Sustainability and Biodiversity Conservation

Mapping and forecasting of fall armyworm pest distribution in East Africa using climate information

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Abstract

Fall Armyworm (FAW) is among the major pests that destroy important food crops. With origins in the Americas, it was first detected in West Africa in 2016 and has since spread rapidly to other African countries and other continents. Studies have investigated FAW behavior and distribution, however, studies of how climate change may affect FAW suitability have been poorly explored. Reports on how FAW prediction is likely to spread in African countries that lack advanced technologies and practices to prevent the pest could be an approach that enables decision-makers to adapt and take control measures in areas at risk. In this research, we identified the climatic factors that influenced the incidence of FAW pest, and mapped and predicted its suitable habitat in the eastern African region. Findings revealed that five variables had the greatest impact on the performance of the model, among 19 bioclimatic variables. With a contribution of 37.8%, the annual precipitation had the most influence, followed by the annual mean temperature which contributed 13%. FAW potential distribution was also predicted under current climatic conditions, (1970–2000), and for future climate change scenarios, SSP1-2.3, SSP3–7.0, and SSP5-8.5, for the periods 2021–2040 (near term), 2041-2060 (mid-term) and 2061–2080 (long-term). This study showed that in the current climatic conditions, most of the area under study is suitable for FAW incidence and that in the future, this suitable habitat will increase northwards and decline in the southern region. Control and monitoring measures should be adopted to prevent the spread and excess damage of the FAW pest in the eastern Africa region. Studies utilizing different climate models, SSP scenarios, and different periods should be the focus of future research. Understanding additional non-climatic elements that affect the growth, development, and distribution of FAW also needs more research.

Keywords: Climate change, Maxent, Shared Socioeconomic-Pathways, Species Distribution Models

Introduction

The impact of climate change on the agricultural sector is a global concern. Unfavorable climates exacerbate the interaction between plants, pathogens, and pests, as they inform the life cycle of pathogens and pests, the ability to cause disease, including, the colonization of new environments and hosts. This also applies to host plants. Abiotic factors such as extreme temperatures, precipitation, wind, and drought further render plants more vulnerable to pests and pathogens. For example, Agrios (2005) positioned temperature and moisture as significant environmental factors that affect the occurrence and development of various infectious plant diseases. With an unprecedented future climate predicted to be characterized by increased warming, even under prescribed climate mitigation scenarios, there is a need to continuously understand how climate change will impact plant-pathogen/pest dynamics. Predicting where the latter will exist is the first important step toward putting in place adequate early preparedness strategies. The effects of climate change on plant diseases and how to manage these diseases in a changing climate are gaining interest within the scientific community. However, few evaluations exist for certain countries, regions, crops, and specific agronomic pests/pathogens/viruses with a notable impact on food security, and nutrition, (Das et al., 2016).

This study focuses therefore on *Spodoptera frugiperda* (Fall armyworm - FAW) pest which has recently become a concern in East Africa, especially in the agriculture sector. FAW, named the hungry caterpillar, is a moth, with origins, in the Americas (Day et al., 2017). FAW caterpillars are known to be serious pests of cereals and other grasses. The pest is postulated to have the ability to feed on 186 plant species, many of which are important staple crops (Early et al., 2018). Maize is the main crop affected by FAW. However, its polyphagous ability put at risk other important food crops such as rice, sorghum, sugarcane, beet, tomato, potato, cotton, and pasture grass (Early et al., 2018; Uzayisenga et al., 2018). FAW can cause extreme damage in plants, with yield losses of up to 73% reported (Hruska & Gould, 1997). According to Baudron et al. (2019), a 54% infestation of maize by FAW could translate to eventual yield losses of about 12%. This subsequently results in huge losses to governments. For example, about 40% of maize yield is lost in Honduras and 72% in Argentina due to FAW (Murúa et al., 2006; Wyckhuys & O’Neil, 2006).

FAW was first observed on the African continent in Western Africa (Nigeria, São Tomé, Benin, and Togo) in 2016. It then quickly spread to other countries, including Eastern Africa (Goergen et al., 2016). Its rapid spread and colonization success has been attributed to its ability to migrate over long distances, infest a diversity of crops, and reproduce continuously in areas with suitable climate conditions (Day et al., 2017; Huesing et al., 2018). Maize, the most-grown crop on the African continent and a staple for more than half of the African population remains the most affected crop (Day et al., 2017). Yield damages of about 20% to 50%, which amounts to about USD ($) 2.5 - 6 billion in annual losses have been reported in Africa. This is especially true in the absence of control measures. According to Goergen et al. (2016), most FAW damage to maize occurs in tropical regions with optimal conditions that allow continuous reproduction. In Kenya, an estimated 1 million tonnes of the country's maize is destroyed by the pest annually (De Groote et al., 2020). By 2018, FAW had ravaged around 15,699 hectares of farmland, a quarter of the country's total area of 63,499 hectares of maize plantations in Rwanda (Hanyurwimfura et al., 2018). In 2017, national estimates mean loss of maize in Zambia were 40% and 45% in Ghana (Day et al., 2017). Zimbabwe's crop losses to FAW were estimated at 11.6% in 2018 (Baudron et al., 2019). Overall, in 2017, already infested African countries losses were estimated to be approximately $13 383 million (Day et al., 2017). In August 2017, 28 African countries had already observed and confirmed the presence of FAW (Day et al., 2017). Currently, about 44 African countries have reported the presence of FAW (Prasanna et al., 2018; Rwomushana, 2019). Climatic conditions such as temperature, and precipitation can directly influence insect invasion, distribution, and spread (Bale et al., 2002). Species Distribution Models (SDMs) and mapping tools have been used to assess climate factors that affect FAW's distribution. Early et al. (2018) utilized an ensemble of SDMs to forecast FAW global extent invasion under the current climatic scenario while Cokola et al. (2020) used MaxEnt to infer bioclimatic regions and climate variables that influence FAW's distribution in South Kivu, eastern Democratic Republic of Congo. Zacarias (2020) and Ramasamy (2022) mapped the current FAW suitable habitat and forecasted its potential future suitable habitat using SDMs. Niassy et al. (2021) studied the impact of rainfall patterns on FAW incidence in East Africa. An ongoing study (Yocgo et al., unpublished) is investigating FAW habitats under future climate scenarios. Such kinds of studies need to be downscaled to specific regions especially regions that have already been invaded by the FAW pest.

The need for more localized studies, using different climate models, under recently defined climate scenarios, and recent FAW data sets, can sharpen decision-making. This therefore prompted this investigation. Eastern Africa was selected as a region of choice in this paper given the most recent occurrences of the pests in the region. The objective of the study is therefore, to assess climate variables that influence FAW distribution in Eastern Africa, and predict its current and future suitable habitats using Maxent and newly developed climate models from the Coupled Model Intercomparison Project 6 (CMIP6). Given that different models have been shown to have different sensitivities to climate change, we compared outputs from the most sensitive model CanEMS5, and the least sensitive INM-CM5-0.

Material and methods

Description of the study area

Our study is limited to eleven Eastern African countries, specifically Tanzania, Burundi, Rwanda, Uganda, Kenya, Somalia, Ethiopia, Djibouti, Eritrea, South Sudan, and Sudan (Chamberlin, 2018). The region's highest altitude point is 5,895 meters above sea level on the peak of Mount Kilimanjaro (Tanzania) and the lowest point is 153 meters below sea level at the bottom of Lake Assal in Djibouti (Chamberlin, 2018). The region's complex topography which is different from the rest of Africa, is characterized by a coastal plain in the east and mostly highlands from the north to south, detached between Kenya and Ethiopia highlands by the Turkana gap. This landscape greatly affects low-level atmospheric circulation and moisture movement, creating a wide variety of climatic conditions, which in turn influences a variety of vegetation landscapes, biodiversity, and anthropogenic activities (Chamberlin, 2018; Yang et al., 2015). The recorded coolest place in East Africa is at Mount Kilimanjaro summit with an annual mean temperature of -7.1°C, and the hottest place is at Dallol, Afar Depression (North Ethiopia) with an annual temperature of 34.6°C. The peak solar radiation (292 $W.m^{-2}$) is found in northern Somalia and the lowest (183 $W.m^{-2}$) is found in Uganda near Mt. Ruwenzori (Chamberlin, 2018).

Occurrence data and data cleaning

The occurrence data was obtained from the Centre for Agriculture and Bioscience International (CABI; (https://www.cabidigitallibrary.org/doi/10.1079/cabicompendium.29810), and the Hand in Hand platform (https://data.apps.fao.org/), a geospatial data repository of the Food and Agriculture Organization (FAO) of the United Nations. Additional FAW occurrence data were obtained from the literature (Niassy et al., 2021). This covered specifically, Ethiopia, Kenya, Uganda, Tanzania, Rwanda, and Burundi. After data cleaning (removing duplicates) and cropping to the Eastern Africa extent, our final dataset comprised 2152 points covering the period 2017 - 2021. Data cleaning was carried out in the R platform (R version 4.1.3 Development Core Team, 2022).

Climate data

The climatic data used in this study was downloaded from WorldClim (https://worldclim.org/data/index.html), a database of historical (current) and future gridded weather and climate data. These data sets have been used in various SDM studies, including studies on FAW (Baloch et al., 2020; Çoban et al., 2020; Cokola et al., 2020; Ramasamy et al., 2022; Tang et al., 2019). In our study, we used all 19 bioclimatic variables (Table 1).

Table 1. Bioclimatic variables derived from Worldclim were used to assess suitable habitats for the FAW pest in the Eastern Africa region.

Code	Bioclimatic variables	Unit
Bio1	Annual Mean Temperature	°C
Bio2	Mean diurnal range (mean of monthly (max temp-min temp))	°C
Bio3	Isothermality (BIO2/BIO7) (×100)	-
Bio4	Temperature Seasonality (standard deviation ×100)	C of V
Bio5	Max Temperature of the Warmest Month	°C
Bio6	Min Temperature of the Coldest Month	°C
Bio7	Temperature Annual Range (BIO5-BIO6)	°C
Bio 8	Mean Temperature of the Wettest Quarter	°C
Bio 9	Mean Temperature of the Driest Quarter	°C
Bio 10	The mean temperature of the warmest quarter	°C
Bio 11	The mean temperature of the coldest quarter	°C
Bio 12	Annual precipitation	mm
Bio 13	Precipitation of the wettest month	mm
Bio 14	Precipitation of the driest month	mm
Bio 15	Precipitation seasonality (Coefficient of Variation)	
Bio 16	Precipitation of the wettest quarter	mm
Bio 17	Precipitation of the driest quarter	mm
Bio 18	Precipitation of the warmest quarter	mm
Bio 19	Precipitation of the coldest quarter	mm

To evaluate the impact of climate change on the future suitability of the FAW pest in East Africa, three Shared socioeconomic pathway (SSP) scenarios were employed. These include SSP1-2.6 which represents an optimistic scenario, SSP3-7.0 represents the middle case scenario, and SSP5-8.5 which represents a pessimistic scenario. The three SSPs originating from the CMIP6 project were obtained for two GCMs. These GCMs include the Canadian Earth System Model version 5 (CanESM5) (Swart et al., 2019) and the Institute for Numerical Mathematics- Climate Model 5 (INM-CM5-0) (Volodin et al., 2019). Periods covering 20-year spans for the near term (2021-2040), mid-term (2041-2060), and long-term (2061-2080) were used in this study. All climate data were obtained at a 30-second resolution (~ 1km).

Modeling procedure

The MaxEnt model (Phillips et al., 2017) was used in this study. MaxEnt has an advantage over other SDMs due to its high accuracy and ability to perform well with small sample sizes (Phillips et al., 2006). We accessed the MaxEnt model in Rstudio (R version 4.2.2 Development Core Team, 2022). Maxent has a built-in function called Jackknife that analyzes which environmental variables contribute to the model's performance. The Maxent model outputs were exported as .tiff files and then imported into ArcGIS 10.4 (https://desktop.arcgis.com/en/arcmap/) for further analysis and visualization. Analysis in ArcGIS consisted of reclassification of these outputs using the classification package. Taking reference from (Qin et al., 2017; Yang et al., 2013), 10 classes were generated to represent FAW suitability classes. 0-0.1 (unsuitable), 0.1-0.2 (low suitable lower), 0.2-0.3 (low suitable middle),0.3- 0.4 (low suitable upper), 0.4-0.5 (moderate suitable lower), 0.5-0.6 (moderate suitable upper), 0.6-0.7 (good suitable lower), 0.7-0.8 (good suitable upper), 0.8-0.9 (highly suitable lower) and 0.9-1 (highly suitable upper).

Model Evaluation

Model validation is a crucial stage in the modeling process to ensure that the model results are accurate. To test the accuracy of the Maxent model, our data set was split into training (80%) and test (20%) data set. The 80% data set was used to calibrate the model, and the remaining 20% was used to validate the model. In this study, the Area Under the Curve (AUC) threshold, a value of the Relative Operating Characteristics (ROC) was used as the evaluation metric. AUC values of 0.5-0.7 are considered low and represent poor model performance. Values of 0.7 - 0.9 are considered moderate, while values above 0.9 represent excellent model performance. The more the ROC curve follows the y-axis and the larger the AUC, the more the model is considered to be accurate (Bowers & Zhou, 2019).

Results

Maxent model performance

After calibrating the Maxent model with the 80% training dataset and all 19 bioclim variables, the model evaluation output using the 20% test dataset produced a high AUC value of 0.942 (Figure 1). This output, therefore, allowed us to use the Maxent model for other downstream projections in this study.

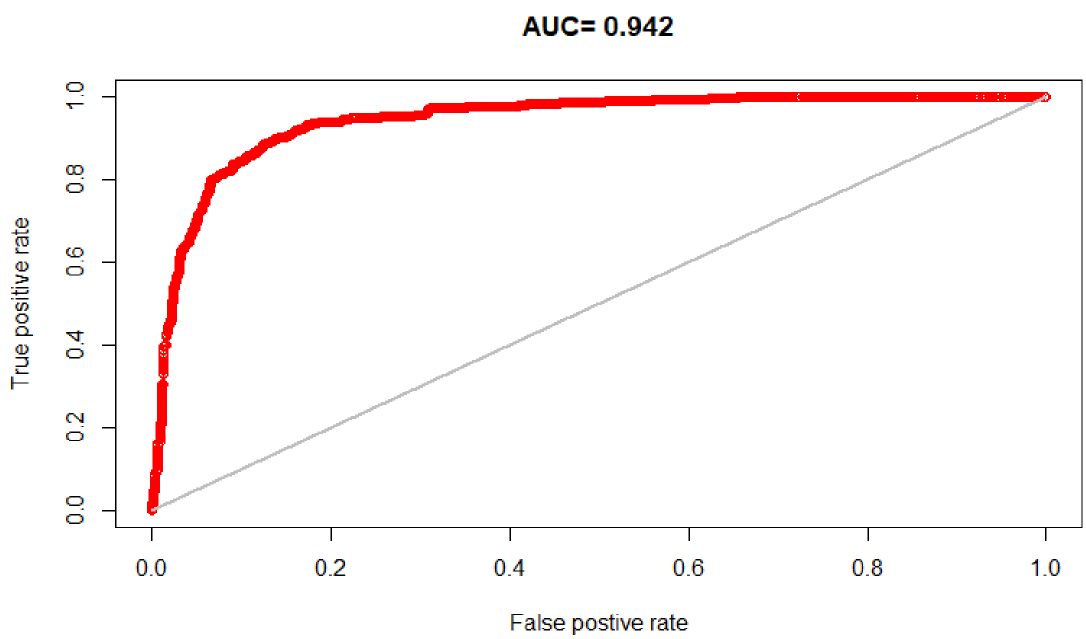

Figure 1. ROC plot of the Maxent model evaluation results using 20% FAW occurrence data for Eastern Africa as the test data set.

Bioclimatic variables contribution to FAW suitability

The Maxent built-in Jackknife test results obtained as a quantitative output from the calibration run of the 80% training dataset depict how each of the 19 variables contributed to the model's performance (Figure 2). We found that bio12 (annual precipitation) contributed the most to the performance (37.8%). This depicts the tune to which annual precipitation as a climate variable impacts the model's performance. The second highest contributor was bio1 (annual mean temperature) with a contribution of 13%. This was followed by bio14 (precipitation of the driest month), bio18 (precipitation of the warmest quarter), and bio15 (precipitation seasonality). They contributed 9%, 8.1%, and 7.9%, respectively.

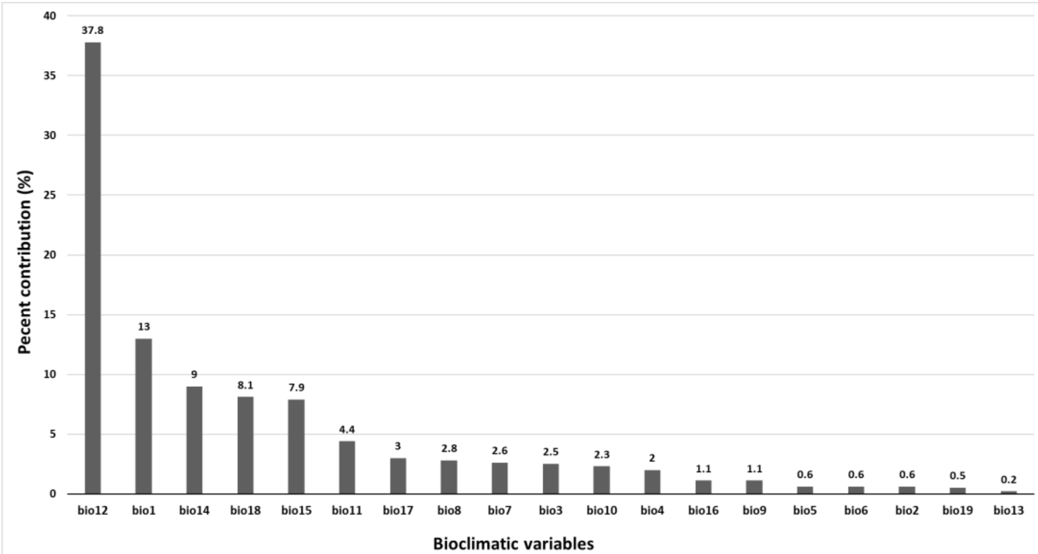

Figure 2. Contribution of the 19 bioclimatic variables to the maxent model performance using 20% FAW occurrence data for Eastern Africa as the training data set.

Current FAW suitable habitats in East Africa

The FAW suitability map under the current climatic conditions (1970-2000) in East Africa, (Figure 4) has a large coverage of unsuitable to most suitable habitats for FAW with a minute coverage of the highly suitable class (0.9 - 1). This highly suitable class (black and red) can be seen in the northeastern part of Tanzania, on its border with Kenya (Figure. 4, black circle). Areas that are still unsuitable for FAW are found in the northern parts of Sudan. In contrast, good suitable classes are found in a large part of western to central Ethiopia, and along the borders of Kenya/Tanzania, Kenya/Uganda, and the eastern corridors of Rwanda and Burundi.

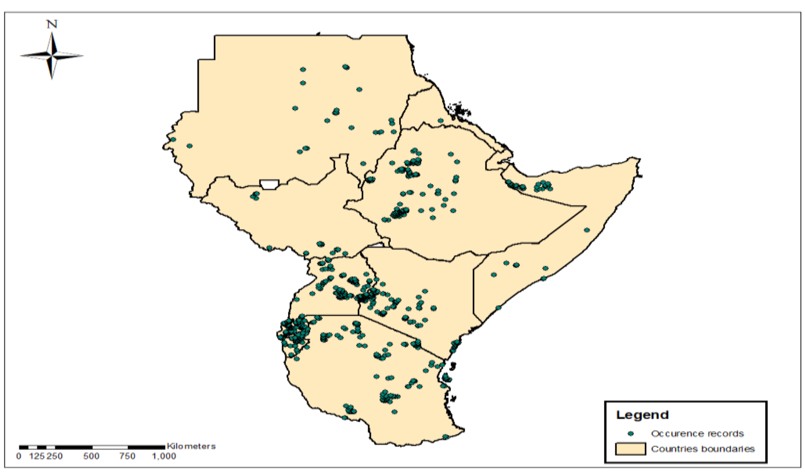

Figure 3. Map showing the current distribution of FAW in Eastern Africa using the MaxEnt model. Occurrence records were obtained from FAO, CABI, and Niassy et al. (2021).

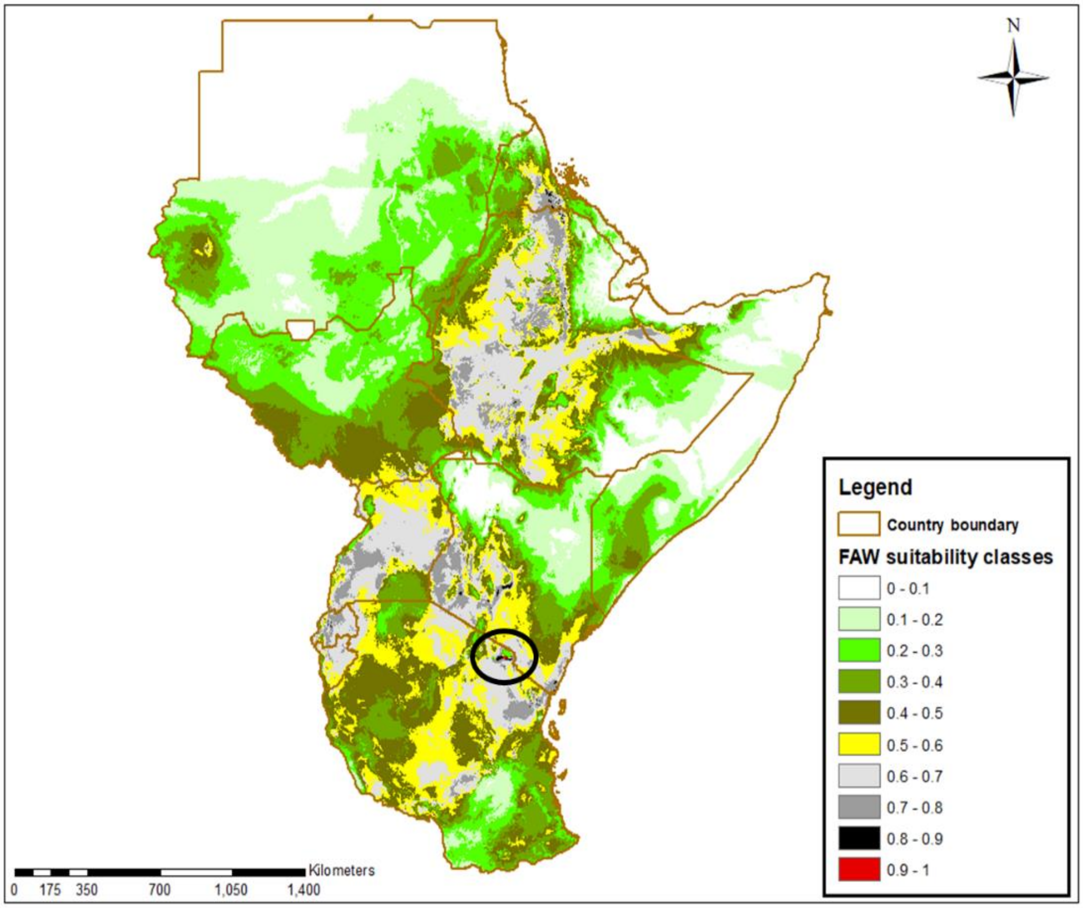

Figure 4. Current suitable habitat classes for FAW in the Eastern Africa region. The zone with the highly suitable area is highlighted with a black circle.

Future suitable habitat for FAW for the SSP1-2.6 scenario

Our results show a decline in FAW suitability habitats in the southern parts of Eastern Africa, in the northern parts of the region, occupied by Sudan, there was the appearance of new suitable habitats. Even Ethiopia, which had the most coverage in good suitable habitats in the current climatic conditions, was losing most of the upper limits of its good suitable habitat. With the two models, we found a visible difference in their projections with INM-CM5-0 projecting zones of highly suitable habitats in south-western Kenya, and southern Eritrea, whereas, with CanESM5, these zones project similar suitable class as the current climatic conditions.

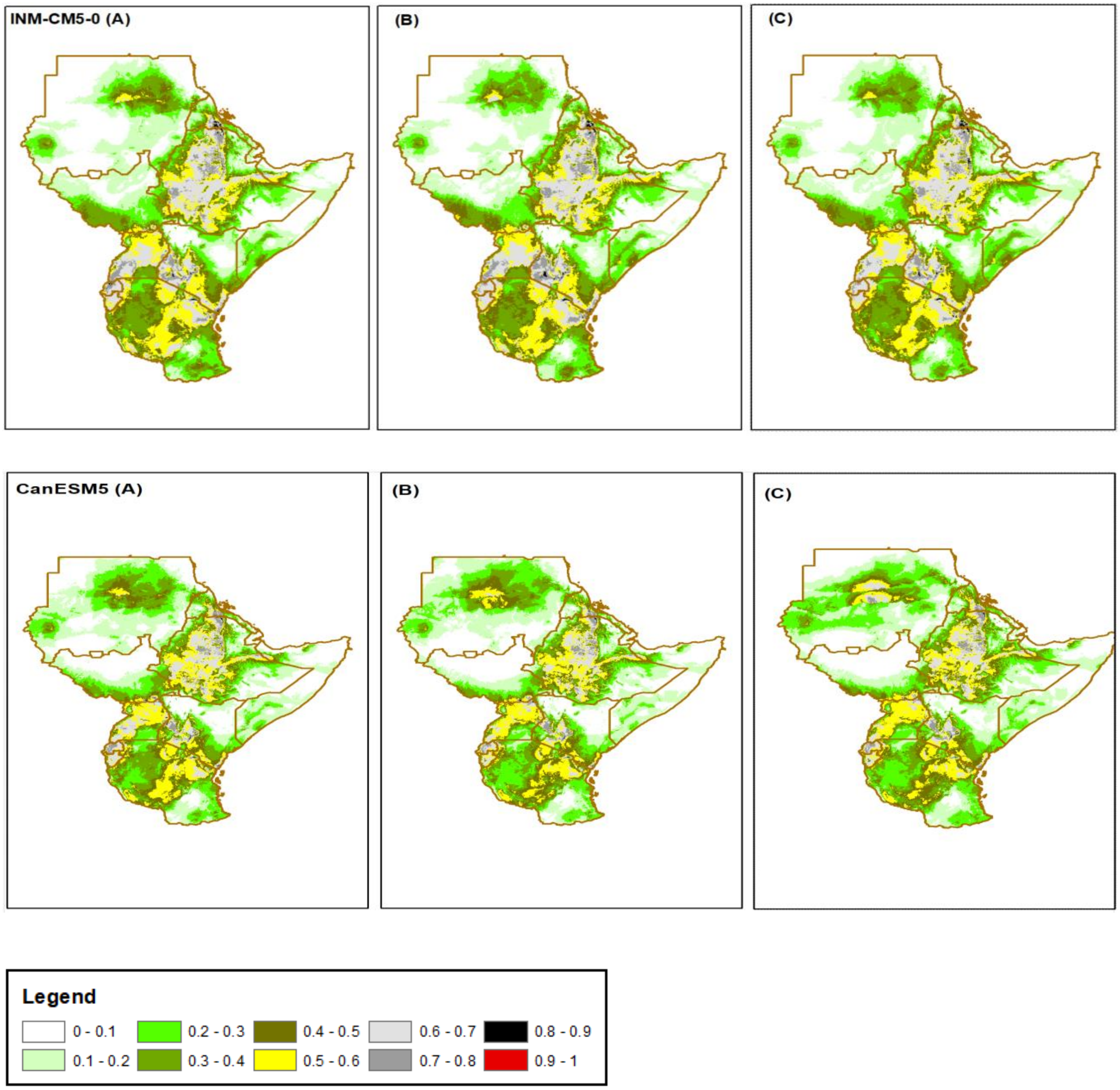

Figure 5. FAW suitable habitat In Eastern Africa in the SSP1-2.6 scenario based on CanESM5 and INM-CM5-0 global circulation models from CMIP6: for (A) near term 2021-2040, (B) mid-term 2041-2060 and (C) long term 2061-2080.

Future suitable habitat for FAW for the SSP3-7.0 scenario

The reduced habitat suitability in the southern parts of Eastern Africa persists in this scenario. In contrast, north of Eastern Africa, Sudan's central to western areas will experience increased suitability to FAW, with CanESM5, parts of Sudan will reach the lower limit of the high suitability habitat in the long term. INM-CM5-0 projects a more northward expansion of FAW suitability. The suitable habitats will continue to decline, as well as the zones along the boundaries of South

Sudan/Sudan, at least in the long term, as projected by both GCMs. Also, both GCMs project a decline in FAW suitability over time in southern Uganda, and western Tanzania.

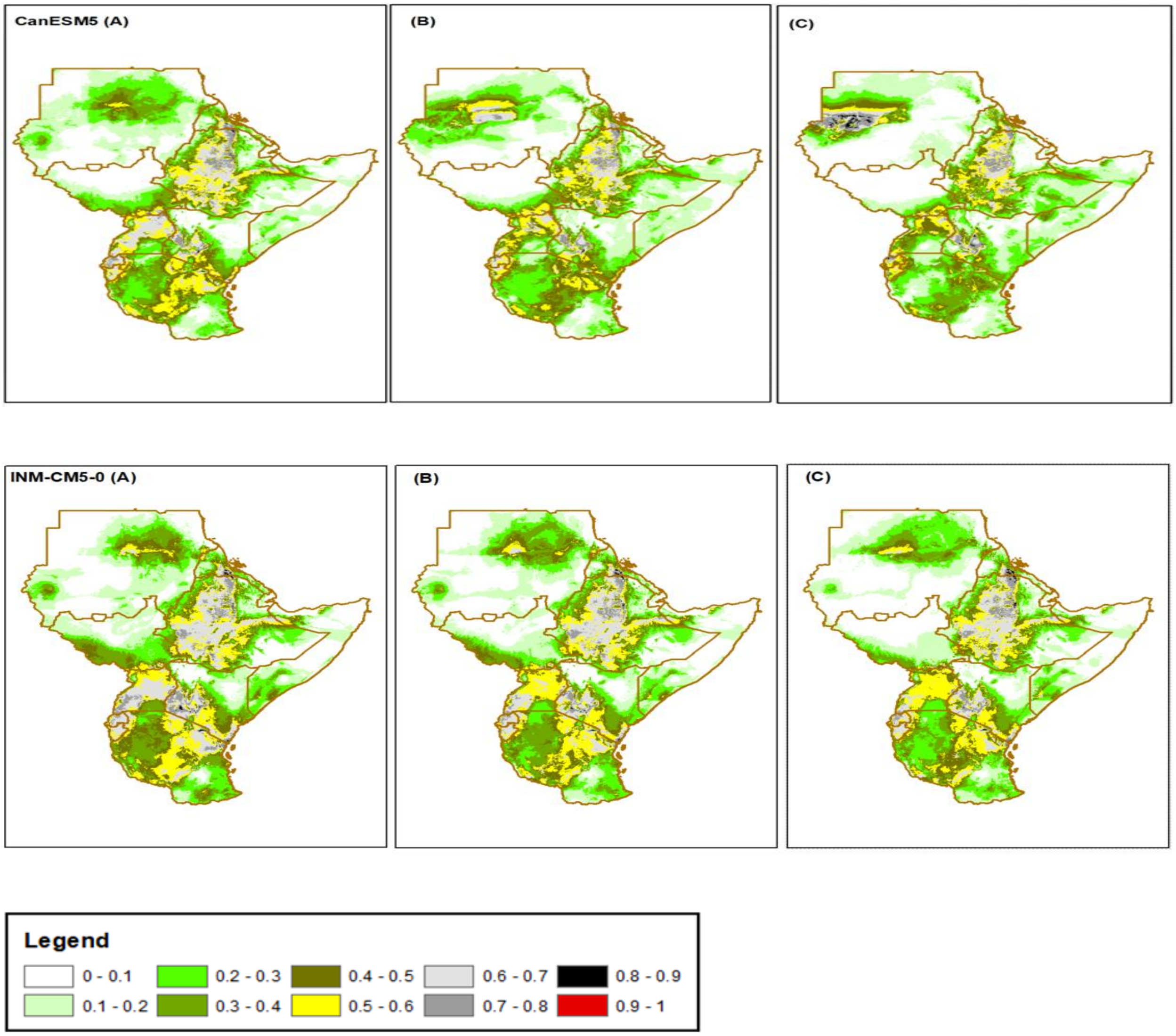

Figure 6. FAW suitable habitat In Eastern Africa in the SSP3-7.0 scenario based on CanESM5 and INM-CM5-0 global circulation models from CMIP6: for (A) near term 2021-2040, (B) mid-term 2041-2060 and (C) long term 2061-2080.

Future suitable habitat for FAW for the 5-8.5 scenario

While the southern parts of East Africa, specifically Tanzania and Uganda will continue to become less suitable to FAW, in the north, represented by Sudan, parts of the country (central-west and north) will continue to experience both an increase and intensification of its suitable habitats. With CanESM5, a lower limit of the highly suitable habitat is projected to a large extent in this region, with the possibility of reaching the upper limit of the highly suitable class in the long term, INM-

CM5-0 projects loss of suitability in that region. However, it also projects a lower limit of the highly suitable habitat in central Ethiopia and southern Eritrea.

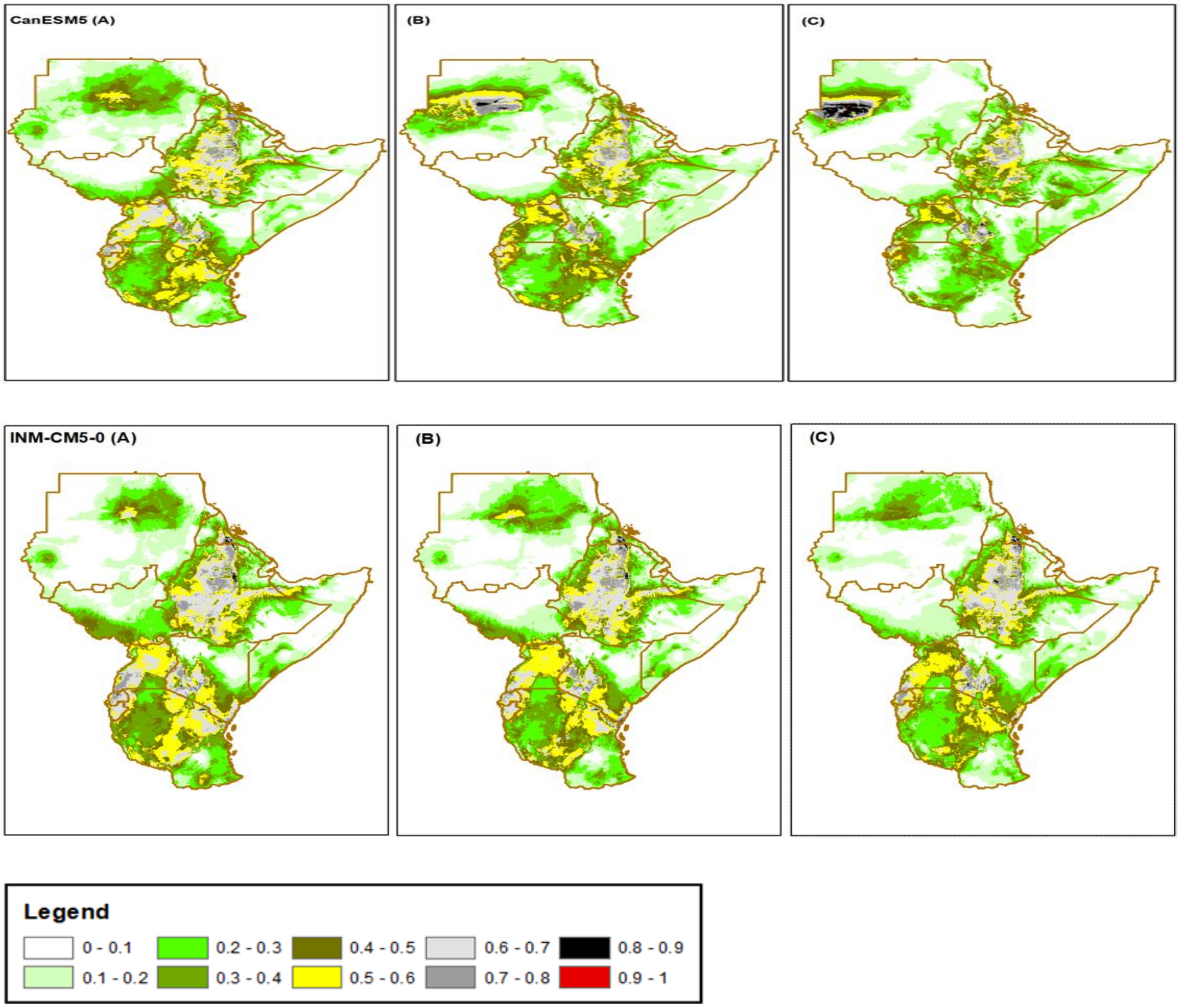

Figure 7. FAW suitable habitat In Eastern Africa in the SSP5-8.5 scenario based on CanESM5 and INM-CM5-0 global circulation models from CMIP6: for (A) near term 2021-2040, (B) mid-term 2041-2060 and (C) long term 2061-2080.

Discussion

Our studies indicate that more than 75% of the Maxent model's overall performance was influenced by just five variables, of which four are related to precipitation and one is related to temperature. The variables are the annual precipitation, annual mean temperature, precipitation of the driest month, precipitation of the warmest quarter, and the precipitation seasonality It can be said that these variables are the major climatic contributors to FAW suitability and distribution in the Eastern Africa region. This to an extent is consistent with published work by Ramasamy et al.

(2022) who conducted a global study on the future suitability of FAW. Our study implicates annual precipitation and annual mean temperature as the two most important contributors to FAW's distribution. While the percentage contribution of bio12 is slightly comparable between the two studies (~ 37% and ~ 42%), that from bio1 is not. The value (22%) found by Ramasamy et al. (2022) is slightly higher than the percentage contribution of this variable in this study. Zacarias (2020) study of global FAW suitability instead positioned annual mean temperature (bio1;19.2%), and precipitation of the driest quarter (bio17;17.3%) as the highest bioclim contributors. Bio12 contributed 11.5% in their study. Cokola et al. (2020) projected FAW's current suitable habitat in South Kivu, DRC. Consistent with the above authors, bio12 was the highest contributor. From these studies in which Africa was involved to some extent, we observe the important role of bio12 (annual precipitation) in the distribution of FAW. Current studies highlighted that although FAW has a broad habitat niche, it will most likely be established in regions with similar climate conditions as its native habitats (Cokola et al., 2020). High precipitation is important in growth and development (Wu et al., 2019).

A second important observation from this study in the current climate condition is the concentration of FAW-suitable habitats in Uganda, Rwanda, Burundi, southwestern Kenya, regions in central and northern Tanzania, central to northern Ethiopia, and southern Eritrea. This study also shows that in the future, the northern parts of Eastern African countries will become a hotspot for FAW, while the southern parts will become cold spots. Such a northward shift in FAW's suitability habitat has been highlighted before (Zacarias, 2022). This was observed in the authors' FAW suitability study, using the previous CMIP5 scenario. Similarly, to this study, they also found increased suitability habitats in parts of Sudan, and decline or no changes in suitability habitats in Ethiopia, Tanzania, Kenya, and other parts of Eastern Africa. Similar findings have also been recently projected by Ramasamy et al. (2022) on this possible northward shift in habitat suitability for FAW. However, they found an expansion in suitable areas south of Sudan and parts of Ethiopia, that spread throughout the country, which was not the case in this study. This was in spite of the fact that these latter authors used the new CMIP6 scenarios, although different GCMs. Irrespective of these reduced suitable habitats found in this study, the region will continue to be vulnerable to the year-round FAW population establishment (Timilsena et al., 2022).

A third important output from our study is that models with different climate sensitivities may over-project or under-project future suitable habitats. In this study, CanESM5 with a higher climate sensitivity clearly showed distinct projections from INM-CM5-0 which has the least climate sensitivity within CMIP6. There remains a dearth of information in understanding the influence of these sensitivities in suitability studies more so because existing studies have not made it a focus of their work (Abdel-Rahman et al., 2023; Timilsena et al., 2022; Zacarias, 2020). In-depth research is, therefore, needed at both global and localized scales to enlighten how climate sensitivities affect modeling outputs. Our findings remain important in allowing affected regions to understand the upper and lower boundaries of their vulnerability to this pest for early intervention.

Conclusions

In this study, mapping and forecasting of fall armyworm pests in Eastern Africa was undertaken using a recent FAW data set. The climate variables influencing armyworm (FAW) pest distribution were analyzed, while its suitability in the Eastern African region was mapped. New CMIP6 data and MaxEnt model were also used for the first time to predict suitable habitats in the region, and further comparing outputs from two GCMs with high and low climate sensitivities. MaxEnt model evaluation produced a high AUC value of 0.942, which allowed us to use this model to infer climate variables that influence FAW in the region. The annual precipitation and annual mean temperature were the two highest contributors to the geographical suitability of the FAW pest. The current climatic conditions favor FAW suitability mostly in the countries in the southern and central regions of our study area. The northern region and the horn of Africa are less and unsuitable for FAW occurrence. By considering SSPs scenarios - SSP1-2.3, SSP3-7.0, and SSP5-8.5 - representing optimistic, moderate, and pessimistic emission scenarios and global warming, respectively, it was clear that in the pessimistic scenario, the spread of FAW will be pronounced in certain eastern African countries, especially Sudan and Ethiopia. Areas like Sudan that were climatically unsuitable to FAW occurrence will become suitable, and be highly vulnerable to this pest. This might tend to promote the spread of the pest into neighboring countries through the long-distance flight potential of the pest over high altitudes, and cross-border activities with neighboring countries. This study therefore recommends that existing prevention measures should be strictly enforced to mitigate both the spread of the pest and global warming. Additionally, new methods should also be investigated to prevent further spread and contain the pest. Given that the pest has migrated from across borders, stricter border control measures in the transportation of biological materials should be enforced to limit its entry via such routes. Control and monitoring measures should be adopted to prevent the spread and excess damage of the FAW pest in the eastern Africa region.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Author contribution

DK and REEY conceptualized the project and contributed to its implementation. PN provided input on the project's concept. NN took the lead in developing and implementing the R codes with the assistance of REEY. REEY also did the quantitative analysis and mapping of the suitability changes. NN reclassified all the outputs in ArcGIS. NN and REEY developed the first draft of the manuscript. All authors have read the content of the manuscript and provided input to the final version. NN has submitted parts of this work as an MSc thesis which now forms the basis of this manuscript.

Data availability statement

All raw data that support the findings of this study are downloadable online:

Fall Armyworm occurrence data

FAO FAW dataset: https://data.apps.fao.org/

CABI FAW dataset: https://www.cabidigitallibrary.org/doi/10.1079/cabicompendium.29810

Niassy et al., (2021): https://datadryad.org/stash/dataset/doi:10.5061/dryad.9kd51c5gg

Climate data

Worlclim: https://worldclim.org/data/index.html

References

Agrios, G. (2005). Plant Pathology 5th Edition: Elsevier Academic Press. Burlington, Ma. USA, 79–103.

Bale, J., Masters, G & Hodkinson, D. (2002). Herbivory in global climate change research: Direct effects of rising temperature on insect herbivores. https://www.researchgate.net/publication/229505883_Herbivory_in_global_climate_change_research_Direct_effects_of_rising_temperature_on_insect_herbivores

Baloch, M. N., Fan, J., Haseeb, M., & Zhang, R. (2020). Mapping Potential Distribution of Spodoptera frugiperda (Lepidoptera: Noctuidae) in Central Asia. Insects, 11(3), 172.

Baudron, F., Zaman-Allah, M. A., Chaipa, I., Chari, N., & Chinwada, P. (2019). Understanding the factors influencing fall armyworm (Spodoptera frugiperda JE Smith) damage in African smallholder maize fields and quantifying its impact on yield. A case study in Eastern Zimbabwe. Crop Protection, 120, 141–150.

Bowers, A. J., & Zhou, X. (2019). Receiver operating characteristic (ROC) area under the curve (AUC): A diagnostic measure for evaluating the accuracy of predictors of education outcomes. Journal of Education for Students Placed at Risk (JESPAR), 24(1), 20–46.

Chamberlin, P. (2018). Climate of Eastern Africa. In Pierre Chamberlin, Oxford Research Encyclopedia of Climate Science. Oxford University Press. https://doi.org/10.1093/acrefore/9780190228620.013.512

Çoban, H. O., Örücü, Ö. K., Örücü, Ö. K., & Arslan, E. S. (2020). MaxEnt Modeling for Predicting the Current and Future Potential Geographical Distribution of Quercus libani Olivier. Sustainability, 12(7), 2671. https://doi.org/10.3390/su12072671

Cokola, M. C., Mugumaarhahama, Y., Bisimwa, E. B., Grégoire, N., Bugeme, D. M., Chuma, G. B., Byamungu, A. N., & Francis, F. (2020). Bioclimatic Zonation and Potential Distribution of Spodoptera Frugiperda (Lepidoptera: Noctuidae) in South Kivu Province, DR Congo.

Das, T., Majumdar, M. H. D., Devi, R. T., & Rajesh, T. (2016). Climate change impacts on plant diseases. SAARC Journal of Agriculture, 14(2), 200–209.

Day, R., Abrahams, P., Bateman, M., Beale, T., Clottey, V., Cock, M., Colmenarez, Y., Corniani, N., Early, R., & Godwin, J. (2017). Fall armyworm: Impacts and implications for Africa. Outlooks on Pest Management, 28(5), 196–201.

Day, R., Abrahams, P., Bateman, M., Beale, T., Clottey, V., Cock, M., Colmenarez, Y., Corniani, N., Early, R., Godwin, J., Gomez, J., Moreno, P. G., Murphy, S. T., Oppong-Mensah, B., Phiri, N., Pratt, C., Silvestri, S., & Witt, A. (2017). Fall Armyworm: Impacts and Implications for Africa. Outlooks on Pest Management, 28(5), 196–201. https://doi.org/10.1564/v28_oct_02

De Groote, H., Kimenju, S. C., Munyua, B., Palmas, S., Kassie, M., & Bruce, A. (2020). Spread and impact of fall armyworm (Spodoptera frugiperda JE Smith) in maize production areas of Kenya. Agriculture, Ecosystems & Environment, 292, 106804.

Early, R., González-Moreno, P., Murphy, S. T., & Day, R. (2018). Forecasting the global extent of invasion of the cereal pest Spodoptera frugiperda, the fall armyworm. doi: https://doi.org/10.1101/391847

Goergen, G., Kumar, P. L., Sankung, S. B., Togola, A., & Tamò, M. (2016). First report of outbreaks of the fall armyworm Spodoptera frugiperda (JE Smith) (Lepidoptera, Noctuidae), a new alien invasive pest in West and Central Africa. PloS One, 11(10).

Hanyurwimfura, D., Nizeyimana, E., Ndikumana, F., Mukanyiligira, D., Diwani, A. B., & Mukamanzi, F. (2018). Monitoring System to Strive against Fall Armyworm in Crops Case Study: Maize in Rwanda. 66–71.

Hruska, A. J., & Gould, F. (1997). Fall armyworm (Lepidoptera: Noctuidae) and Diatraea lineolata (Lepidoptera: Pyralidae): Impact of larval population level and temporal occurrence on maize yield in Nicaragua. Journal of Economic Entomology, 90(2), 611–622.

Huesing, J., Prasanna, B., McGrath, D., Chinwada, P., Jepson, P., & Capinera, J. (2018). Integrated pest management of fall armyworm in Africa: An introduction. Fall Armyworm in Africa: A Guide for Integrated Pest Management. CIMMYT, Mexico, CDMX.

Murúa, G., Molina-Ochoa, J., & Coviella, C. (2006). Population dynamics of the fall armyworm, Spodoptera frugiperda (Lepidoptera: Noctuidae), and its parasitoids in northwestern Argentina. Florida Entomologist, 89(2), 175–182.

Niassy, S., Agbodzavu, M. K., Kimathi, E., Mutune, B., Abdel-Rahman, E. F. M., Salifu, D., Hailu, G., Belayneh, Y. T., Felege, E., & Tonnang, H. E. (2021). Bioecology of fall armyworm Spodoptera frugiperda (JE Smith), its management, and potential patterns of seasonal spread in Africa. PloS One, 16(6), e0249042.

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. Ecological Modelling, 190(3), 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026

Phillips, S. J., Dudík, M., & Schapire, R. E. (2017). Maxent software for modeling species niches and distributions (Version 3.4.1). https://biodiversityinformatics.amnh.org/open_source/maxent.

Prasanna, B., Huesing, J., Eddy, R., & Peschke, V. (2018). Fall armyworm in Africa: A guide for integrated pest management.

Qin, A., Liu, B., Guo, Q., Bussmann, R. W., Ma, F., Jian, Z., Xu, G., & Pei, S. (2017). Maxent modeling for predicting impacts of climate change on the potential distribution of Thuja sutchuenensis Franch., an extremely endangered conifer from southwestern China. Global Ecology and Conservation, 10, 139–146.

Ramasamy, M., Das, B., & Ramesh, R. (2022). Predicting climate change impacts on potential worldwide distribution of fall armyworm based on CMIP6 projections. Journal of Pest Science, 95(2), 841–854. https://doi.org/10.1007/s10340-021-01411-1

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., et al. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Global Environmental Change, 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rwomushana, I. (2019). Spodoptera frugiperda (fall armyworm). Invasive Species Compendium, (29810). https://doi.org/10.1079/cabicompendium.29810

Swart, N. C., Cole, J. N. S., Kharin, V. V., Lazare, M., Scinocca, J. F., et al. (2019). CCCma CanESM5 model output prepared for CMIP6 ScenarioMIP [Data set]. Earth System Grid Federation. https://doi.org/10.22033/ESGF/CMIP6.1317

Tang, J., Li, J., Lu, H., Lu, F., & Lu, B. (2019). Potential distribution of an invasive pest, Eu platypus parallels, in China as predicted by Maxent. Pest Management Science, 75(6), 1630–1637.

Timilsena, B. P., Niassy, S., Kimathi, E., Abdel-Rahman, E. M., Seidl-Adams, I., et al. (2022). Potential distribution of fall armyworm in Africa and beyond, considering climate change and irrigation patterns. Scientific Reports, 12(1), Article 1. https://doi.org/10.1038/s41598-021-04369-3

Uzayisenga, B., Waweru, B., Kajuga, J., Karangwa, P., Uwumukiza, B., et al. (2018). The first record of the fall armyworm, Spodoptera frugiperda (JE Smith, 1797) (Lepidoptera: Noctuidae), was in Rwanda. African Entomology, 26(1), 244–246.

Volodin, E., Mortikov, E., Gritsun, A., Lykossov, V., Galin, V., et al. (2019). *INM INM-CM5-0* model output prepared for CMIP6 CMIP piControl [Data set]. Earth System Grid Federation. https://doi.org/10.22033/ESGF/CMIP6.5081

Wu, Q. L., He, L. M., Shen, X. J., Jiang, Y. Y., Liu, J., Hu, G., & Wu, K. M. (2019). Estimation of the potential infestation area of newly-invaded fall armyworm Spodoptera frugiperda in the Yangtze River Valley of China. Insects, 10(9), 298.

Wyckhuys, K. A., & O'Neil, R. J. (2006). Population dynamics of Spodoptera frugiperda Smith (Lepidoptera: Noctuidae) and associated arthropod natural enemies in Honduran subsistence maize. Crop Protection, 25(11), 1180–1190.

Yang, Kushwaha, S. P. S., Saran, S., Xu, J., & Roy, P. S. (2013). Maxent modeling for predicting the potential distribution of medicinal plant, Justicia adhatoda L. in Lesser Himalayan foothills. Ecological Engineering, 51, 83–87. https://doi.org/10.1016/j.ecoleng.2012.12.004

Yang, W., Seager, R., Cane, M., & Lyon, B. (2015). The Annual Cycle of East African Precipitation. Journal of Climate, 28, 2385–2404. https://doi.org/10.1175/JCLI-D-14-00484.1

Zacarias, D. A. (2020). Global bioclimatic suitability for the fall armyworm, Spodoptera frugiperda (Lepidoptera: Noctuidae), and potential co-occurrence with major host crops under climate change scenarios. Climatic Change, 161(4), 555–566. https://doi.org/10.1007/s10584-020-02722-5