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Harnessing data science to improve integrated management of invasive pest species across Africa: An application to Fall armyworm (*Spodoptera frugiperda*) (J.E. Smith) (Lepidoptera: Noctuidae)

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A R T I C L E I N F O

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A B S T R A C T

After five years of its first report on the African continent, Fall armyworm (FAW), *Spodoptera frugiperda* (J.E. Smith) is considered a major threat to maize, sorghum, and millet production in sub-Saharan Africa. Despite the rigorous work already conducted to reduce FAW prevalence, the dynamics and invasion mechanisms of FAW in Africa are still poorly understood. This study

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Spatial
Temporal

applied interdisciplinary tools, analytics, and algorithms on a FAW dataset with a spatial lens to provide insights and project the intensity of FAW infestation across Africa. The data collected between January 2018 and December 2020 in selected locations were matched with the monthly average data of the climatic and environmental variables. The multilevel analytics aimed to identify the key factors that influence the dynamics of spatial and temporal pest density and occurrence at a 2 km x 2 km grid resolution. The seasonal variations of the identified factors and dynamics were used to calibrate rule-based analytics employed to simulate the monthly densities and occurrence of the FAW for the years 2018, 2019, and 2020. Three FAW density level classes were inferred, i.e., low (0–10 FAW moth per trap), moderate (11–30 FAW moth per trap), and high (>30 FAW moth per trap). Results show that monthly density projections were sensitive to the type of FAW host vegetation and the seasonal variability of climatic factors. Moreover, the diversity in the climate patterns and cropping systems across the African sub-regions are considered the main drivers of FAW abundance and variation. An optimum overall accuracy of 53% was obtained across the three years and at a continental scale, however, a gradual increase in prediction accuracy was observed among the years, with 2020 predictions providing accuracies greater than 70%. Apart from the low amount of data in 2018 and 2019, the average level of accuracy obtained could also be explained by the non-inclusion of data related to certain key factors such as the influence of natural enemies (predators, parasitoids, and pathogens) into the analysis. Further detailed data on the occurrence and efficiency of FAW natural enemies in the region may help to complete the tri-trophic interactions between the host plants, pests, and beneficial organisms. Nevertheless, the tool developed in this study provides a framework for field monitoring of FAW in Africa that may be a basis for a future decision support system (DSS).

1. Introduction

Invasive insect pests present a permanent threat to agricultural activities and crop production worldwide (Sileshi et al., 2019). Effective monitoring of invasive pests and reliable prediction of future trends in their dynamics, spread, the interaction of host plants, and natural regulatory factors is critical to guide the development and implementation of areawide management strategies for invasive species (Sileshi et al., 2019; Wang et al., 2020).

The Fall armyworm (FAW), *Spodoptera frugiperda* is a lepidopteran pest native to tropical and subtropical regions of the Americas and its first successful invasion outside the native region was reported in Africa, more precisely in Nigeria, Togo, and Benin in 2016 (Goergen et al., 2016). By late 2017, it had expanded its infestation range to about 40 sub-Saharan African countries (Cock et al., 2017; Du Plessis et al., 2018). Currently, the pest has spread to over 45 African countries, including few North African countries (Niassy et al., 2021). In January 2019, FAW was also recorded in Asia, particularly in India, Thailand, Myanmar, and China (Wang et al., 2020; Wu et al., 2019). Subsequently, the pest has further spread to Australia, Korea, Japan, and countries in Oceania and the Middle East by 2021 (Rwomushana, 2019). This quick spread across continents might have been accelerated by the high natural wind-assisted flight capability of FAW, which allows it to reach several hundreds of kilometers in a single day (Early et al., 2018).

FAW can exploit a wide range of host plants, with the potential to survive on more than 350 plant species belonging to about 70 families (Casmuz et al., 2010; Montezano et al., 2018). The most common host plants belong to the families *Poaceae*, *Asteraceae*, and *Fabaceae* (Early et al., 2018), with maize being the most preferred host crop in Africa, together with sorghum and millet (Rwomushana et al., 2018). These FAW preferred crops are the staple crops for most sub-Saharan African countries. Although the presence of FAW has also been recorded on many other host crops in Africa, the damages and related losses on maize exceed any other crop (Rwomushana et al., 2018). Without any control measures in place, maize yield losses due to FAW can exceed 50% of the total annual production of the affected countries, especially in the low and medium maize producing areas (De Groote et al., 2020), leading to serious economic and social implications. Thus, the successful management and control of such a serious invasive pest species needs to be proactive and preemptive based on real-time early warning and anticipated intervention (Early et al., 2018; Sokame et al., 2020a, 2020b).

In North America, where FAW is endemic, migration starts from Texas and Florida in the late winter or spring (February – May). Populations are noticed in the northern areas in late summer and fall, hence the name fall armyworm (Nagoshi et al., 2012). In Africa, FAW appears to have been established in cereal-based agro-ecosystems (Goergen et al., 2016). However, cropping systems, farming practices, and the agroecosystems in Africa are different from those of north, central and south America. Therefore, the FAW temporal and spatial infestation spread in different parts of Africa could be influenced by these factors which are yet to be established.

Many models have been developed worldwide to help understand the dynamics and behavior of FAW using different frameworks and modeling techniques. For example, Ramirez-Cabral et al. (2017) and Paudel Timilsena et al. (2022) developed a CLIMEX model to spatially project the impact of climate change on future establishment scenarios for north and south America and Africa, respectively. Again, the study of Early et al. (2018) combined effects of temperature and precipitation on FAW life-history, presence and pseudo absence datasets in Africa, north and south America were analyzed to build a world map using a FAW suitability index and the 'biomod2' R-package while comparing techniques such as artificial neural networks (ANN), random forest (RF), and generalized linear models (GLM) (Early et al., 2018). In 2019, a computational model was developed by Garcia et al. (2019) to describe the spatio-temporal dynamics of FAW in *Bacillus turgeniencis* (Bt) transgenic corn areas and non-Bt transgenic corn areas, using the following variables; crop area, thermal requirements of FAW, and weekly temperature recordings, migration rate, rate of larval movement, and insect resistance to the transgenic Bt crop. The model was subsequently tested in the field using data collected in northern Florida, USA.

In Wu et al. (2019) the numerical trajectory modeling approach was used to predict FAW's potential flight pathway and population range in China (tropical and sub-tropical regions), considering the insect flight ability and meteorological data (wind speed, temperature, rainfall, and relative humidity). More recently, Li et al. (2020) adopted the trajectory analytics approach, using the FAW flight ability and meteorological data to predict the migration pathways in eastern China.

Although many studies have demonstrated that almost the entire sub-Saharan African continent is suitable for the FAW's long-term establishment (Rwomushana et al., 2018), the dispersal and migration patterns of FAW in Africa have not been fully understood to provide mechanisms and solutions to real-time early warning. This is due to the lack of understanding of infestation dynamics over seasons in all sub-Saharan Africa and its sub-regions (central, eastern, southern, and western). Furthermore, the variability of environmental and climatic factors in a year, coupled with the diversity of farming culture, increases the complexity of predicting FAW densities across sub-Saharan Africa.

The advancement in data science and analytics provides a new paradigm to understand the population dynamics of highly mobile, polyphagous, and serious pests such as the FAW. Such advancements unify statistics, data analytics, informatics, and related methods, facilitating a deep understanding of the actual phenomena (van der Aalst, 2016). Data science is a relatively new field that combines mathematics, computer science, and statistical methods, processes, algorithms, and systems to extract knowledge, patterns, and insights from structured and unstructured data (Raschka et al., 2020; Chemura et al., 2021). Estimating the density level of a pest insect

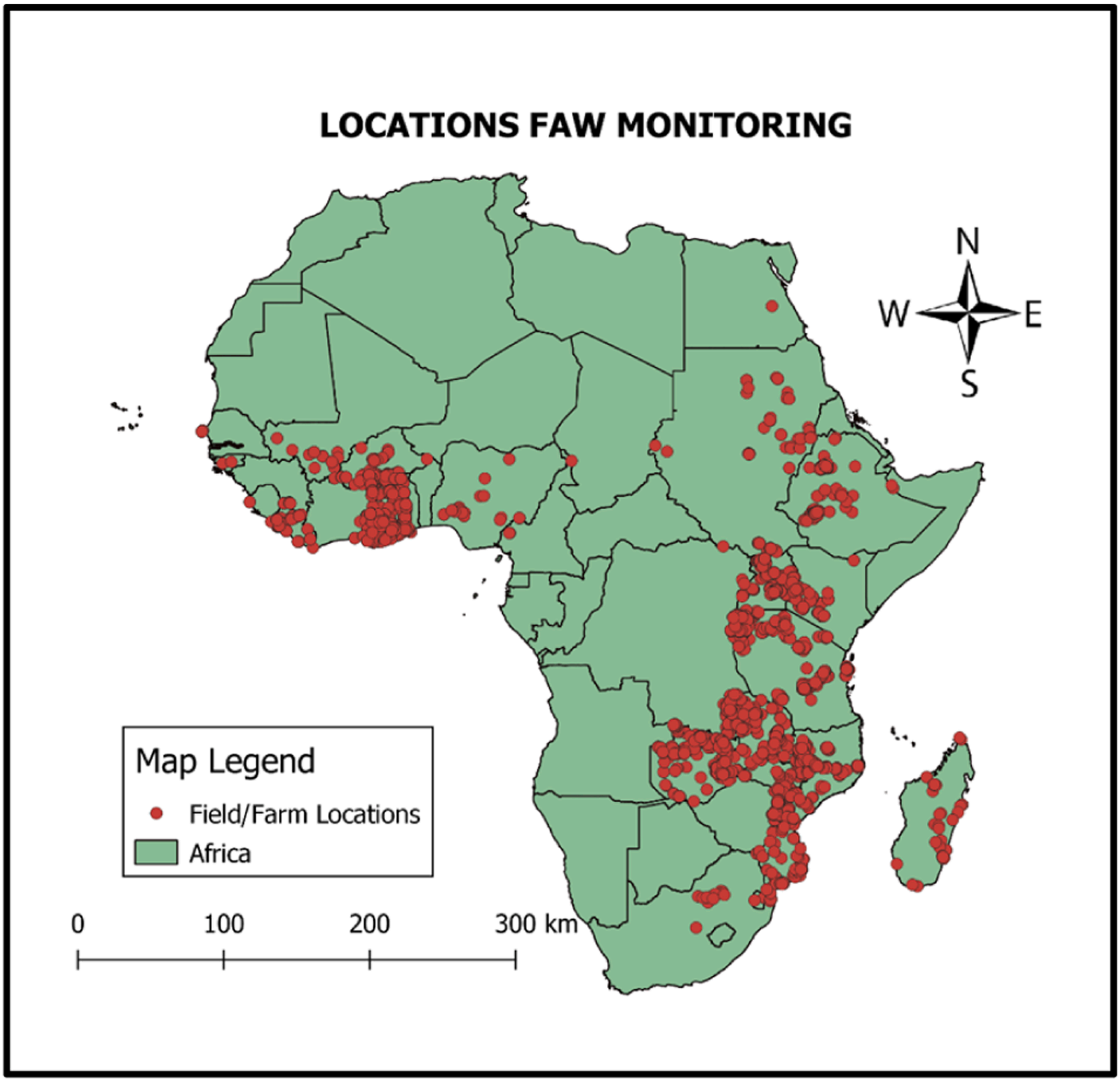

Fig. 1. The African continent (green) and the location of the field survey of Fall armyworm (FAW) density (red dots).

in a crop is complex but can be addressed using empirical and mechanistic modeling approaches such as rule-based modeling (Liebhold and Tobin, 2008; Bell et al., 2013). The rule-based modeling approach has been successfully used to analyze the dynamics of biological interactions between living organisms and abiotic factors (Morton-Firth and Bray, 1998; Faeder et al., 2009; Chylek et al., 2013; Forbes et al., 2017; Boutillier et al., 2018) and involves a set of rules portraying the dynamics of a system, especially when the use of a mathematical model is difficult or impossible (Chylek et al., 2013). The set rules are then customized to describe and characterize the interactions among components of the system whose dynamics are being mimicked through deterministic or stochastic simulations. Although its application is common in studies of biochemical systems, its usage may be extended to address problems in the context of ecology, agriculture, or spatial modeling (Ibrahim et al., 2013; Vodovotz and An, 2015). The advantage presented by allowing the inclusion of mechanistic and detailed interaction that affect insect pest dynamics makes data science with rule-based modeling the most suitable approach to address the purpose of this work.

Therefore, the present study aimed to use the data science and rule-based modeling approach to match, predict, and map the density level of FAW on crops across Africa using the following data collected from sub-Saharan Africa: field trap monitoring of FAW, weather data (temperature, rainfall, solar radiation, wind speed), farming system data, the elevation of the location of data collection and month of the year. The proposed approach targets to provide the first step towards information and knowledge on where to prioritize and implement a FAW control strategy.

2. Materials and methods

2.1. Study area

The study included all regions of sub-Saharan Africa, however, data used for the continent-wide project were obtained from some selected farm locations in various countries where field monitoring of FAW density had been conducted (Fig. 1). The motivation to use the entire continent was informed by the timely need for a method that provides accurate and holistic information across the sub-regions in sub-Saharan Africa coupled with the highly migratory pattern of this invasive pest.

2.2. Data description and analytics

2.2.1. Collection of environmental and climatic variables data used to develop the mixed and rule-based models

The long-term FAW field data monitoring initiative by the United Nations Food and Agriculture Organization (FAO) using the FAW monitoring and early warning system (FAMEWS) was used as the main locational and density data source. The data were downloaded from the FAO platform (http://www.fao.org/fall-armyworm/en/) in a.csv file format upon obtaining required permissions. In this dataset, the variables recorded during the field monitoring include: (i) **Date**: i.e. the date the survey was conducted; (ii) **CropSystem**: the cropping system used on the farm; (iii) **CropStage**: the developmental stage of the main crop on the farm location at the time of data collection; (iv) **CropMain**: the main crop on the farm (either maize, sorghum, or rice); (v) **CropIrrigation**: a yes/no variable for irrigation use or not, respectively; and (vi) **Density**: number of FAW male adults found in the pheromone traps at a given time during field counts.

The universal bucket traps associated with FAW pheromone (lure blend: z9-12Ac (0.25%); Z7-12Ac (0.5%); z11-16Ac (17.54%) and Z9-14Ac (81.7%)) were used for this field survey. They were suspended about 1.5 m above the ground with one trap covering 0.5–2 ha; placed both inside and outside the maize farm. The traps were examined and emptied every week while the pheromone was changed every 3–6 weeks and the damaged traps replaced while the trapped moths were examined for FAW identification and quantification.

Considering that trap counts can only show trends of the population over time and, the number of males is equal to the number of females, this study used data collected from January 2018 to December 2020, which corresponds to more than 15,000 observations from the various field locations across 17 countries (Benin, Burundi, Burkina Faso, Ethiopia, Ghana, Guinea, Madagascar, Malawi, Mozambique, Liberia, Kenya, Tanzania, Togo, Rwanda, Uganda, South Africa, and Zambia) in sub-Saharan Africa. Data were subjected to a rigorous cleaning procedure to remove duplicated records and missing values and the datasets received from the different sub-regions were standardized as follows: two data observations were considered duplicates if the columns of the date of the record (date), geographic coordinates (latitude, longitude), and the main crop were identical. The data cleaning process was performed semi-automatically in R software 4.1.0 (RCoreTeam, 2020). Out of the total of 15,000 data points obtained 8231 observations were retained after the data cleaning process.

The climatic variables used in this study were wind speed, solar radiation, temperature, rainfall, and landscape elevation. The selection of these variables was motivated by other studies that have reported the dependency of FAW occurrence and density on these environmental and climatic variables (Ramirez-Cabral et al., 2017; Early et al., 2018; Garcia et al., 2019; Sokame et al., 2020a, 2020b). The temperature, solar radiation, and wind speed dataset were obtained from the WorldClim database (http://www.worldclim.org/current) (Fick and Hijmans, 2017). Similarly, the rainfall data were obtained from the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) database at 0.05° resolution satellite imagery (https://www.chc.ucsb.edu/data/chirps) (Funk et al., 2015). The landscape elevation data were obtained from the Shuttle Radar Topography Mission (SRTM), provided by the Earth Resources Observation and Science (EROS) Center (https://www.usgs.gov/centers/eros).

The downloaded climatic data were monthly mean raster datasets either in tagged image file format (.tiff) or American Standard Code for Information Interchange (.asc). For each of these variables, we extracted the pixel values to the FAW field dataset using the geographic location of the 8231 point coordinates and the 'extract' function in the 'raster' package in R (Hijmans, 2020). The dataset

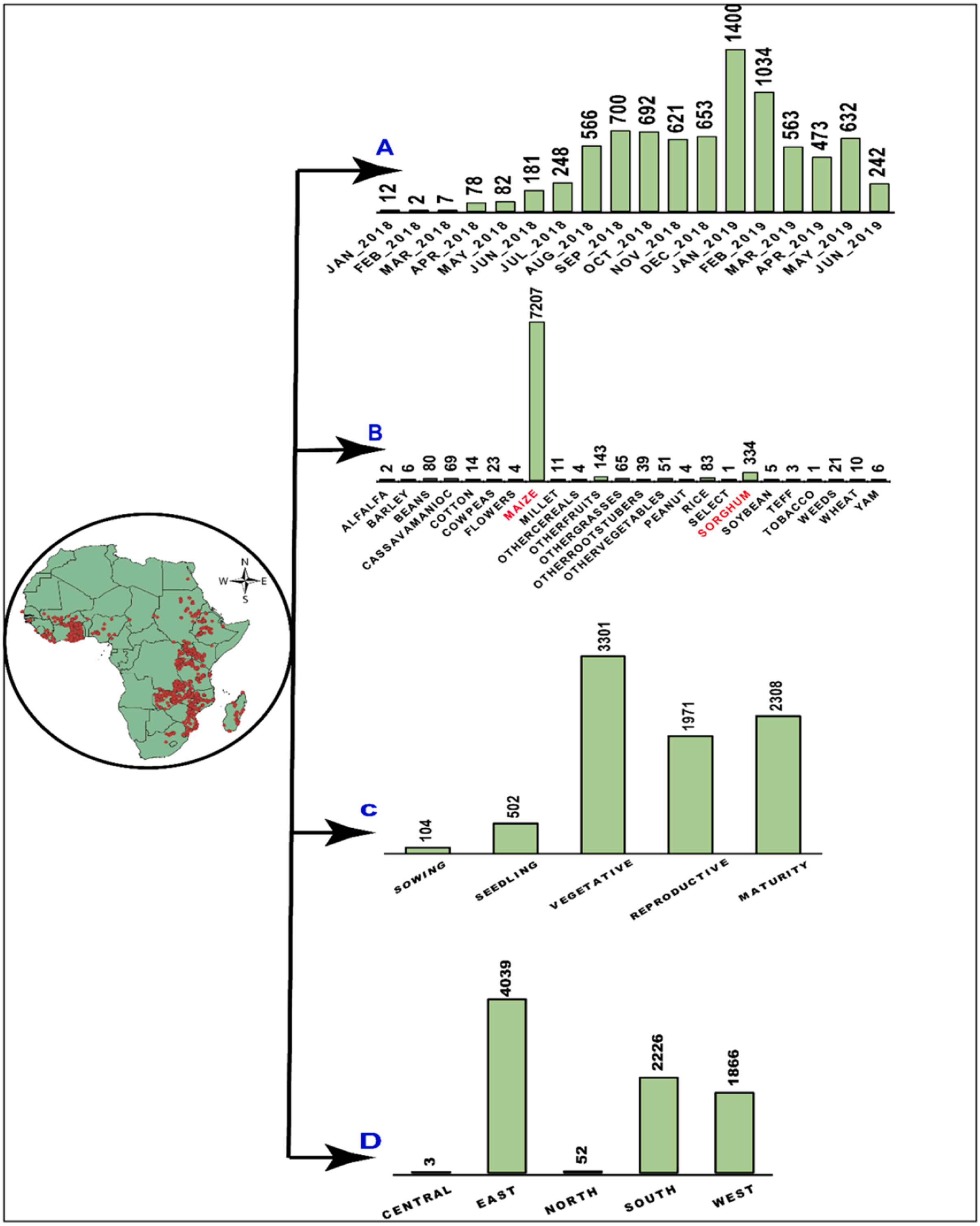

Fig. 2. Trend of Fall armyworm (FAW) records variation from field monitoring data where (A) shows the monthly density of FAW in Africa from January 2018 to June 2019, (B) shows the FAW density in Africa per host plant, (C) shows the FAW density based on the host plant developmental stage, and (D) shows the FAW records for each sub-region in Africa.

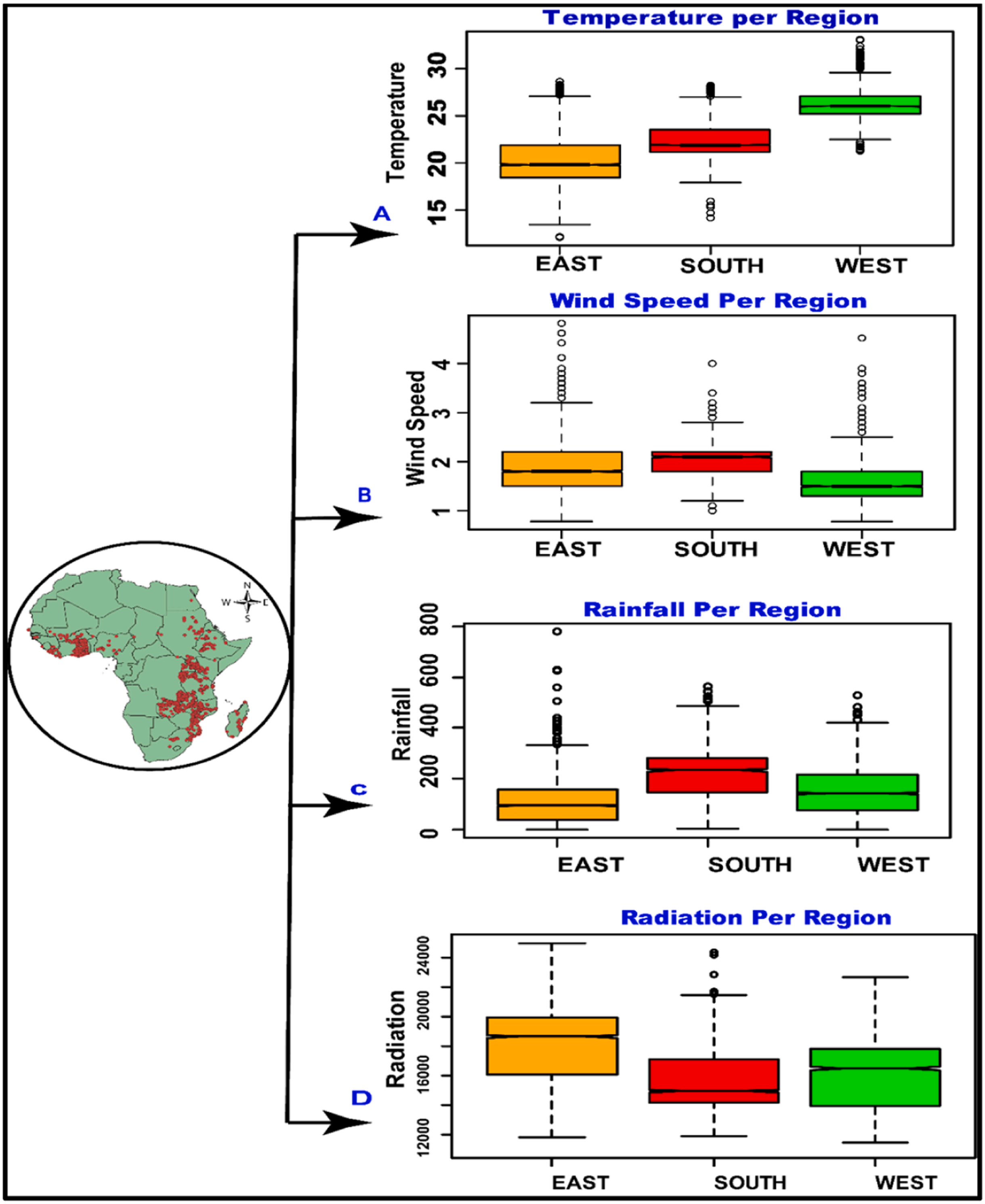

Fig. 3. Seasonal variations of climatic factors in areas of Fall armyworm (FAW) field occurrence in the three selected African sub-regions, namely east, south, and west. The considered climatic factors are (A) temperature, (B) wind speed, (C) rainfall, and (D) radiation.

was subdivided into the five Africa sub-geographical regions, i.e., north, south, east, west, and central, using the coordinate references. This classification was needed to explore the variations of the spatiotemporal effects due to weather and seasonal variations in the five sub-geographic regions, which are likely to influence the crop calendars and associated occurrence and density of the FAW differently at any timestep.

2.2.2. Multilevel analysis

A multilevel analysis was done using the cleaned dataset by designing a linear mixed-effect model to explore and identify key factors (fixed and random) having a considerable impact on the density and occurrence of FAW in sub-Saharan Africa. After a quick exploration of the FAW population density variations observed from the field, we hypothesized that time, space, or the combination of both would influence the occurrence and density of the FAW. The following hypotheses were used to guide the analysis: The variation of FAW density is randomly affected by (i) the time (day, week, or month of the year); (ii) the spatial locations (sites) of the area where the collection is made; and (iii) both the time and the spatial location.

The multilevel analysis that was used refers to the application of mixed-effects models to hierarchical data (Pinheiro et al., 2020). A mixed or multilevel model was the most suitable statistical tool in this study as it is often used for analyzing time-series data or repeated observation across groups or individuals (nested data) (Rosenblatt, 2019). Also, it is appropriate for research designs of ecological, biological, and socio-ecological processes that operate at more than one scale. We aimed to determine if a group of given factors could predict an individual outcome, in our case, the density and occurrence of FAW in sub-Saharan Africa (Rosenblatt, 2019). The specificity of the mixed models is that they incorporate the fixed and the random effects of the process together. A random effect simply refers to the main source of variability (Rosenblatt, 2019).

In this study, we predicted the density variation of FAW using fixed effects including the wind speed, radiation, temperature, precipitation, elevation of location, cropping system, crop stage, main crop, irrigation system, and farm area and month of year. The variables for the random effects include the date of farm data monitoring and the sub-region of the trap (PointRegion) within farms. Using these factors, three statistical models were designed, respectively in relation to the three hypotheses. The first model considered the temporal variation as the random effect, the second model considered the spatial variation as the random effect while the third model considered both the temporal and spatial variations as random effects. The derived three models are given as shown in Eqs. (1)–(3) using the R-package ‘nlme’ v3.1-147, respectively (Pinheiro et al., 2020).

mixedModel1 ← lme(FawDensity ~ WindSpeed + Radiation+ Temperature + RainValue +Elevation + cropSystem +cropStage+ cropMain + monthOfYr + cropIrriga + cropFiel, random = ~1|date, data = fawDataAfrica) (1)

mixedModel2 ← lme(FawDensity ~ WindSpeed + Radiation+ Temperature + RainValue +Elevation + cropSystem +cropStage + cropMain + monthOfYr + cropIrriga + cropFiel, random = ~1| PointRegion, data = fawDataAfrica) (2)

mixedModel3 ← lme(FawDensity ~ WindSpeed + Radiation+ Temperature + RainValue +Elevation + cropSystem + cropStage + cropMain + monthOfYr + cropIrriga + cropFiel, random = ~1| PointRegion /date, data = fawDataAfrica) (3)

A preliminary stage to select the best model was done using the lowest Akaike information criterion (AIC) value. An analysis of variance (ANOVA) together with the likelihood ratio test (LRT) were conducted on the third model to test the significance of the contribution of each of the factors on FAW densities. A detailed statistical analysis was done on the linear-mixed modeling outputs to set the rules and estimate the boundaries and values of the biotic and abiotic parameters needed for the rule-based modeling prediction. Response curves of the different variables were developed and observed to assess the relative influence of each variable on the density of the FAW.

2.2.3. Calibration of the ‘rules’ from descriptive analytics

The analytics started by observing the monthly FAW density across sub-Saharan Africa for the entire period of field monitoring (Fig. 2A). Thereafter, we assessed the variation of the FAW density on diverse host plants, which helped identify the preferred host of the pest in sub-Saharan Africa (Fig. 2B). Maize and sorghum were the plants having the highest FAW density. Therefore, their physical cropping area was integrated while defining the spatial projection rules by considering the area suitable for cropping these host plants. In Fig. 2C, we explored the general infestation level based on the host plant crop stage, while the variation of FAW density per region is shown in Fig. 2D. Few monitoring operations were undertaken in the central and northern regions compared to the eastern (Kenya, Tanzania, Uganda, Ethiopia, Rwanda), southern (Malawi, Madagascar, South Africa, Zambia, Mozambique), and western (Nigeria, Mali, Benin, Burkina Faso, Guinea, Liberia), regions of Africa; hence, only data from these three African sub-regions were considered in defining the rules for spatial projections.

Boxplots were used to explore the dispersion of the climatic factors for each of the three sub-regions based on five synoptic numbers, namely: the minimum, the first quartile (Q1), the median, the third quartile (Q3), and the maximum (Fig. 3). The considered climatic factors include temperature, rainfall, radiation, and wind speed. The threshold outputs from this quartile analysis were then used to design the set of ‘rules’ for spatial projection and mapping of the FAW density level of infestation.

2.2.4. Spatial projection process

The spatial projection was conducted by dividing the entire African continent into a regular 2 km x 2 km squared grid. The 2×2 km scale was adopted to match the geographical scale covered by a single trap during the field data collection process. One trap was assumed to represent the catches of an area between 0.5 ha to 2 ha (Niassy et al., 2021). However, considering the high flight ability of FAW combined with the difficulty to obtain high resolution remotely sensed environmental and climate data for the entire African continent, the 2 × 2 km grid resolution was therefore considered optimum for this study.

Using the spatial join function in QGIS software (QGIS Development Team, 2014), all trap locations that occurred within each of the 2 × 2 km grids were considered to belong to the same spatial location and were summed up to the central coordinate of the 2 × 2 km grid. In each grid, the data was summed in a monthly aggregation of the FAW density. A mean monthly summary from all the traps in a sub-region was done to study the general spatial variability for that region over the years 2018 and 2019 (Figs. 4B, 5B, and 6B). Furthermore, the trends of FAW density for each region were observed by selecting grid locations that were consistent with the trap monitoring that was done over the field survey to plot the yearly trend of FAW density (Figs. 4C, 5C, and 6C). Further analyses were conducted to observe the cumulative shifts in densities across the regions, i.e., to explore if the decrease in one sub-region increased in another as is usually the case in North America with seasonal migrations (Niassy et al., 2021). Additionally, this analysis was done to assess and observe the variations within the same region but at different geographic locations. The spatial analysis was also conducted based on the below assumption:

Let Δ, representing a spatial location marked out by geographic extent coordinates and $\rho$the spatial projection, defined as a continuous function on the domain Δ.

Δ and ρ can be characterized as follow: $\Delta = \{(lon, lat) \in R^2 | lon_{\min} \leq lon \leq lon_{\max}, lat_{\min} \leq lat \leq lat_{\max}\}$ where $lon$and $lat$are respectively longitude and the latitude delimiting the area of interest. Then,

$$\rho : \Delta \to \mathbb{Z}_+ \Big| \forall_{\{i\in N;\Delta_i\in\Delta;d\in\mathbb{Z}_+\}}, \rho(\Delta_i) = \sum(\cap F_{\Delta_i}) = d_{\Delta_i}$$

Where d_{Δ_i}correspond to FAW density in the spatial area $\Delta_i$and $F_{\Delta i}$the set of climatic and environmental factors in consideration in the area.

The preliminary analysis of the trends of the FAW density per month and region revealed that the climate seasonality of the region influences the density, which significantly increases during the cropping seasons on the two main host crops, i.e., maize and sorghum. The seasonal rainfall pattern grouped per region and the general cropping calendar of maize and sorghum were therefore considered as the foundations for determining the type of analytics and defining the rules for the projections and mapping of the pest density across sub-Saharan Africa (Table 1).

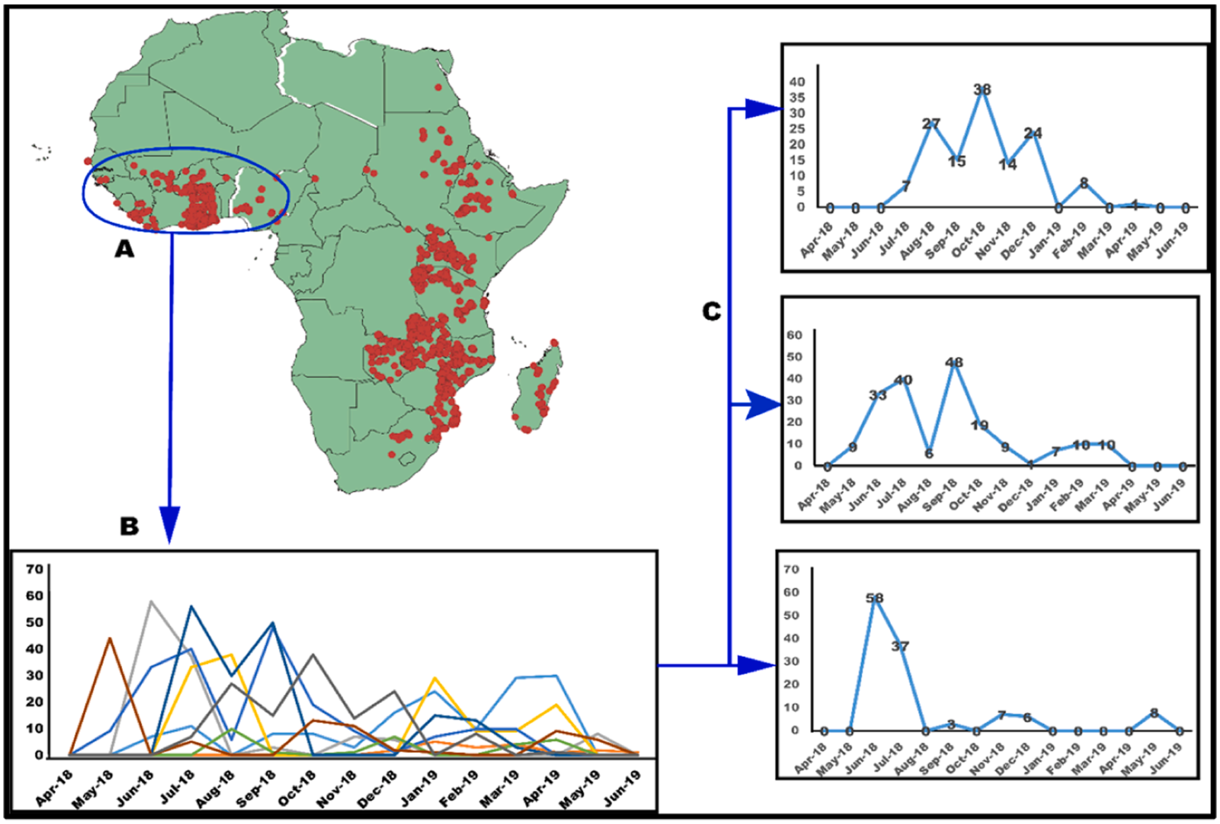

Fig. 4. The Fall armyworm (FAW) density in a spatial grid-scale of 2 km x 2 km in the western region of Africa given by (A) the trap's locations of the subset of data used, (B) the global trend of the density for grids with a high frequency of records different from zero in the region for 2018 and 2019, and (C) the monthly progression of FAW density for three randomly selected grid locations in the western region for 2018 and 2019.

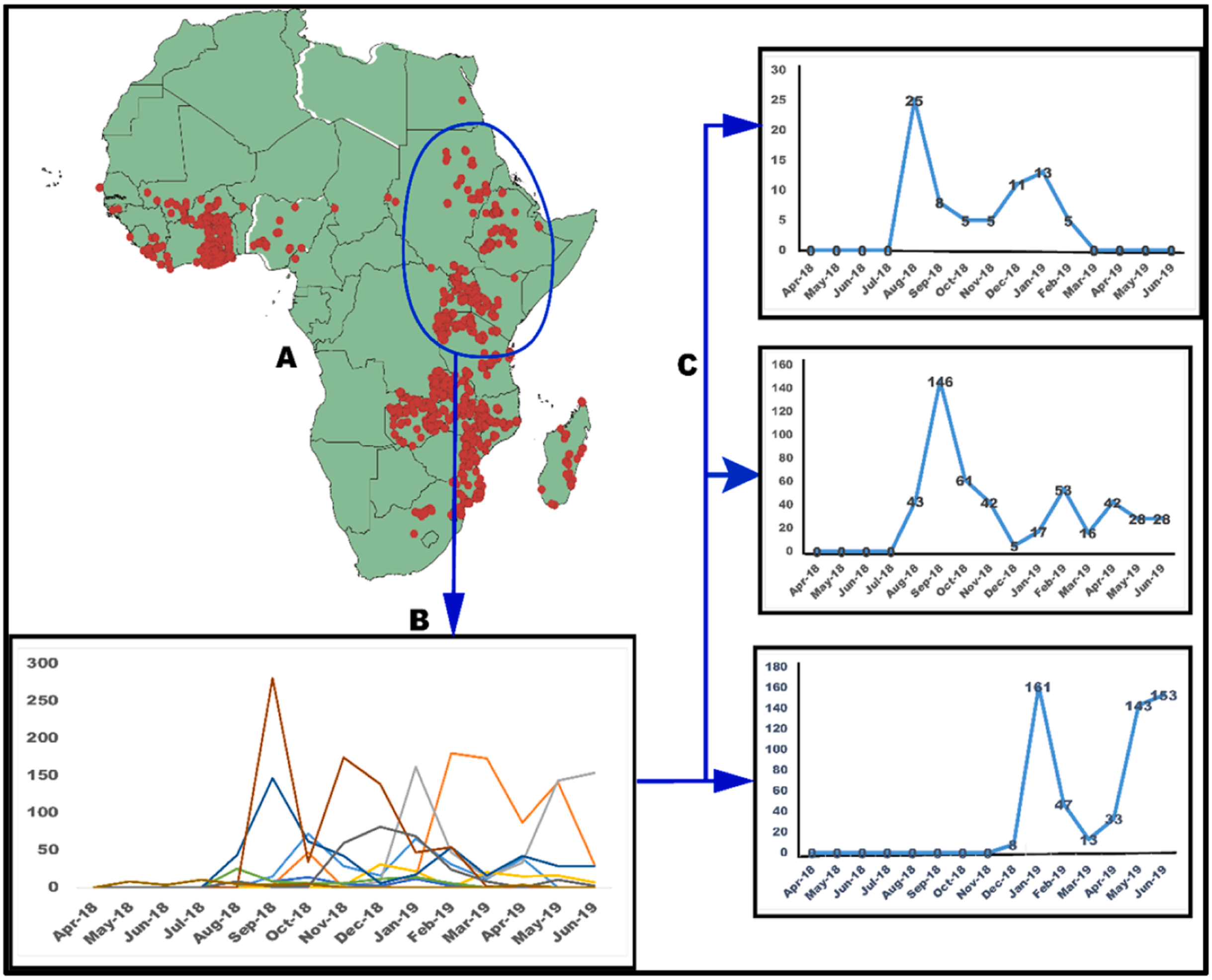

Fig. 5. The Fall armyworm (FAW) density for spatial grid-scale of 2 km x 2 km in the eastern region of Africa given by (A) the trap's locations of the subset of data used, (B) the global trend of the density for grids with a high frequency of records different from zero in the region for 2018 and 2019, and (C) the monthly progression of FAW density for three randomly selected grid locations in the eastern region for 2018 and 2019.

Moreover, to ensure the coverage of all the areas where maize and sorghum were suitable together with other potential host plants, considering the very wide host range of FAW, the African landcover (https://www.esa.int/ESA_Multimedia/Images/2017/10/African_land_cover) data provided by the European space agency (ESA) at 20 m spatial resolution was also used in designing the 'rules'. Using the land cover classification, we assumed that every location classified within a vegetation class has the potential to grow FAW host plants.

2.3. *Definition of rules used in the modeling experiments*

The definition of model rules for the estimation of the density level of FAW infestation in Africa requires a critical approximation of the available records at the boundaries of each class. The determination of cutoff boundaries of the respective environmental and climatic variables used to predict the density classes used in this study were established by computing the quantiles which were matched against the observed monthly FAW densities recorded in the field. Using the monthly field data recorded from January 2018 to December 2019, the mean density of each location from the two years of the collection was matched to the minimum, i.e., the first quartile (Q1), the median (Q2), the third quartile (Q3), and the maximum (Q4) of the monthly density. Relationships to each quartile were established, analyzed, and matched to establish the duration (when), mechanism (how), and the quantity (percentage) of the environmental and climatic variable that would influence the density as well as the cutoff (threshold) when it would cease to have an effect. Subsequently, the annual mean for each quartile was calculated to represent the boundary of each class.

In this study, the lower boundary corresponded to the median value, while the upper boundary corresponded with the value of the third quartile. Three density levels were inferred from this analysis based on the FAW densities observed in the field at the a given corresponding time in which the environmental and climatic variables were observed and classified as follows: 'low', 'moderate', and

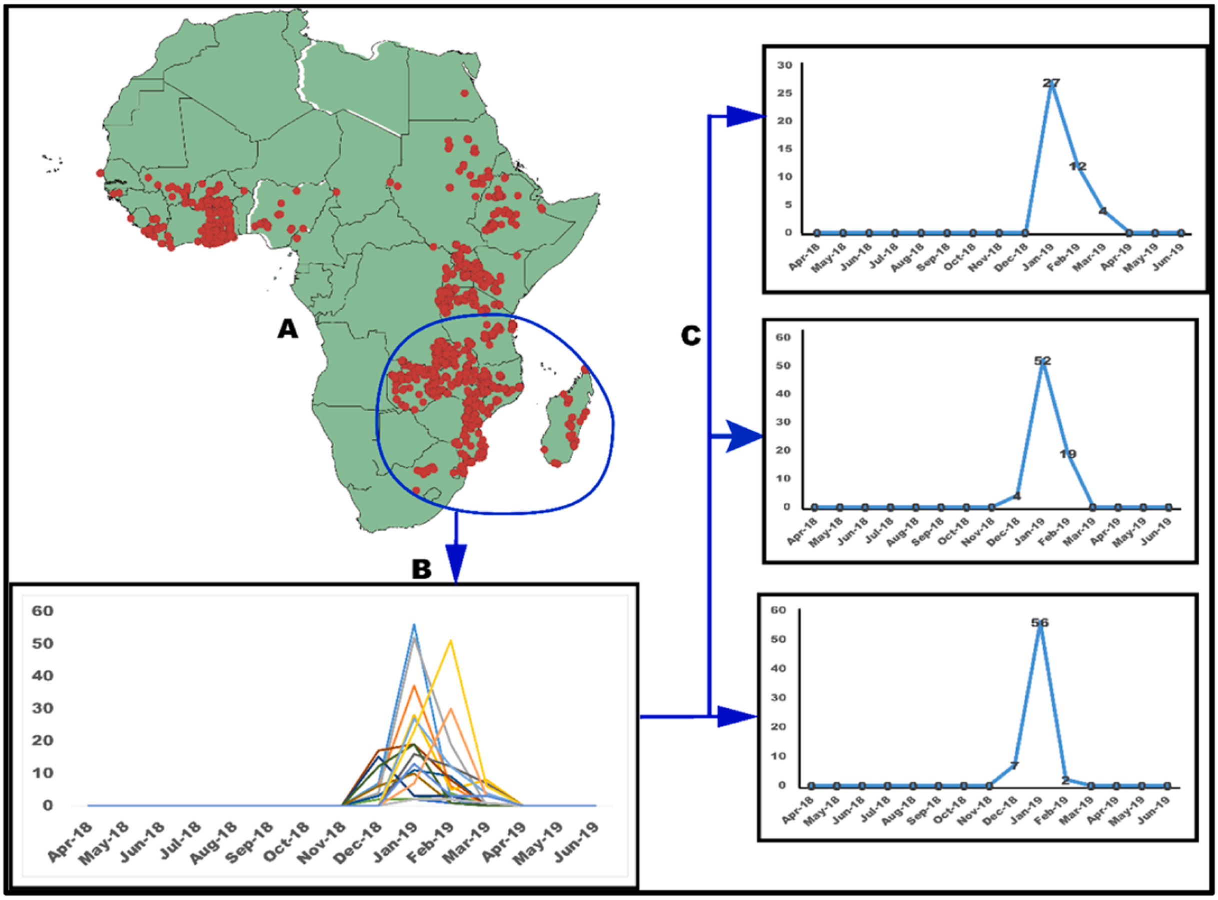

Fig. 6. The Fall armyworm (FAW) density for spatial grid-scale of 2 km x 2 km in the southern region of Africa given by (A) the trap's locations of the subset of data used, (B) the global trend of the density for grids with a high frequency of records different from zero in the region for 2018 and 2019, and (C) the monthly progression of FAW density for three randomly selected grid locations in the southern region for 2018 and 2019.

Table 1
Adopted seasonality based on climates and cropping calendar in sub-Saharan Africa per sub-region.

Sub-Saharan Africa sub-regions	Maize cropping period	Sorghum cropping period	Others
South	December – March	April – May, November	June – October
East	April – July and November – January	February – March and August – September	October
West	April–July and September – November	August	December – March

'high'. The difference in the level of intensity for each of the selected environmental and climatic variables was estimated by their monthly measure of dispersal per region. The low-density level is given by the lower boundary, i.e., FAW density < lower boundary, while moderate density is between the lower and the upper boundaries, i.e., lower boundary ≤ FAW density ≤ upper boundary. The high-density level is greater than the upper boundary, i.e., FAW density > upper boundary. Due to the variation in seasonality in the different subregions, each environmental or climatic factor was computed based on the average monthly quantiles from the matched subregional dataset. The high level of FAW density was observed between Q1 and Q3 ([Q1, Q3]), while the moderate level was between the min and the max value excluding the range from Q1 to Q3 ([Min, Max]\ [Q1, Q3]).

2.4. Model simulations and spatial predictions

Fig. 7 summarizes the flow chart of the rules characterizing the FAW density level of infestation. The algorithm was designed to iterate between the different 'set of rules' i.e., using the upper and lower boundaries of each of the explanatory variables, and evaluate the conditions until the best condition was met in a tree-like design (Fig. 7). Thus, the output from each grid is determined by a series of 'rules' set for each condition of the environmental and climatic variables to produce a pixel value with either 'high', 'moderate', or 'low' density of FAW. This process was conducted in each pixel grid of 2 km x 2 km covering the entire continent as demonstrated in

Fig. 7. Summary of the 'rules' for estimating the Fall armyworm (FAW) density level of infestation. Maize and sorghum are considered the main host plants of the pest. The green arrow shows the algorithmic iterations if the timing was within the sorghum planting period and cropping area.

Figs. 7 and 8.

The algorithm in Fig. 8 summarizes the design of the rule-based modeling process for mapping the density level of FAW infestation in sub-Saharan Africa. The implementation and simulation of the rule-based modeling algorithm were done using R packages including 'dplyr' (Wickman and Francois, 2016), 'raster' (Hijmans, 2020), 'sp' (Pebesma et al., 2017), 'reshape2' (Wickham, 2012), and 'rgdal' (Bivand et al., 2017). The map for the density level of infestation of FAW in sub-Saharan Africa was produced monthly.

2.5. Model validation

The FAW density data collected across sub-Saharan Africa from 2018, 2019, and 2020 was used to evaluate and validate the model. The same 2 km x 2 km grid used to harmonize the trap data was used to extract predicted density values from the output raster files generated from the rule-based modeling approach. The central coordinates of each grid were used as the reference location to match the observed density with the predicted density at that location. Therefore, for each coordinate, the monthly predicted and observed values were gathered to validate and evaluate the performance of the modeling approach. The obtained predicted and observed density values were thereafter categorized into the three density levels of infestation, i.e., low (<11), moderate (11 – 30), and high

```
Input Variables:
        spatial2kmGrid: Co  location of all 2km obtained from the division of Africa Fco
        monthlyVarialbesData: Co temperature, wind Speed, Radiation, Rainvalue, ....   Fco
        PlantCroppingArea: Co Maize, sorghum Fco

 Begin:
   Co: Loading data   Fco
   Initialization
     Uploading spatial grid and montlyvariablesData

For each month from January to December
  For every grid of spatial2kmGrid
          locationID ← getGridID(grid )// each grid of the spatialGrid has an unique ID
          regionLocation ← getRegion(grid )// Identify the region(N,S,E,W,C) of the grid
  maizeCroppingPeriod  ← getMaizeCroppingPeriod() // cropping maize period of the region
  othersCroppingPeriod  ← getCroppingPeriod() // Cropping period for sorghum
     If (month ∈ maizeCroppingPeriod) and (PlantCroppingArea > 0) and (montlyVariablesData = HighlySuitable)
             locationIDState ← High
      elseIf (month ∈ maizeCroppingPeriod) and (PlantCroppingArea > 0) and (montlyVariablesData = LightlySuitable)
            locationIDState ← moderate
      else (month ∈ maizeCroppingPeriod)       locationIDState ← low
     EndIf
     If (month ∈ othersCroppingPeriod) and (PlantCroppingArea > 0) and (montlyVariablesData = HighlySuitable)
            locationIDState ← moderate
      else (month ∈ othersCroppingPeriod )
             locationIDState ← low
      EndIf

    If (month ∉othersCroppingPeriod) and(month ∉ maizeCroppingPeriod) and (PlantCroppingArea > 0)
             locationIDState ← Low
      EndIf

  EndFor

 EndFor
  Output
        Return: Projection Map of the monthly prediction of the FAW level of potential density invasion
End
```

Fig. 8. The summary outline of the algorithm used in the 'rule-based' classification of the Fall armyworm (FAW) density level of infestation in sub-Saharan Africa.

(>30). For each of the coordinates, the predicted FAW infestation level class was compared with the observed class, and if the classes were the same, a value '1' was assigned representing a correctly predicted infestation level. Similarly, if the class values between the observed and the predicted were different, a value '0' was assigned to signify a mismatch between the observed and the predicted classes. A proportion (%) of the correctly predicted classes ('1') was compared with the misclassifications ('0') in each month and across the years. A bar graph of the mean monthly accuracy and line graphs of the trend of accuracy across the months and years were used to present the results. This procedure was followed for each of the three years across the twelve months.

3. Results

3.1. Mixed modeling

The preliminary results of the mixed models revealed that the model that considered both the time and space as random effects had the lowest AIC. These preliminary results prompted the selection of the third model, as demonstrated in Table 2. This spatiotemporal approach was used in the modeling process since these results showed that FAW occurrence and density were subject to environmental, climatic, spatial, and time variations (monthly in the context of this work).

3.2. Analysis of variance of the mixed models

Furthermore, the ANOVA, LRT together with the response curves of the used variables obtained from the third model confirmed the significant contribution of each of these factors on the FAW density level of infestation occurrence as presented in Table 3 and Fig. 9.

3.3. Determination of the upper and lower boundary 'rules'

Table 4 presents the results of the measure of the dispersion of FAW density obtained per year, representing the estimated boundary of each class. The FAW density data showed a wide range of density values across the continent; however, the quartile analysis reduced this wide variation to three classes for ease of comparison, as shown in Table 4.

The final values of the lower and upper boundaries were 11 and 30, respectively. These values informed the classes low, moderate, and high classes (Table 5).

3.4. Model validation

Relatively high accuracies of the prediction density of FAW were observed across the months and years, with an optimum overall accuracy of 53% across the three years (Fig. 10). Predictions of FAW in September, October, November, and December showed relatively high accuracy rates than other months. Comparatively, a progression in improvement in the overall accuracies across the years was observed with the densities of FAW in the year 2020 predicted better than previous years, i.e., 2018 and 2019 (>80%) (Fig. 10). There were low values of accuracy observed in February and March of the year 2018. These months corresponded to the period when very little data were obtained from the FAO database, i.e., n = 1 for February 2018 and n = 3 for March 2018.

3.5. Spatial prediction of Fall armyworm density across Africa

The spatial projection of FAW density across Africa shows that FAW intensity follows the observed crop calendars and seasonal variations within the different subregions in Africa. The highest density in January to April was observed in central and southern Africa, while the May to July period shows high intensities of FAW in countries located around the equator (Fig. 11). On the other hand, the month of August showed the least level of infestation across the entire continent, with moderate infestations mostly observed in countries around the equator. This cycle of infestation was observed to oscillate again from October to December, descending from the equator countries toward central and southern Africa.

4. Discussion

Estimation of the occurrence and density of highly dynamic pests such as the FAW presents a challenging task that requires creative and innovative conceptual approaches. The study becomes more critical and complex when the exploration includes the spatial and temporal variability of the pest across an expansive landscape such as the African continent. Our approach to harness data science provided a systematic comparison of data analytics to project and predict the FAW density level of infestation across the entire African continent. Using data collected from a three-year field monitoring project, combined with the influence of cropping systems, subregional climatic variability, rainfall quantity, temperature fluctuations, and the availability of main host plants - in our case, maize, and sorghum - proved very relevant to the project and predict the density of a pest that can exist on many host crops and within complex environments. Data science analytics were conducted to estimate the effect of these factors on the fluctuation of FAW density together

Table 2
Comparison of the three mixed models using the Akaike information criterion (AIC).

Model	Degree of freedom	AIC
mixedModel1	59	73,534.58
mixedModel2	59	73,366.65
mixedModel3	60	73,282.77

Table 3
Effect of each variable of the third model using the linear mixed model. See Appendix for the detailed table with the estimated value or parameters and confidence interval.

Variable	denDF	LRT	*Pr (Chi)*
Fixed Effect			
Wind speed	7189	0.256	0.6127
Solar Radiation	7189	7.364	0.0066 (**)
Mean monthly temperature	7189	37.376	9.74e-10(***)
Rainfall	7189	14.808	0.0001(***)
Elevation	7189	8.412	0.0037 (**)
Farm area	7189	25.209	5.14e-07 (***)
Cropping system	7189	18.627	0.0009 (***)
Crop stage	7189	22.97	0.0001(***)
Main crop	7189	63.377	1.224e-05 (***)
Month of the year	7189	38.465	0.0021 (**)
Irrigation status	7189	36.539	1.163e-08 (***)
Random Effect			
Date of collection:	1	85.883	2.2e-16 (***)
Country/ region	1	171.380	2.2e-16 (***)

Significance level: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

with the linear mixed models (multilevel analysis) to identify and explore the variability of the most significant factors. The 'rules' generated from the data analytics were then used in a rule-based modeling approach to spatially project the monthly variation of FAW density level of infestation. Further, this study demonstrated that the fluctuation of spatial density is sensitive to the environmental and climatic variations occurring across the different sub-regions of Africa. These results were validated using in-field observed data with optimal accuracy.

Since the first official report of FAW in Africa, i.e., in 2016, many modeling tasks have been undertaken worldwide to help improve the understanding of the spatial dynamics of the pest to anticipate the potential dispersal and damages on crops (Farias et al., 2001; Early et al., 2018; Garcia et al., 2019; Wu et al., 2019; Li et al., 2020). These studies were provided in addition to earlier studies developed before the first official report of FAW in Africa (Farias et al., 2001; Ramirez-Cabral et al., 2017; Westbrook et al., 2019). Although these models were very useful and informative in predicting the migration pathways of FAW, mainly in Asia and America (Li et al., 2020; Wu et al., 2019), very few attempts to understand the spatial dynamics of the pest within the Africa context were made (Early et al., 2018). The models targeting Africa, such as by (Early et al., 2018), were derived from species distribution models (SDMs) that fundamentally estimate the potential suitability of an area for FAW invasion or establishment. These studies could not inform the probability of FAW occurrence in a given year or the precision of the local interaction due to spatial heterogeneity of the landscape and a multitude of factors that influence occurrence across the different months of the year (DeAngelis and Yurek, 2017). The methodology adopted in the study is the first of its kind and presents more advantages compared to the spatially implicit approaches such as SDM (DeAngelis and Yurek, 2017). The results obtained in this study are useful in providing potential monthly infestation within a 2 x 2 km grid, which enhances and informs the ability to pinpoint priority locations for intervention within a specified timescale. Moreover, none of the previous studies has classified and spatially projected FAW density of infestation to the entire African landscape, which characterizes the innovation of this work.

Although the overall model accuracy obtained in this study across the three years was optimal (± 53%), it could be further improved by enhancing the standardization of data collection by the different citizen science data collectors, particularly regarding coordinates and trap locational data. It was observed that most of the FAMEWS trap data points were clustered randomly within the same grid yet belonging to the same coordinate, hence a 2 x 2 km grid was developed to aggregate all the data points occurring in one grid to one central coordinate. This approach reduced the data variability in space and time as they were aggregated according to the collection date. Apart from the low amount of data in the early years (2018 and 2019), the average level of accuracy obtained could also be explained by the non-inclusion of data related to certain key factors such as the influence of natural enemies (predators, parasitoids, and pathogens) into the analytics (Sokame et al., 2020a, 2020b). As studies progress, detailed data on the occurrence and efficiency of FAW natural enemies will be collected to complete the tri-trophic interactions between the host plants, pests, and beneficial organisms (Abdala-Roberts et al., 2019). It is also important to note that insect catches vary according to a multitude of factors: position of the trap, lure, trap type, trap density, microclimate, presence, and number of females, temperature and humidity, the fieldworker, the taxonomist (specimens misidentified), kairomone effect and certainly more.

In addition, our predictions were evaluated by comparing field monitoring data collected in the three years (2018, 2019, and 2020) using the long-term average bioclimatic data. This approach can be improved by acquiring real-time bioclimatic data to match the timing of predictions. Even though some of the predicted classes were different from the observed, the predicted classes were generally found within a class of lower density compared to the one from the field monitoring. This could be explained by the variability of bioclimatic factors across the years, particularly rainfall that has been reported to negatively affect FAW density in the field by washing and reducing the eggs and larvae from the host plant hence the density of the adults (Hailu et al., 2021; Sokame et al., 2020a, 2020b).

Climate variability significantly influences the distribution and abundance of insects such as FAW (Barton et al., 2019; Xu et al., 2020). This was demonstrated by the cyclic spatial distribution of the FAW following the subregional cropping calendars and the seasonal variation. Again, the temperature variable has also been reported by earlier studies as a paramount factor for the insect's

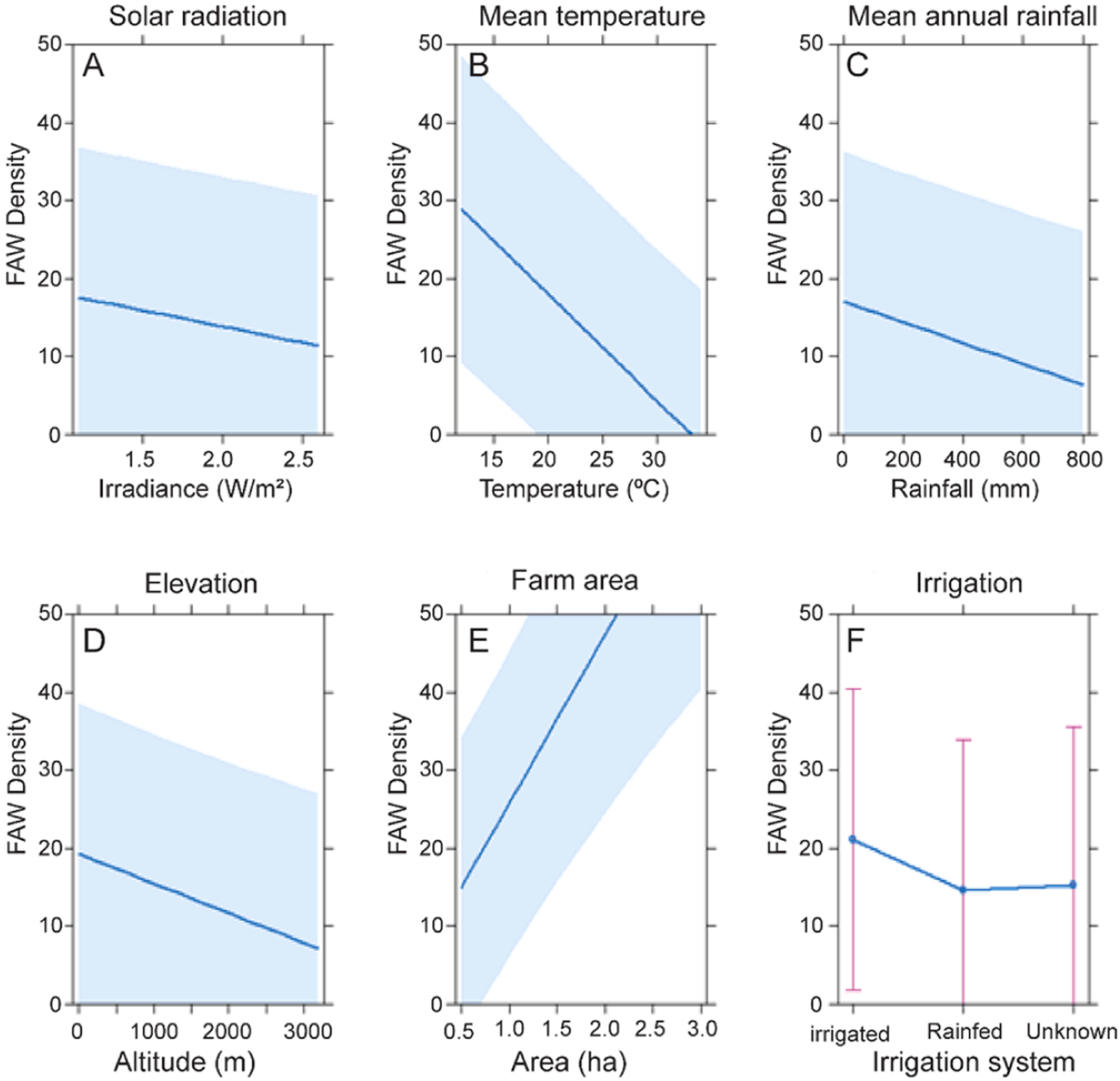

Fig. 9. Response curves and effect of environmental and climatic factors on FAW incidence.

Table 4
Adopted seasonality base of cropping calendar in Africa per sub-region.

	2018	2019
Min	4	1
Q1	6.13	3.89
Median (Q2)	9.83	10.04
Q3	30.5	28.07

Table 5
Global FAW density level classification.

Low density	< 11
Moderate density	[11–30]
High density	> 30

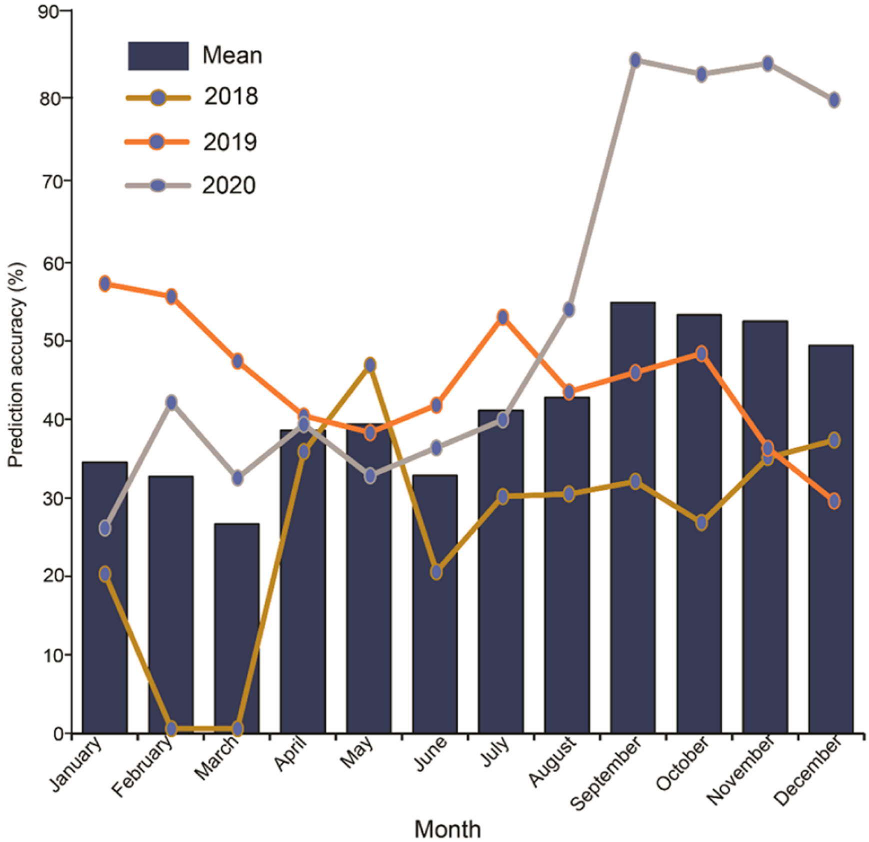

Fig. 10. Fall armyworm density prediction accuracy across the months i.e., January to December, and across the three years i.e., 2018, 2019, and 2020. The bars show the mean densities per month across the three years while the lines show the trend for each year. The brown line shows the prediction accuracy trend for 2018, while the orange and gray lines show the prediction accuracy trend for 2019 and 2020, respectively.

development, survival, and dynamics (Estay et al., 2014; Mudereri et al., 2020). Although temperature highly affects the general temporal variability of insect population abundance (Estay et al., 2014), it does not individually determine their dynamics and migration patterns which are also highly sensitive to seasonal variation of environmental and climatic factors occurring over the year (Zidon et al., 2016; Nnzeru et al., 2021). These results were also demonstrated in Africa by (Early et al., 2018), who combined the effect of temperature and precipitation on FAW life history to build SDMs. On the other hand, our work is the first attempt to combine temperature, rainfall, wind speed, and radiation to explore their combined effect on the FAW density variability as informed by perpetual data collected from the field. This is paramount considering the role played by these factors for a successful implementation of biological control strategy in an integrated pest management context (Prasanna et al., 2018). Some virus-based bioinsecticides, whose virulence is highly dependent on temperature, humidity, and radiation, have been reported to have a high potential for use against FAW, especially when applied on maize plants from V6 to V8 leaf stage (Prasanna et al., 2018).

Complex dynamic processes in the agroecosystem are better understood when designed using mechanistic modeling approaches (Nathaniel, 2006; Etterson et al., 2017). This includes techniques like mathematical equations or rule-based modeling techniques. Rule-based models enable an analysis of complex problems through system thinking and dynamic components that relate and interact with one another (Chylek et al., 2013; Forbes et al., 2017). The peculiarity of rule-based modeling compared to machine learning approaches is that it enables the consideration of the little available detail of FAW biophysical interactions with their ecosystems. However, both approaches require a careful selection of the appropriate parameters since the modeling depends on the availability of correct and consistent data.

The dynamics of FAW incidence in agroecological production across SSA display exclusive patterns that cannot be explained only by the density variation. In most geographical sub-regions of Africa, FAW is highly abundant at a specific time but completely absent at another (Rwomushana et al., 2018). This suggests that FAW dynamics are subject to seasonal environmental and climatic change (Ramirez-Cabral et al., 2017; Baudron et al., 2019; Feldmann et al., 2019). The maps generated in this study demonstrate that the density level of infestations across the continent is sensitive to the monthly variations of climatic and environmental factors and the availability of the host (Draper et al., 2019; Qin et al., 2017; Ramirez-Cabral et al., 2017). Moreover, the occurrence of FAW in a given area depends on the suitable interaction of a wide range of factors whose mechanisms of interaction are still not well understood (Rwomushana et al., 2018; Baudron et al., 2019). These factors vary from the farm size area and its geographical location to the cropping calendar of the FAW host plant over the year and the control mechanism that is implemented on the farm (De Groote et al.,

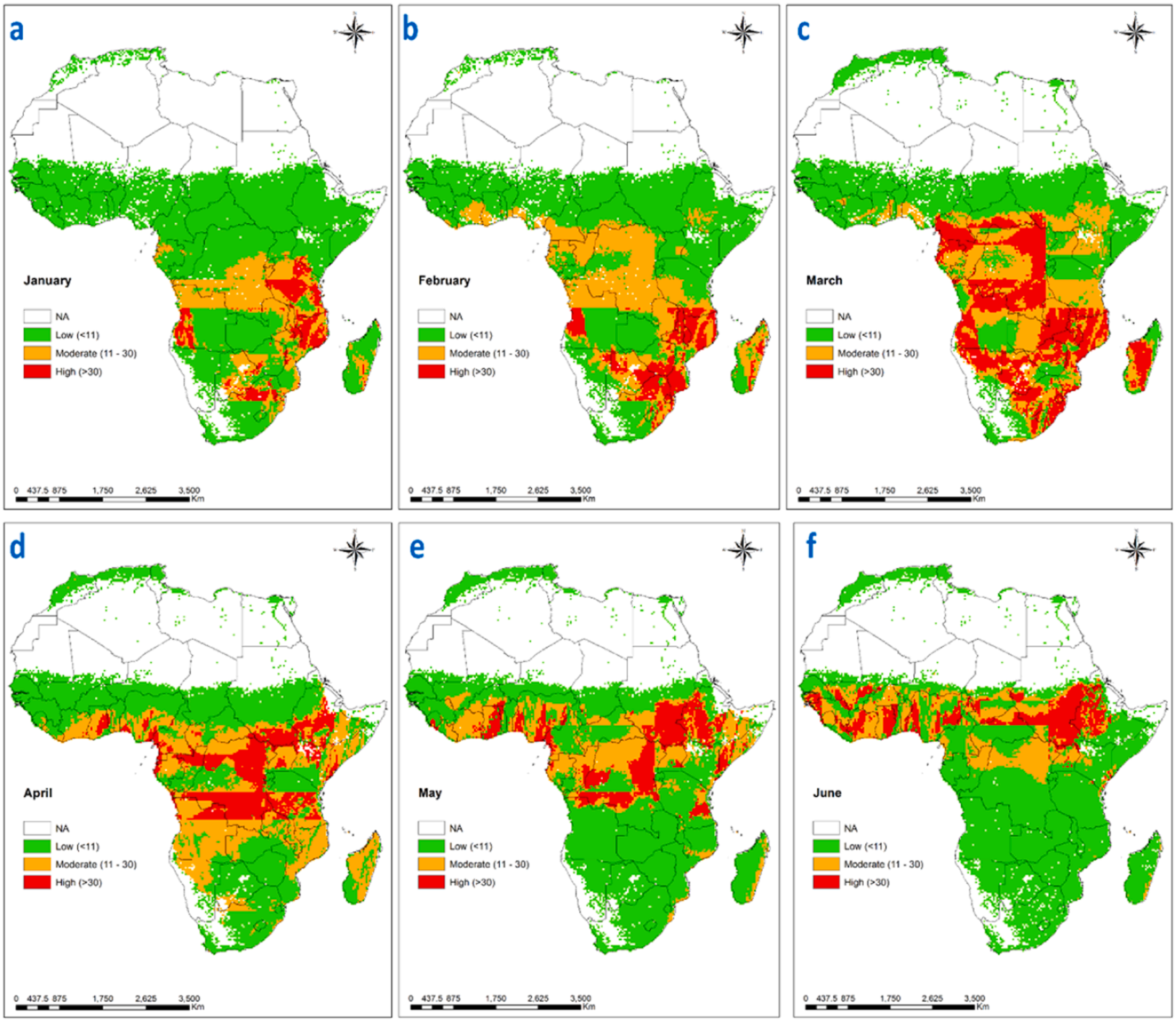

Fig. 11. Spatial projection of the Fall armyworm (FAW) density level of infestation in Africa for **(a)** January, **(b)** February, **(c)** March, **(d)** April, **(e)** May, **(f)** June, **(g)** July, **(h)** August, **(i)** September, **(j)** October, **(k)** November, **(l)** December. Areas in white are not suitable for the presence of FAW, while the areas in green, yellow, and red correspond to the FAW density level low, moderate, and high, respectively.

2020).

The analysis of the linear-mixed model obtained during the data analytical process has helped strengthen the hypothesis and highlight the role of these variables on the FAW density level of infestation, which supports previous studies (CABI, 2017). However, the spatially projected FAW density level may differ in some locations since some of the weather data used were a long-term average and not matched with the time frame of data collection. This is understandable considering the difficulty to get real-time and accurate environmental and climatic data at the entire Africa continent scale. Therefore, the accuracy of the spatial projection will likely improve if the model is locally projected using real-time data from the localized weather stations.

The output from this study is part of a framework for establishing a FAW early warning system in Africa; however, more remains to be done for this approach to be effectively useful to farmers. Future studies can consider embedding this model into a platform that provides access to local weather station data for real-time estimation of the level of density infestation at scale. The VIPS platform (https://www.nibio.no/en/services/vips) developed by The Norwegian Institute of Bioeconomy Research (NIBIO) has been identified as an example and a suitable candidate platform to address the purpose and providing the most effective solutions to farmers. This provides an opportunity to easily monitor FAW infestation through a simple mobile application.

Other than host plant and climatic factors, the role of natural enemies (Sokame et al., 2021) and phytosanitary interventions, e.g. chemical and biopesticide use, need to be integrated. This study could help estimate the magnitude and value of management strategies to enable stakeholders to prioritize the best-bet FAW IPM tactic for a given situation. Furthermore, it would be useful to estimate the FAW economic threshold level on maize to identify the approximate density from which relevant damages are expected and require

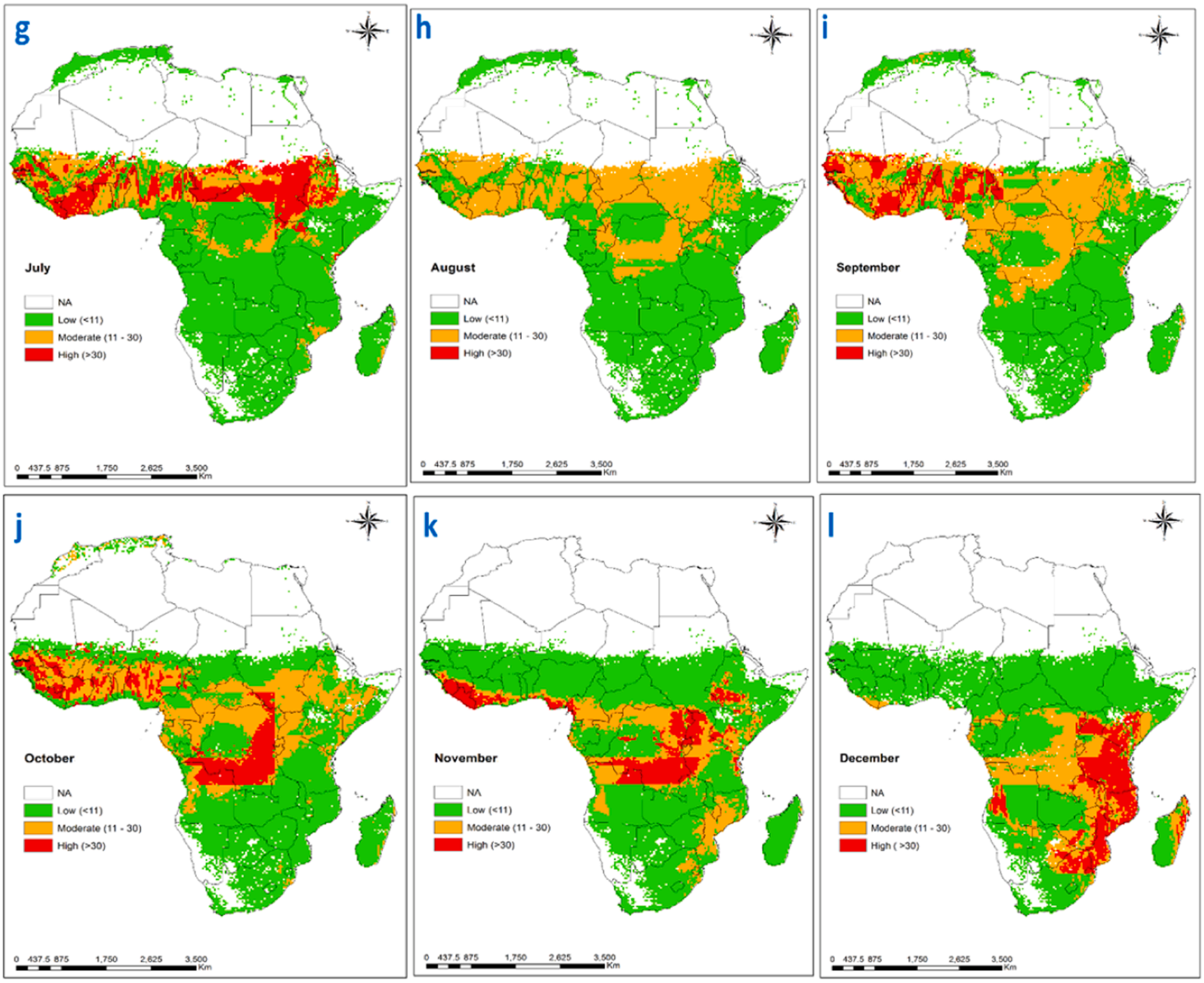

Fig. 11. (*continued*).

control measures to be implemented. All these achievements put together will ease the adoption of a proactive control measure as recommended by FAO (Feldmann et al., 2019) for the effective management of FAW in Africa.

5. Limitations of the study

The data for the evaluation used in this study were collected in 2020 after several pest management strategies and control methods were developed and implemented (i.e., in 2018/2019) to reduce pest damages and infestation in maize farms. The model in its current form does not take into consideration the effect of the various actions such as the use of pesticides i.e., chemical, or biological; natural enemies i.e., predators, parasitoids, and pathogens that were initiated by farmers and agricultural officers to reduce crop damage by FAW in farms in the study area. Future work might have to consider these parameters and limitations to improve the predictions accuracy.

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CRediT authorship contribution statement

H.E.Z.T., S.N., S.S., R.A.G., S.A.M., S.E., S.K.: Conceptualization. **E.M.A**: Conceptualization, Supervision, Writing – original draft. **R.A.G., B.T.M., E.K., H.E.Z.T., K.M.A., G.T.T.Y.**: Data curation. **R.A.G., B.T.M., E.K., H.E.Z.T., K.M.A., G.T.T.Y.**: Formal analysis. **S.S., K.H.T., M.T., J.C.R., B.H., M.E., M.S., S.E., Y.B., S.K.**: Funding acquisition. **R.A.G., H.E.Z.T., S.S., S.N.**: Methodology. **S.S., M.S., S.E., S.K.**: Project administration. **H.E.Z.T., S.A.M., S.E.**: Resources. **H.E.Z.T., S.S., S.A.M., S.E.**: Supervision. **R.A.G., H.E.Z.T., S.S., S.A.M., B.T.M., G.T.T.Y., M.T.**: Writing – original draft. **H.E.Z.T., S.A.M., Y.B., S.E., S.K., B.H., J.C.R., K.H.T.**: Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data accessibility statement

Data associated with this research shall be archived in the Dryad database.

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Appendix

Estimated values of parameters with their respective confidence interval.

FAW Density			
Predictors	Estimates	CI	p
(Intercept)	33.16	-4.76 – 71.08	0.086
WindSpeed	1.13	-3.57 – 5.83	0.637
Radiation	**-6.05**	**-10.42 – − 1.68**	**0.007**
Temperature	**-29.94**	**-39.50 – − 20.38**	**< 0.001**
RainValue	**-10.47**	**-15.78 – − 5.16**	**< 0.001**
Elevation	**-12.15**	**-20.13 – − 4.18**	**0.003**
cropFiel 1	**54.18**	**32.88 – 75.49**	**< 0.001**
cropSystem [pushPull]	3.98	-4.42 – 12.38	0.353
cropSystem [rotation]	**1.96**	**0.11 – 3.81**	**0.038**
cropSystem [seasonal]	-0.68	-2.33 – 0.97	0.418
cropSystem [unknown]	0.33	-5.99 – 6.65	0.918
cropStage [reproductive]	**3.34**	**1.87 – 4.81**	**< 0.001**
cropStage [seedling]	1.42	-0.84 – 3.68	0.219
cropStage [sowing]	-1.28	-5.57 – 3.00	0.557
cropStage [vegetative]	**2.34**	**0.90 – 3.78**	**0.001**
cropMain [barley]	1.61	-32.20 – 35.41	0.926
cropMain [beans]	-4.2	-33.79 – 25.39	0.781
cropMain [cassavaManioc]	1.97	-27.72 – 31.65	0.897
cropMain [cotton]	12.27	-19.11 – 43.64	0.443
cropMain [cowpeas]	-0.8	-31.28 – 29.69	0.959
cropMain [flowers]	-1.95	-38.06 – 34.15	0.916
cropMain [maize]	4.28	-24.93 – 33.49	0.774
cropMain [millet]	9.1	-22.69 – 40.90	0.575
cropMain [otherCereals]	-0.02	-35.90 – 35.85	0.999
cropMain [otherFruits]	-2.15	-31.59 – 27.30	0.886
cropMain [otherGrasses]	-0.2	-29.91 – 29.50	0.989
cropMain[otherRootsTubers]	9.95	-20.04 – 39.95	0.515
cropMain[otherVegetables]	-1.46	-31.25 – 28.32	0.923
cropMain [peanut]	13.79	-21.90 – 49.48	0.449

(*continued on next page*)

(*continued*)

FAW Density			
Predictors	Estimates	CI	p
cropMain [rice]	1.38	-28.21 – 30.97	0.927
cropMain [Select]	-1.93	-52.65 – 48.78	0.94
cropMain [sorghum]	-0.9	-30.22 – 28.42	0.952
cropMain [soybean]	0.81	-33.76 – 35.38	0.963
cropMain [teff]	1.82	-35.87 – 39.50	0.925
cropMain [tobacco]	-0.44	-51.84 – 50.97	0.987
cropMain [weeds]	13.44	-17.23 – 44.11	0.39
cropMain [wheat]	-14.69	-46.77 – 17.38	0.369
cropMain [yam]	-6.75	-40.74 – 27.25	0.697
monthOfYr [01/2019]	4.54	-8.62 – 17.71	0.498
monthOfYr [02/2018]	20.17	-12.90 – 53.23	0.232
monthOfYr [02/2019]	5.54	-7.67 – 18.74	0.411
monthOfYr [03/2018]	7.4	-13.62 – 28.41	0.49
monthOfYr [03/2019]	5.8	-7.44 – 19.05	0.39
monthOfYr [04/2018]	3.61	-10.63 – 17.85	0.619
monthOfYr [04/2019]	4.73	-8.52 – 17.99	0.484
monthOfYr [05/2018]	1.52	-12.63 – 15.67	0.833
monthOfYr [05/2019]	3.93	-9.29 – 17.14	0.56
monthOfYr [06/2018]	1.23	-12.38 – 14.84	0.859
monthOfYr [06/2019]	12.08	-1.50 – 25.66	0.081
monthOfYr [07/2018]	7.8	-5.67 – 21.27	0.256
monthOfYr [08/2018]	3.72	-9.55 – 16.99	0.583
monthOfYr [09/2018]	1.46	-11.77 – 14.68	0.829
monthOfYr [10/2018]	1.28	-11.94 – 14.50	0.849
monthOfYr [11/2018]	1.9	-11.34 – 15.14	0.779
monthOfYr [12/2018]	3.06	-10.17 – 16.29	0.65
cropIrriga [rainFed]	**-6.52**	**-8.62 – − 4.41**	**< 0.001**
cropIrriga [unknown]	-5.9	-12.91 – 1.12	0.1
Random Effects			
σ2	425.28		
τ00 dateCollection	21.27		
τ00 countryRegion	7.22		
N dateCollection	432		
N countryRegion	5		
Observations	8186		
Marginal R2 / Conditional R2	0.065 / NA		

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