 shows the validation of the *Striga hermonthica* predictive models using independent presence records that were not used during the MaxEnt model development. The results from the descriptive statistical metrics indicated that the model had a habitat suitability mean of 0.63 and a skewness of −1.13. The variance was lower than the mean indicating a negatively skewed habitat suitability distribution. This indicates that the majority of *Striga hermonthica* habitat suitability scores in western Kenya ranged between 0.7 and 1, which shows that our MaxEnt model predicted high and very high *Striga* suitability scores for current known areas of *Striga* occurrence (Figure 6). This demonstrates the high performance of the MaxEnt models in predicting the habitat suitability of *Striga* in western Kenya.

3.3 | *Striga* habitat suitability under current and future climate scenarios

Figure 7 shows the *Striga hermonthica* predicted suitability levels across the five study counties under the current and future climate scenarios. The warm colours (red scale) indicate regions with high habitat suitability of *Striga*. The results showed that the eastern part of Siaya, northern Kisumu, the south and eastern part of Homabay, and vast areas of Vihiga and Migori county provide conducive environmental conditions for the development and spread of *Striga hermonthica* (Figure 7). In western Kenya, 19 sub-counties are shown to have a very high habitat suitability of *Striga hermonthica* in the study site. The projected future scenarios indicate that there will be an increase in *Striga hermonthica* occurrence across all five counties. The maps indicate that there will likely be an increase in the spatial coverage of the regions suitable for *Striga*, compared with the distribution maps of the current climatic conditions (Figure 7A) with 2.6 climate scenario (Figure 7B) and 8.5 climate scenarios (Figure 7C).

Table 1 shows the relative changes in area (km^2) and area percentage in suitability for *Striga hermonthica* in comparison with the total area. The positive values for percentage change indicate increases in the area covered while the negative values indicate decreases in area for the respective suitability level. Currently, an area of 1767 km^2 (10% of the total area) is highly suitable for *Striga hermonthica* occurrence (Table 1), but future projections show a range between 2106 km^2 (19% of the total area) and 2712 km^2 (53% of the

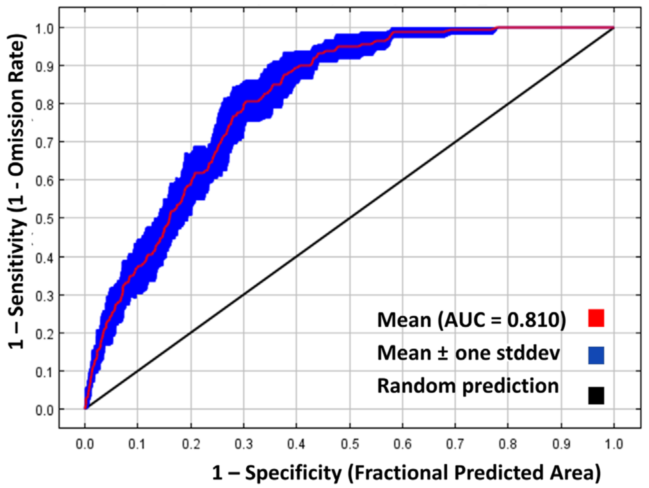


FIGURE 5 Area under curve (AUC) of maximum entropy (MaxEnt) models for evaluating the performance of predicting *Striga hermonthica* habitat suitability in western Kenya. The mean plot of the replicated models is shown in red, while the standard deviation of the replicated models is shown in blue, and the predictions made at random are shown in black.

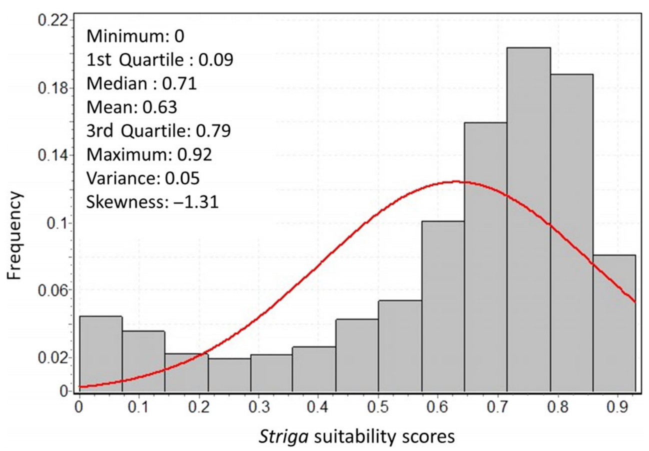


FIGURE 6 Histogram and normal distribution fit for *Striga hermonthica* habitat suitability scores extracted using 1000 known *Striga* occurrence points in western Kenya. The red line shows the normal distribution curve.

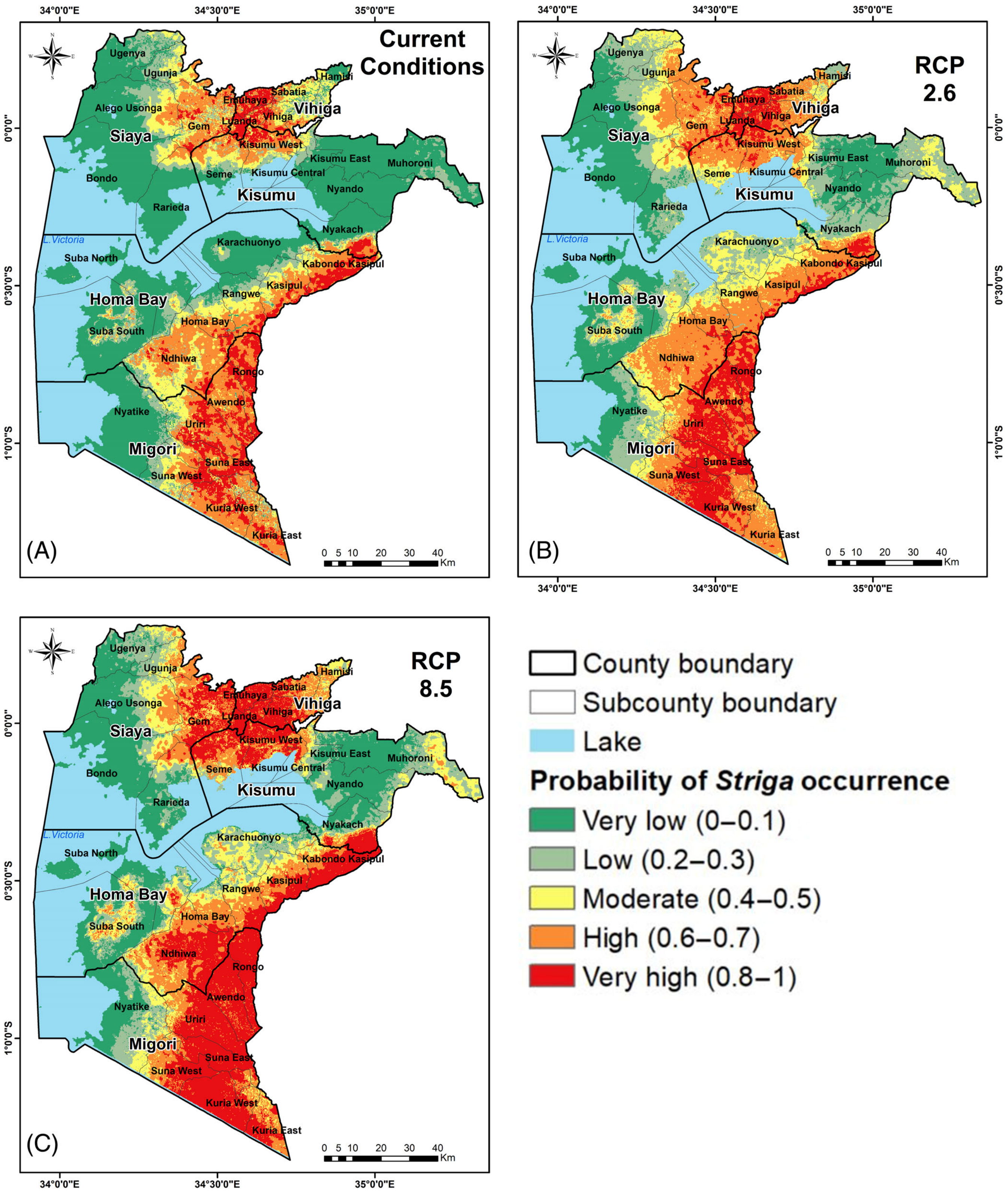


FIGURE 7 Predictions of *Striga hermonthica* habitat suitability based on (A) current climatic conditions and (B and C) future climate change in 2050 at two global warming scenarios RCP 2.6 and RCP 8.5 respectively. The lake layer was sourced from https://data.humdata.org.

total area) suitable for *Striga hermonthica* at the minimum carbon (RCP 2.6) and the maximum carbon emission scenarios (RCP 8.5) respectively. Furthermore, the results indicated that regions that have a very low probability under the current scenario will decrease by 13% and 23% at the RCP 2.6 and RCP 8.5 future climate scenarios respectively.

TABLE 1 Area (km^2) covered by *Striga hermonthica* per suitability levels for the current and future global warming (RCP 2.6 and RCP 8.5) scenarios in the study area. 'Change' describes the shift in *Striga hermonthica* habitat suitability ranges between current and future climate change scenarios.

	Area coverage			Change	
***Striga* suitability range**	**Current (km^2)**	**RCP 2.6 (km^2)**	**RCP 8.5 (km^2)**	**RCP 2.6, % change**	**RCP 8.5, % change**
Very low (0–0.2)	7824	6829	6006	−13	−23
Low (0.2–0.4)	2560	3388	3540	+32	+38
Moderate (0.4–0.6)	1684	1640	1962	−3	+17
High (0.6–0.8)	3278	3149	2892	−4	−12
Very high (0.8–1)	1767	2106	2712	+19	+53

4 | DISCUSSION

This study presents maps of the potential distributions of *Striga hermonthica* in the western Kenya region using ENM. Specifically, the MaxEnt model was successful in predicting suitable habitat sites for *Striga hermonthica* under the current climate conditions, which indicates good predictive power for the future climate scenarios used. The high AUC (>0.8) of the MaxEnt model showed that the model performance was highly accurate (Phillips et al., 2017), proving its dependability in understanding the occurrence risks of *Striga hermonthica* in western Kenya. The MaxEnt model outputs were robust, as indicated by the level of optimization attained through the knowledge-informed variable selection and model calibration. Therefore, the model outputs obtained were considered reliable in understanding and monitoring *Striga hermonthica* occurrence and risk in the western Kenya region.

The MaxEnt predictive model illustrated that *Striga hermonthica* has a potentially broad distribution in western Kenya and will continue to extend its ecological suitability range in the future. The model estimated that *Striga hermonthica* suitability will increase by 19% in the conservative climate scenario (RCP 2.6) and by 53% under the business as usual climate change scenario (RCP 8.5). This indicates that there will be a substantial increase in *Striga hermonthica* suitable habitats by 2050. Furthermore, the results indicated that climate change will have a direct impact on the spread of *Striga hermonthica* in western Kenya. This finding is supported by various studies (Mandumbu et al., 2017; Midega et al., 2015; Mudereri, Dube, et al., 2020) which noted that *Striga* habitat range will increase under the changing climate. Some of the areas predicted in this study to have suitable conditions for *Striga* invasion may not have been invaded yet. Therefore, such areas indicate suitable localities where *Striga* is already occurring or potentially suitable areas where *Striga* could occur in the future.

Of the 34 sub-counties in the five study counties, 19 were predicted to have high risk of *Striga* distribution under the current conditions. In particular, most of the counties bordering Lake Victoria were predicted to have low (0–0.4) risks of *Striga* spread. This could be attributable to the low precipitation (annual rainfall <1000 mm) received in the counties neighbouring the Lake Victoria region that are characterised by the dry conditions. Moreover, these conditions are not conducive for maize crop production per se, which is one of the main host plant for *Striga* (Khan, Pickett, et al., 2006). This is also reflected in the maize yields records of 2018 collected by the Kenyan Ministry of Agriculture (http://kilimodata.developlocal.org/) where sub-counties, such as Bondo, Nyando, Mbita, Suba, Ugunja Kisumu East, Rarienda Nyakach and Muhoroni, produced less than 1000 tons of maize. Other potential host plants for *Striga* in the region include Sorghum (*Sorghum bicolor*), upland rice (*Oryza sativa*) and pearl millet (*Pennisetum glaucum*).

In general, relevant climatic and edaphic factors considered suitable for the species of interest could make ENM more robust and reliable (Kimathi et al., 2020). This study shows that annual temperature, precipitation, and elevation played a key role in defining the suitable habitat for *Striga hermonthica*. Elevation was anticipated to influence the occurrence and spread of *Striga* by indirectly influencing variables such as precipitation, temperature, and vegetation including crops, as well as the angle, direction, and intensity of the sun's radiation on the earth's surface. It is interesting to note that the MaxEnt model response curves highlighted the fact that *Striga hermonthica* thrives in areas with high temperatures of up to 34°C and heavy precipitation of up to 2000 mm in a year. Previous studies have demonstrated that *Striga* is highly affected by temperature and precipitation (Kristian & Bärbel, 2014; Ramesh et al., 2017). A study by Bellis et al. (2020) indicated that suitable habitats of *Striga hermonthica* were predicted to be high in locations with mean annual precipitation of ∼500 to 1300 mm, which coincides with our results. Likewise, a study by Mandumbu et al. (2017) reported that alternating wet seasons and rising temperatures in degraded soils could accelerate the rate of *Striga* germination.

These findings, therefore, highlight the important role that climate can play as a potential, direct driver that causes an increase in the severity and spread of *Striga*. On the other hand, our results illustrated that soil variables were similarly important for predicting *Striga hermonthica* distribution and suitable habitats. *Striga* thrives in a variety of soil types, especially degraded soils containing low organic content (Khan, Midega, et al., 2006). Moreover, our modelling experiment revealed that the high suitability of *Striga hermonthica* was predicted in cropland areas. This reinforces the fact that *Striga* is highly dependent on suitable host plants, which are mainly maize and sorghum in western Kenya region (Muranaka et al., 2017).

Overall, our study provides a predictive model for *Striga hermonthica* habitat suitability and distribution, which could be utilised by policymakers for developing *Striga* early warning systems and management strategies. Furthermore, the outcome of the present study proves that it is possible to use ENM tools in identifying habitat niches of *Striga* in a spatial space at a landscape scale. Mapping hotspot areas that are currently infested by *Striga* and then predicting habitats that are suitable for future *Striga* infestation can help in directing the limited management resources to the most vulnerable hotspots and in effectively identifying appropriate management strategies. If *Striga* distribution maps were to be incorporated together with crop productivity factors like soil fertility, policymaking for food and nutrition security could be considerably enhanced. The distribution maps can be utilised for identifying current and future hotspot areas, which could guide in the implementation of strategies for managing *Striga* (Jamil et al., 2021; Midega et al., 2015).

However, our study did not establish chronological timesteps, the rate and direction of spread of *Striga* into new areas, because of the limitation of our dataset. *Striga* seeds can be dispersed by various factors including floods, wind, sharing of contaminated farm tools, livestock movement and planting of contaminated crop seeds (Emeghebe et al., 2004). Since *Striga* transmission modes such as wind and water (Mohamed et al., 2007) can be quantified, future studies could explore *Striga*'s dispersal ability over space and time. The distribution of *Striga* in an invaded range may not reflect its entire ecological niche, especially when the species is not in equilibrium (Merow et al., 2016; Václavík & Meentemeyer, 2012). Hence, there is a great need to fit models with data from both native and invaded ranges and establish the equilibrium status of *Striga* in Kenya and beyond. Furthermore, our study utilised a LULC layer, which included a general crop class, as a predictor variable in the *Striga* habitat suitability experiment. Specific crop types (e.g., maize and sorghum) would have provided more relevant information for understanding how much the type of land cover influences *Striga* habitat suitability. This aspect was not considered in this study because of a lack of specific crop type data in Kenya. It is suggested that future studies should include cultivated areas of the respective host crops in predicting *Striga* suitable habitat and distribution in the study area and across other (and neighbouring) areas in Western Kenya such as Busia, Kakamega and Bungoma. Furthermore, predicted habitat suitability of *Striga* and not the host crops. This entails that those areas where any of the other potential host crops are grown, such as sorghum, rice and pearl millet, can be checked against our *Striga* suitability maps.

5 | CONCLUSIONS

Our study identified the current *Striga hermonthica* risk areas and the potential habitat suitability based on the future climate change scenarios. Approximately 10% (1767 km^2) of the total study area is currently highly suitable for *Striga hermonthica* occurrence, with and an increment in suitability of up to 53% (2712 km^2) in the future. This output confirms the hypothesis that climate change will modify the distribution ranges of the species over wider areas, which is crucial for understanding the dynamics of *Striga* under climate change scenarios. Our results showed that the *Striga* invasion is likely to intensify into areas with levels of moderate infestation.

Immediate action needs to be taken to channel intervention measures for managing the spread and intensity of *Striga* in these regions. These *Striga* distribution maps facilitate making precise interventions at scale, which could be achieved through identifying and using fit -for -purpose farming systems that could guide the farmers to deploy proper and sustainable *Striga* management systems in hotspots. Such interventions could help to secure the food production and livelihoods of farmers in the coming decades. Thus, using these developed species distribution maps and climate scenarios and integrating them into land management decision systems could help prepare policy makers, crop protection services, extension services and farmers for current and future infestations.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the link http://dmmg.icipe.org/dataportal/dataset/push-pull-for-sub-saharan.

ORCID

Emily Kimathi https://orcid.org/0000-0002-1320-2301
Elfatih M. Abdel-Rahman https://orcid.org/0000-0002-5694-0291
Catherine Lukhoba https://orcid.org/0000-0002-6492-0768
Asaah Ndambi https://orcid.org/0000-0001-8563-2805
Bester Tawona Mudereri https://orcid.org/0000-0001-9407-7890
Saliou Niassy https://orcid.org/0000-0002-7251-2051
Henri E. Z. Tonnang https://orcid.org/0000-0002-9424-9186
Tobias Landmann https://orcid.org/0000-0001-6512-5806

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