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Leveraging computational intelligence to identify and map suitable sites for scaling up augmentative biological control of cereal crop pests

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HIGHLIGHTS

- Biological control (BC) technologies are necessary to address the significant constraint that Fall armyworm (FAW) poses in cereal production in Africa.
- The study employs a step-by-step modeling approach to map suitable sites of BC technologies, specifically parasitoids (*Cotesia icipe*).
- Pest infestation levels are estimated using an evolutionary adaptive Neuro-Fuzzy inference system with a high coefficient of determination (R2) > 0.89.
- We utilize fuzzy inference theory to accurately map the suitability of different regions in Kenya for the adoption of augmentative biocontrol using the parasitoids *C. icipe* in maize farms.
- Artificial intelligence-based methods provide an effective advisory tool for guiding the deployment of biological control agents, such as parasitoids, for sustainable FAW management.

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ABSTRACT

Fall armyworm (FAW) *Spodoptera frugiperda* (J. E. Smith) is a major pest affecting cereal production in Africa. Biological control (BC) technologies are being promoted as a sustainable alternative to chemical control, which can lead to health risks and environmental hazards. However, effective deployment of these technologies requires site-specific recommendations. In this study, we use a step-by-step modelling approach to map suitable sites for BC technologies, focusing on the parasitoid *Cotesia icipe* using the FAW level of infestation, the ecological niche of the parasitoid, and the FAW host crop. The level of pest infestation was estimated using an evolutionary adaptive Neuro-Fuzzy inference system ($R^2 > 0.89$) while the pest ecological niche was obtained using the maximum entropy algorithm (area under curve, AUC > 0.9). A fuzzy operator was used to combine all fuzzified variables into a single layer that represents the landscape's overall suitability for *C. icipe* in maize farms. Our computational findings indicate that *C. icipe* holds substantial promise as a BC agent in maize farms, with suitability levels consistently surpassing 90% throughout maize cropping seasons. The findings demonstrate that the utilization of artificial intelligence, combined with data science and knowledge representation, serves as an effective advisory tool for guiding the deployment of BC agents, such as parasitoids, for the sustainable management of FAW. This approach enables informed decision-making and enhances the efficacy of FAW management strategies by providing valuable insights and recommendations based on data-driven and computer intelligence analyses.

1. Introduction

The fall armyworm (FAW), *Spodoptera frugiperda* (J. E. Smith), is one of the most recent invasive agricultural pest species recorded in Africa (Goergen et al., 2016). Since the first report in 2016, FAW has become a key cereal pest throughout the continent, impeding the attainment of optimum yield without the adoption of efficient control measures. While FAW is recognized as a polyphagous noctuid (Montezano et al., 2018), a

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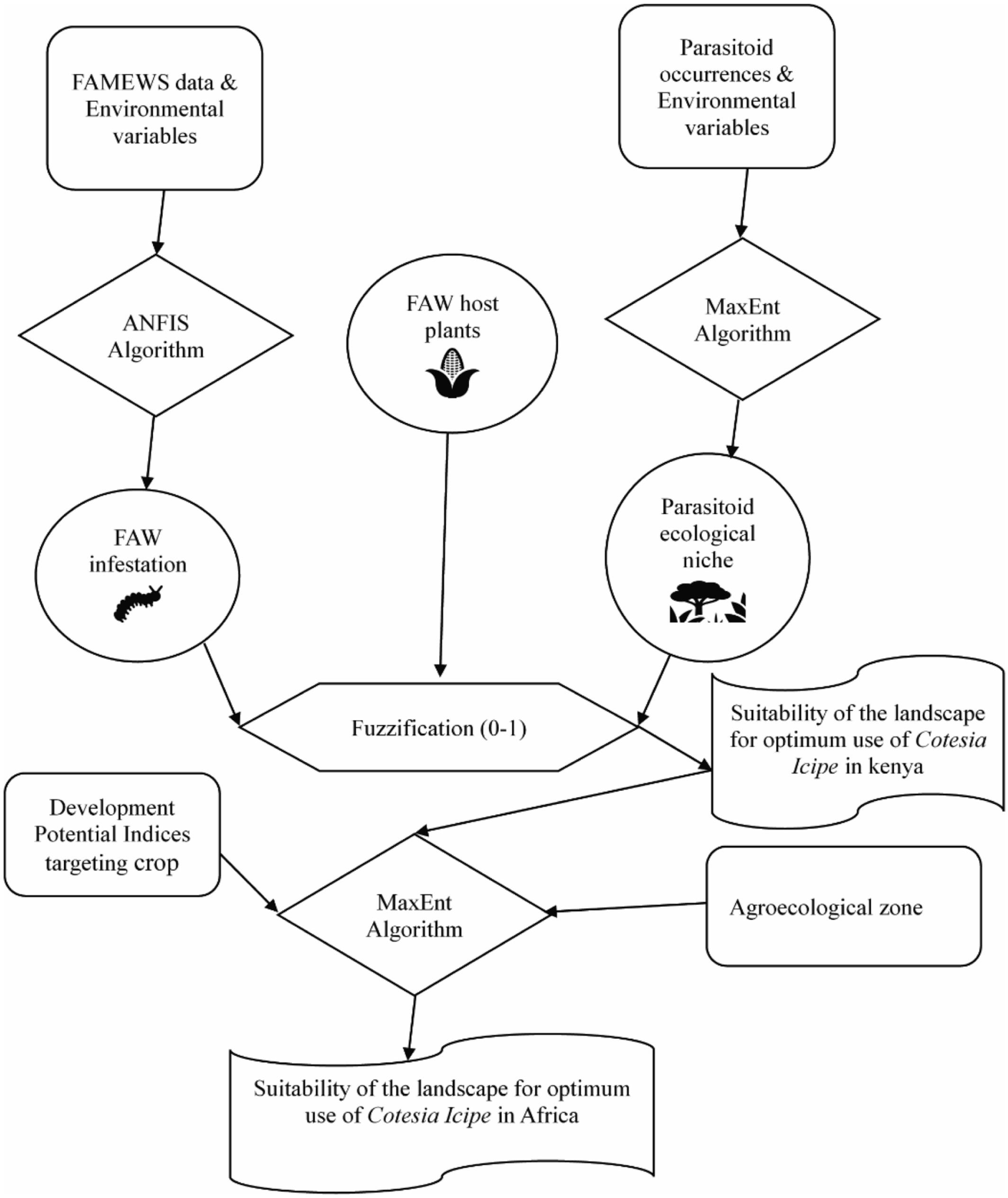

Fig. 1. Methodological flow diagram illustrating the step-by-step modelling approach for strategic deployment of *C. icipe* against fall armyworm in Africa.

recent study by Volp et al. (2022) suggests that certain crops may not be as vulnerable as previously thought. Among the affected crops, maize has endured the most significant impact, closely followed by sorghum. In Africa, maize remains the primary host crop, especially at the seedling and vegetative stages (Guimapi et al., 2022; Rwomushana et al., 2018). Therefore without proper FAW control, maize yield losses are estimated at 50% in low and medium producing zones (De Groote et al., 2020).

Generally, chemical control, such as conventional pesticides, is the primary control strategy used by farmers. However, chemical control, although effective, is often financially inaccessible to smallholder farmers due to its cost (Baudron et al., 2019). Moreover, it has environmental consequences and has been documented to lead to pest resistance in certain instances (Muraro et al., 2022; Suganthi et al., 2022). Hence, environmentally friendly methods for mitigating the risk of crop losses are needed (Agboka et al., 2022a) through Integrated Pest Management (IPM), and to reduce health risks, protect the environment (Soares et al., 2016), and partially replace conventional pesticides. FAW IPM package includes monitoring techniques, cultural practices such as maize legume intercropping and biological control (BC) using natural enemies such as predators and parasitoids (Niassy et al., 2019; Sisay et al., 2019; Tepa-Yotto et al., 2021). One of the most successful and applied FAW IPM in Africa is the BC approach.

BC approaches generally include classical, augmentative, and conservational methods. In classical BC natural enemies such as insect predators and parasitoids are introduced to manage the population of invasive pests. In contrast, augmentative BC consists of boosting the population of natural enemies through supplementation (Van Lenteren, 2000; Perez-Alvarez,Nault,and Poveda, 2019; Collier and Van Steenwyk, 2004). Conservational BC, on the other hand, focuses on modifying landscape habitats to support and sustain the population of natural enemies (Pollard and Holland, 2006; Bone et al., 2009).

Cotesia icipe Fernandez-Triana and Fiaboe (Hymenoptera: Braconidae) have been identified as the dominant indigenous parasitoid of FAW, boosting a natural parasitism rate of 33.8–45.3 % (Mohamed et al.,

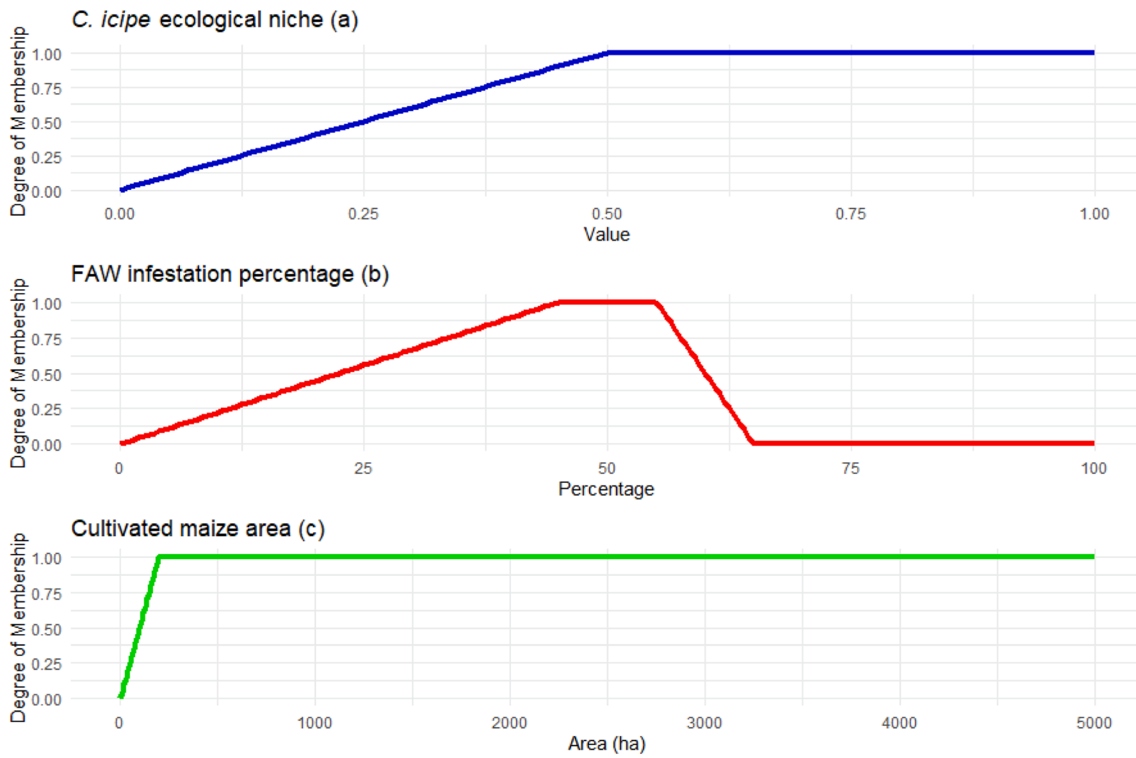

Fig. 2. Visualization of membership functions for *C. icipe* ecological niche, fall armyworm infestation percentage, and cultivated maize area.

2021; Sisay et al., 2019). While this parasitoid shows promise as a BC agent for FAW, pinpointing target-specific deployment areas for efficient control remains a significant challenge. This challenge is exacerbated by Africa's diverse agroecological zones and socio-cultural diversity (Kyalo, 2019), making it difficult to replicate BC technologies due to varying environmental conditions and cultural practices.

The emergence of advanced artificial intelligence (AI) algorithms has revolutionized our ability to understand and model complex biological and environmental interactions, including agroecological suitability for specific insect species. This shift has led to the adoption of advanced computational techniques like Fuzzy Logic and machine learning algorithms, in agricultural pest management. Fuzzy Logic, rooted in classical set theory, provides a nuanced graded assessment of data, crucial for variables such as pest presence or environmental conditions that do not fit neatly into binary categories (Agboka et al., 2022b; Landmann et al., 2023). Meanwhile, machine learning algorithms excel at recognizing patterns, predicting outcomes, and extracting actionable insights from vast datasets (Tonnang et al., 2017). The synergy of these methodologies is at the forefront of agricultural technologies, enabling precise and proactive responses to challenges like pest invasions (Ibrahim et al., 2022). Although their integration into agriculture, especially in FAW management, is an emerging field.

In this study, we propose a methodology that harnesses data science and AI algorithms to recommend suitable sites for scaling up the native parasitoid, *Cotesia icipe*, for effective management and control of the invasive *Spodoptera frugiperda* in Kenya and Africa. Our approach combines data exploration and AI systems to comprehend, analyse, and resolve complex interactions in the agroecosystem. By integrating multiple information, methods, and approaches, our methodology adapts and learns to perform optimally in ever-changing scenarios (Begg & Lai, 2008). The resulting models will support the promotion and expansion of best practices for FAW management in Kenya and beyond, ultimately leading to improved crop yields, reduced health risks, and minimized environmental harm.

2. Methods

2.1. Overall methodology and assumptions

Our study combined data science techniques and AI algorithms to strategically deploy the native parasitoid, *C. icipe*, against the invasive FAW, in Kenya and across Africa. We used a Neuro-fuzzy algorithm, to predict FAW infestation levels and the maximum entropy algorithm (MaxEnt) for the geospatial assessment of *C. icipe* ecological niche. This provided insights into FAW-prone areas and parasitoid-favorable regions.

The integration of these results with maize cultivation data layers in a Fuzzy set leads to a comprehensive map highlighting optimal regions in Kenya where *C. icipe* can serve as an effective BC against FAW. This multi-layered approach allows for a nuanced understanding of the interplay between FAW infestation, maize cultivation, and *C. icipe* potential efficacy.

Expanding our perspective, we incorporated additional data layers, including agroecological zones and the Crop Development Index to extend our predictions from Kenya to the entire African continent. This provides a pan-African perspective on the strategic deployment of *C. icipe* for FAW management as illustrated in Fig. 1.

In modelling the parasitoid suitability relative to its host, we made three (3) specific assumptions to simplify the complexity while preserving essential ecological principles:

1) We have directed our focus towards augmentative control methods aimed at bolstering the ecosystem's innate resilience against invasive insect pests, such as the FAW. Our study draws from prevalence data collected in farms, shedding light on the inherent interactions between the FAW and indigenous parasitoids in the ecosystem.
2) The host-plant range for FAW was specifically delineated to maize cultivation areas. This geographical constraint inherently defines the extent and relevance of our developed models, as their predictions are closely tied to regions where maize farming is prevalent.

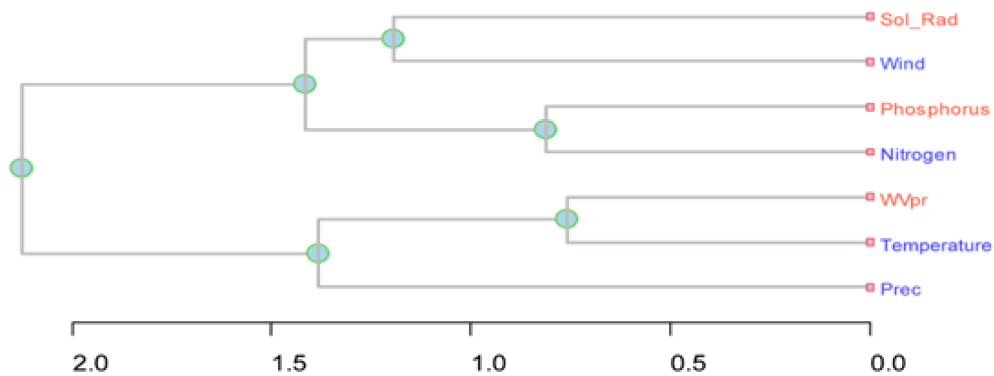

Fig. 3. Dendrogram obtained from cluster analysis with Pearson correlation coefficient. The variables selected for developing the evolutionary Adaptive-Network-based Fuzzy Inference System (GA-ANFIS) are in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3) We utilize the diverse agroecological zones of Kenya as foundational reference points, establishing them as a prototype for making broader projections across the African continent.

2.2. Variables preprocessing and model development

2.2.1. Model development and performance assessment

In this section, we outline our methodology for creating a fuzzy membership function, to evaluate the suitability of *C. icipe* in controlling FAW infestations in maize fields in Kenya. We focused on key variables: the ecological niche of *C. icipe* parasitoid, FAW infestation level, and the presence of maize. These variables were chosen based on expert consultations and field study patterns. To transform this complex data into a model, we employed a 'fuzzification' process. Raw variable values were converted into fuzzy degrees ranging from 0 and 1. Thresholds and value ranges for fuzzification were determined through expert insights and field observations. For instance, experts provided optimal suitability ranges for each variable, and our hands-on field observations confirmed or adjusted these insights to align with real-world scenarios. In our fuzzy membership function, a degree of 1 symbolizes the optimal contribution, while a degree of 0 represents the least desirable outcome. This allows for quantitative representation, laying the foundation for subsequent analyses (Fig. 2).

Furthermore, a Fuzzy operator combined all fuzzified variables into a single layer to represent the overall suitability of the landscape for deploying and scaling the BC technology. The algebraic product (compensatory operator) of each layer (Robinson, 2003) was used to produce a single layer containing suitable sites μSS based on the defined variables. The Fuzzy operator (Bone et al., 2005; Garcia et al., 2019a) was computed in R statistical software (R Core Team, 2020), and the formula is as follows:

$$\mu SS = \mu(Inf) \times \mu(Env) \times \mu(Zea) \tag{1}$$

where $\mu(RDS) =$ the Fuzzy membership function for the impact of FAW infestation level in maize farms; $\mu(Env) =$ the Fuzzy membership function for the prevailing environmental condition; and$\mu(Zea) =$ the Fuzzy membership function for the presence of maize.

Model accuracy was assessed by comparing predicted suitability with actual field recovery points, a method previously employed by Agboka et al., (2022a).

The field observations used for this assessment were collected from periodic recovery exercises by *icipe*. It is crucial to state that, the data used for validation exclusively came from the *icipe* database and had no overlap with the data used for the model's development. To quantify the model's overall accuracy, we calculated the ratio of correct predictions to the total predictions. Correct predictions were those that aligned with recovery points falling within the intermediate and optimum classes. This systematic approach provides a robust evaluation of the model's performance.

2.2.2. Fuzzy model variables preprocessing

We identified three key variables to assess the suitability of deploying *C. icipe* as a BC agent. These variables include FAW infestation levels in maize farms, the presence of FAW host plants (specifically maize), and the ecological niche of *C. icipe*. These factors were thoroughly analyzed to evaluate the feasibility of deploying *C. icipe* for biological pest control.

a) FAW infestation levels

The FAW prevalence data (number of infested plants), which covers the period from January 2018 to December 2020, were obtained from Africa's Food and Agriculture Organization's (FAO) sustainable management program, collected by the FAW Monitoring and Early Warning System (FAMEWS) application. This data source was accessed via the Food and Agriculture Organization (FAO) platform (http://www.fao.org/fall-armyworm/en/) in a CSV format. We calculated FAW prevalence as a percentage using the following formula (FAO, 2018):

$$I = \frac{N_I}{T_n} \tag{2}$$

where I is the prevalence of infestation, N_I is the number of infested plants and T_n represents the total number of plants scouted.

Recent studies support the idea that fluctuations and dynamics in the population of FAW are strongly influenced by current climatic conditions (Caniço et al., 2020). Climatic factors such as temperature, precipitation, wind speed, solar radiation, and water vapour pressure were sourced from the WorldClim platform (www.worldclim.org) at an approximate spatial resolution of 1 km (Booth, 2018; Fick & Hijmans, 2017). In addition, the availability and intake of soil nutrients, particularly nitrogen, play a significant role in the growth of host plants (Gu et al., 2022). This, in turn, has a direct impact on the abundance of pests like FAW and the intensity of their attack (Bala et al., 2018). To analyse soil-nutriment-related factors, soil data at a resolution of 250 m containing nitrogen and phosphorus nutrient values, was downloaded from https://www.isric.org/.

To reduce dimensionality and address correlations within our datasets, we employed statistical techniques in R software (R Core Team, 2020). Specifically, we utilized Pearson's correlation coefficient and conducted cluster analysis, visualizing the results with a dendrogram. The variables with the lowest correlations (as depicted in Fig. 3) were subsequently selected as input parameters for our evolutionary Adaptive Neuro-Fuzzy Inference System (ANFIS) model.

The model was developed in Matlab software (The Mathworks, 2021). The data were partitioned into 70% to develop the model and

Table 1
Categorisation of the infestation prevalence level determined by quantile estimates derived from the available data, which represented the intensity of fall armyworm infestation in Kenya.

Quantiles	Infestation class	Proportion (%)
[Min(0), 1st Qu (8 %)]	Low	14.63
>1st Qu (8 %)], <= Median (24 %)]	Moderate	28.10
>Median (24 %)],<= 3rd Qu (44 %)]	High	28.00
>3rd Qu (44 %), <=Maximum (100 %)	Very High	29.27

30% for accuracy assessment. The evolutionary Adaptive Neuro-Fuzzy inference system (GA-ANFIS) is a subset of AI models based on the Takagi–Sugeno Fuzzy inference system (Jang, 1993) powered by a genetic algorithm. The GA-ANFIS integrates the benefits of neural networks, Fuzzy logic, Fuzzy inference system, and genetic algorithm into a single framework (Walia et al., 2015) to automatically generate a set of optimal connection weights required to train the Neuro-Fuzzy efficiently, creating a robust model. The rules of the first-degree Fuzzy Sugeno model (Sugeno & Kang, 1988) are as follows: *r1, r2,…, rn*, where n represents the number of rules (Nikolić et al., 2015):

$$Rule: if\ w\ is\ C\ and\ z\ is\ D,\ \ then\ \ r = ax + by + c \tag{3}$$

where C, and B, are the membership functions for multiple inputs, including w and z. For a zero-order Sugeno model, the output level r is a constant (a = b = 0). The degree of membership quantifies the contribution of a variable in the context of our model. It can range between 0 and 1, with 0 indicating no membership and 1 indicating full membership or maximum contribution of that particular variable.

As our study centered on Kenya, we segmented the area into 1 km × 1 km grids using Quantum GIS (QGIS, 2009). For each grid's centroid coordinates, we then extracted the least correlated corresponding raster variables specifically wind, nitrogen, temperature, and precipitation for those specific locations. The GA-ANFIS model was run in 3000 iterations for accurate prediction with optimum cross-over and mutation rate (Angelova & Pencheva, 2011). Following our analysis with the ANFIS machine learning model, the resultant predictions were transformed into a spatial format. We utilized QGIS (QGIS, 2009) to rasterize these predictions, converting the model's output data into georeferenced raster layers. This process enabled us to visualize and further analyze the spatial distribution of our predicted data within the context of our study area.

The metrics used in evaluating the models' performances include the coefficient of determination (R^2), and root mean squared error (RMSE). The equations of the performance evaluation metrics are defined in Eqs. (4) to (5).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{4}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{5}$$

where $\hat{y}_i$ and y_i are respectively the predicted and observed FAW infestation in the ith month, i = 1, 2,….., n and $\bar{y}$ the average of the observed values.

Moreover, as maize was considered the dominant host plant for the FAW, the FAO's general cropping calendar (FAO, 2017) on maize in East Africa (April – July and November – January) is used as the time frame for the projections and mapping of the proposed BC technology sites. The monthly predictions that align with the existing cropping calendar were merged using QGIS (QGIS, 2009) to create a consolidated raster layer representing the average implementation of the proposed management technology for each season.

The obtained outputs were categorised based on accumulated knowledge and field observation for easy interpretability and further analysis (fuzzification). For example, maize plants with a meagre percentage of pest infestation (less than 10%) do not require advanced control action. Therefore, this group was considered a low class.

Additional classes were derived using a combination of data quantiles and expert knowledge, as presented in Table 1.

b) Maize presence

Several studies have reported that FAW has found a conducive environment and is established in Africa, with maize as the primary host plant (Garcia et al., 2019b; Guimapi et al., 2022; Li et al., 2020; Wu et al., 2019). Therefore, the study domain is areas where maize is grown; these were sourced from the MapSPAM data centre (https://www.mapspam.info/data/) (Institute, 2020) at 10 km^2 spatial resolution. All datasets were resampled to a consistent 1 km resolution to ensure uniformity in our geospatial analysis. The MapSPAM data were processed using the "Raster Calculator" tool in QGIS (QGIS, 2009) and categorised to indicate the presence or absence of maize crops.

c) Ecological niche of *Cotesia icipe*

Species distributions are strongly influenced by prevailing environmental conditions such as temperature and rainfall (Qin et al., 2017). In this study, we hypothesized that the performance of *C. icipe* is closely associated with the ecological niche of the parasitoid. The modelling experiment for assessing the ecological niche of *C. icipe* was conducted using the MaxEnt algorithm (Phillips et al., 2006). MaxEnt was chosen for its statistical robustness, adaptability to different environments, and its ability to handle presence-only data, which was the case in our study (Marchioro & Krechemer, 2018)**.** This algorithm has proven effective in species distribution modelling and has been widely utilized in ecological research (Elith et al., 2011). The geocoded locations of the parasitoid (n = 15) were sourced from the database of the International Centre of Insect Physiology and Ecology (*icipe*). These data were obtained from field studies conducted in Kenya, specifically in regions such as Kilifi, Kwale, Taita Taveta, Makueni, and Machakos (Mohamed et al., 2021), with a single occurrence data point sourced from the open-source biodiversity database of the Global Biodiversity Information Facility (GBIF) (https://www.gbif.org). Environmental variables considered for modelling consisted of 19 bioclimatic variables sourced from the Worldclim data portal (https://worldclim.org/) (Booth, 2018; Fick & Hijmans, 2017) at 1 km resolution. The Landcover variable was sourced from the European space agency (https://www.esa-landcover-cci.org/). We also performed a Pearson's collinearity test on the 20 environmental variables to identify and address multicollinearity, reducing dimensionality in the predictor variables. By exploring the dendrogram generated from the Pearson's correlation coefficient, we selected eight variables (bio2, bio9, bio10, bio12, bio15, bio16, bio17, Landuse/land cover) that were least correlated and suitable for model development.

The model was replicated three times using the sub-sample method, with each replication using a different subset of the data. The outputs of the three replicates were combined to create an ensemble of probability outputs, which allowed us to determine the optimum niche and performance of the model. In each replication, 70% of the species occurrence points were used for training the model, while the remaining 30% were retained for testing the model's performance. The model outputs, generated with a receiver operating curve (AUC) > 0.9 based on scores ranging from 0 (very low) to 1 (optimal) were mapped using QGIS (QGIS, 2009). The suitability score for each model was categorised into five classes: very low (0–0.2), low (0.2–0.4), moderate (0.4–0.6), high (0.6–0.8) and very high (0.8–1).

2.3. Extrapolation of the base model to Africa

By using the spatially well-distributed base model obtained for Kenya, we were able to obtain a representative sample of the study area,

Table 2
Performance metrics of evolutionary Adaptive-network-based Fuzzy Inference System on predicting insect pest infestation in maize farms.

Performance metrics	Train	Test
R^2	0.926	0.890
RMSE	10.901	15.600

ensuring that the analysis captured the variability across different regions (Hyman et al., 2013). To streamline the analysis process, we employed a simplification technique using QGIS (QGIS, 2009). Specifically, we averaged the predictions for two distinct seasons: April to July and November to January. The Maxent algorithm was again used to extrapolate and predict the potential suitability of the BC agents across Africa, using socioeconomic and agroecological zone data as predictor layers. To enrich the predictive modelling process, we incorporated socioeconomic data, specifically the Global Development Potential Indices targeting crops at a resolution of 500 x 500 m (Oakleaf et al., 2020). These data were obtained from the Socioeconomic Data and Applications Center (SEDAC), which is a data center within NASA's Earth Observing System Data and Information System (EOSDIS). SEDAC is hosted by the Center for International Earth Science Information Network (CIESIN) at Columbia University (https://sedac.ciesin.columbia.edu/data/sets).

3. Results

In this study, a hybrid model incorporating various techniques, including neural networks, fuzzy logic, a fuzzy inference system, and a genetic algorithm, was employed for predicting FAW infestation within maize farms. This integrated approach significantly enhanced the robustness of the predictions.

The results reveal that the Genetic Algorithm-based Adaptive-network-based Fuzzy Inference System (GA-ANFIS) effectively explained the variation between observed and estimated values. As demonstrated in Table 2, the hybrid model yielded high R2 values (close to 1) and reasonable RMSE values, underscoring its accuracy in predicting FAW-infested plants within maize farms. These findings highlight the model's robustness and effectiveness, offering valuable insights for optimizing pest management strategies in maize cultivation.

Fig. 4 presents the interpolated maps illustrating the degree of suitability across different regions in Kenya for the implementation of augmentative biocontrol using *C.icipe* in maize farms. The validation results demonstrate the efficacy of the developed index based on the Fuzzy inference theory, achieving a classification accuracy of 100% in distinguishing areas of high and low suitability for scaling up the parasitoid in Kenya. Computational findings suggest that *C. icipe* holds substantial potential as a biocontrol agent in maize farms, with area suitability exceeding 90% throughout the two maize cropping seasons. Central Kenya emerges as particularly favorable for implementing this augmentative BC technology. The southwestern region of the country shows intermediate levels of success (>0.20 %) when adopting the technology. Additionally, the coastal regions exhibit high suitability (>0.55 %) for releasing the BC agent, with some exceptions within the coastal belts to be less conducive (<0.20 %) for release.

These results highlight the potential and applicability of *C. icipe* as an effective biocontrol solution in maize farms across Kenya showing particularly promising conditions for its implementation. The detailed suitability maps offer valuable insights for guiding decision-making and prioritizing areas for the deployment of this augmentative BC technology.

The extrapolation of the predicted outputs to Africa, achieved by

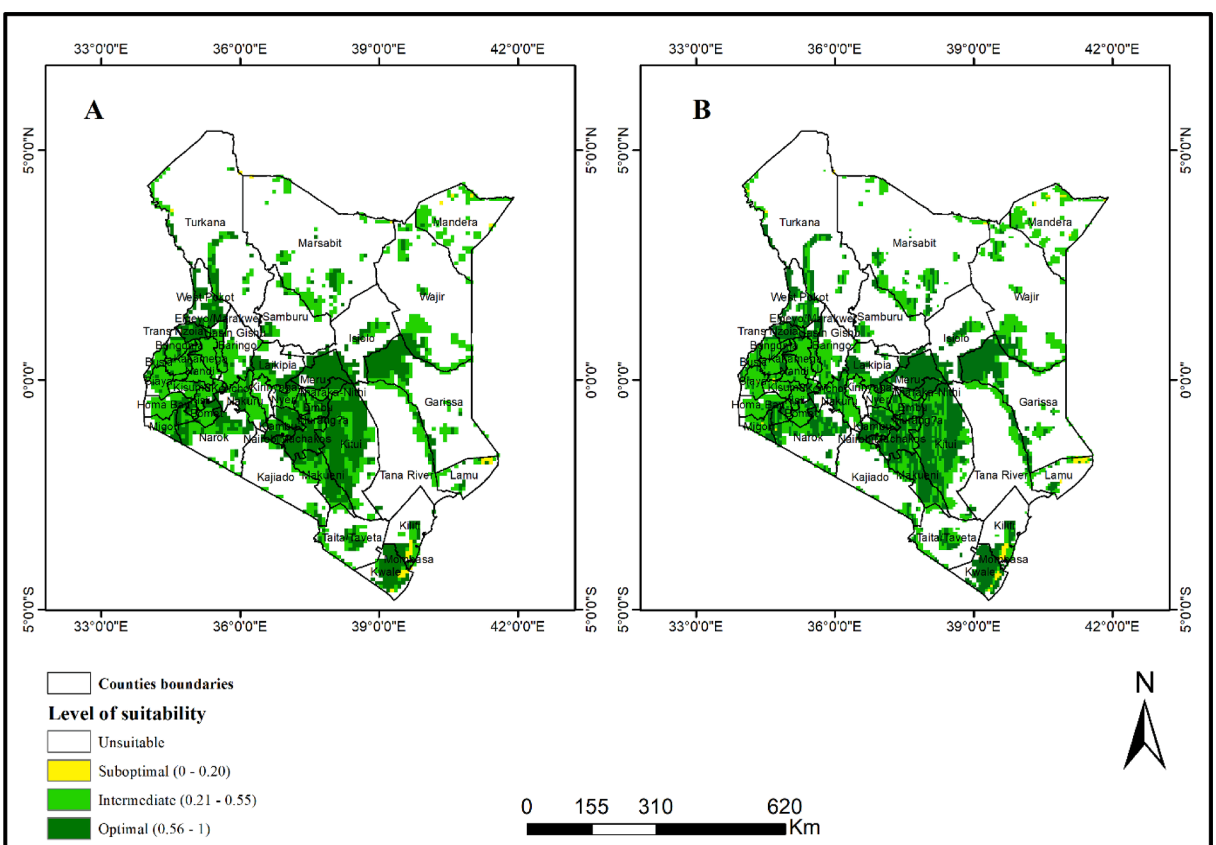

Fig. 4. Generated suitable sites for *C. icipe* candidate technology displayed in Kenya's two maize cropping seasons: (A) is the first season from April to July and (B) represents the second cropping season from November to January.

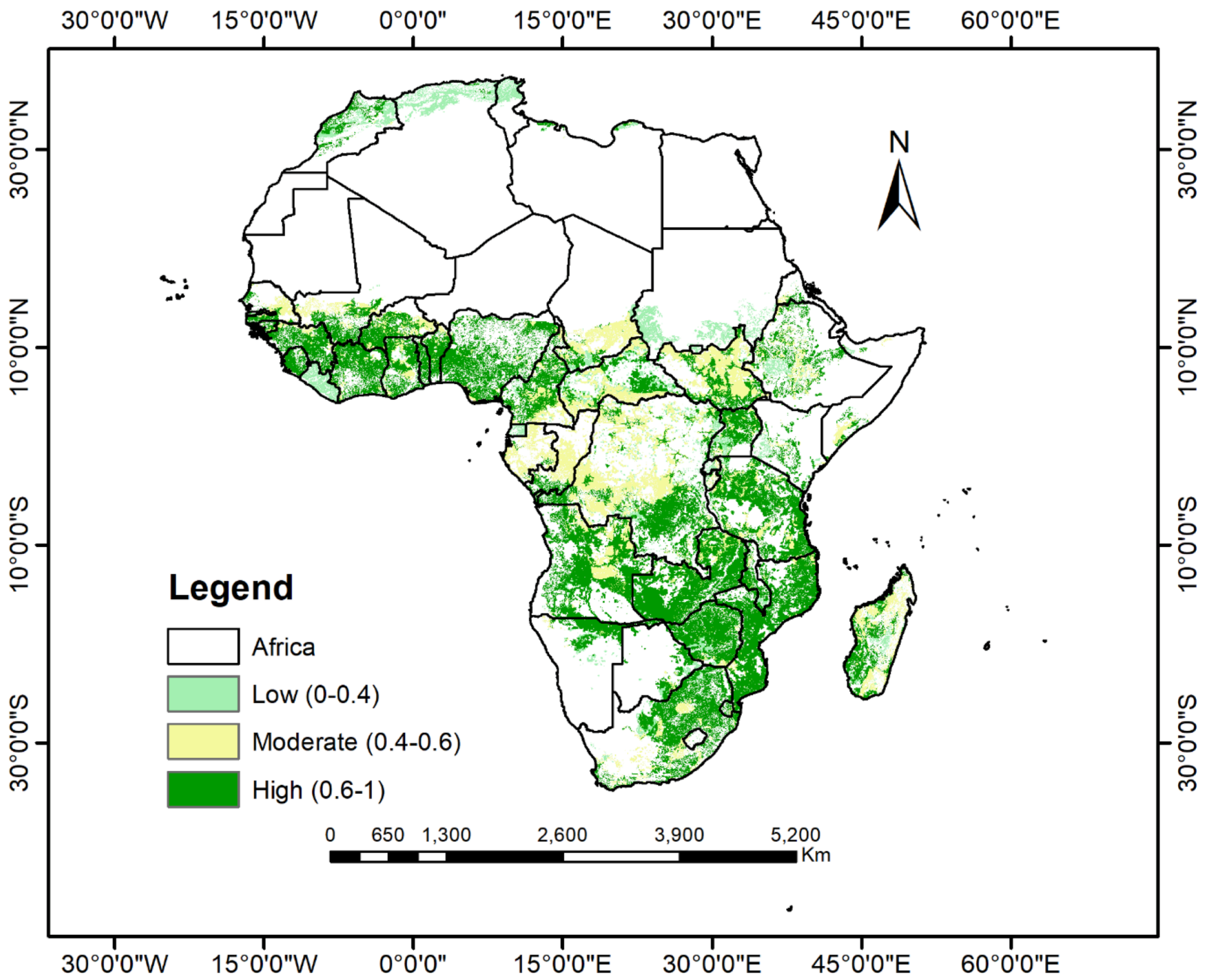

Fig. 5. Continental suitability for utilizing *C. icipe* as a biocontrol agent to combat fall armyworm infestations in maize farms across Africa.

utilizing agroecological similarity and the Global Development Potential Indices targeting crops, exhibited an average AUC greater than 0.8. This extrapolation process confirmed that the release of parasitoids would generally be effective in most maize-harvested areas in Sub-Saharan Africa.

Fig. 5 provides a representation of the suitability of the African landscape for the augmentative BC technology, as extrapolated from the Kenya model to Africa. The results presented in Fig. 5 demonstrate an appropriate level of suitability for deploying this BC technology across several regions. The corresponding maps visually illustrate the high suitability of *C. icipe* parasitoid in most maize-harvested areas throughout Africa. These maps further support the notion that the BC technology can be successfully implemented in a wide range of maize-growing regions across the continent. These findings highlight the potential for utilizing *C. icipe* parasitoid as an effective BC approach in Sub-Saharan Africa, particularly in areas where maize is extensively cultivated. The results offer valuable insights for decision-makers and stakeholders involved in pest management and agricultural practices in the region

4. Discussion

This study offers a comprehensive approach to understanding and managing FAW infestations by strategically deploying *C. icipe* as a promising BC agent. The approach comprised several components: First, a GA-ANFIS (Genetic Algorithm and Adaptive Neuro-Fuzzy Inference System) model was employed to accurately simulate pest infestation levels by incorporating climatic and soil variables. Next, an ecological niche model was used to predict suitable sites for *C. icipe* deployment based on environmental conditions and host plant availability. These predicted sites, along with estimated infestation level and maize availability, guided the identification of suitable locations for deploying the BC technology. To validate the baseline model, the focus was primarily on Kenya where the accuracy of the model was assessed by comparing the recovered parasitoid occurrence points with sites demonstrating potential suitability score for deploying the BC technology. The results confirmed the practicality and acceptability of the model in the Kenyan context. The innovative approach demonstrates the value of integrating AI algorithms to address the complexities of environmental conditions and interactions involved in the coexistence of the host plant, fall armyworm (FAW), and its parasitoids. The assumptions made during the model's conceptualization have proven to be meaningful and realistic, offering valuable insights for effectively deploying the BC technology.

The results underscore the utility of employing AI algorithms to mimic complex dynamics systems (Carter & Finn, 1999; Jacobs et al., 2015; Mackinson, 2000; Shariati et al., 2017; Wongnak et al., 2022) such as insects, plants, weather, soil and natural enemies and their interactions. The advanced hybrid system showcased their advantage by delivering high precision in performance metrics compared to other modelling methods, despite a limited dataset (Liu et al., 2021). This also justifies the growing interest in using and applying hybrids and ensemble models in solving ecological and environmental problems (Rohman et al., 2015).

The suitability of the Africa landscape for *C. icipe* demonstrates the prominence and potential of deploying this parasitoid as the primary BC agent against FAW (Tepa-yotto et al., 2021). This extensive potential distribution is attributed to the resilience mechanism of the selected technology making it adaptable to a variety of successful agroecologies, including areas with less favorable climatic conditions (Thorat & Nath, 2018). Additionally, parasitoids with innate dispersal abilities (Lindstedt et al., 2019), facilitated their wide dissemination as highly effective BC agents across Africa (Mohamed et al., 2021; Tepa-yotto et al., 2021).

Overall, BC offers numerous advantages, including reduced toxicity, rapid biodegradability, and the ability to target specific pests while maintaining ecological balance (Akutse et al., 2020; Bhushan et al., 2011; Harding & Raizada, 2015; Kumar, 2015). Identifying suitable sites for BC dissemination at scale provides a valuable tool for deploying safer FAW management strategies within the continent. This tool is expected to promote the adoption of IPM technologies, enhancing the likelihood of success and reducing the need for widespread pesticide use (Jolly, 1988; Rubiano & Soto, 2009). In addition, the generated maps from this study can guide agricultural practitioners and other stakeholders in effectively managing FAW infestation at scale. Furthermore, the maps can inform decision-making by indicating where to adopt and deploy BC in specific sites to control pests and optimize crop yield. This approach also contributes to minimise the use of pesticides, reducing harm to non-target organisms, and mitigating environmental hazards.

The findings of the study open up possibilities for transferring environmentally friendly control methods aimed at targeting insect pest infestation hotspots. However, it is essential to acknowledge some limitations, such as data availability and the unique agrarian landscape of Africa, where diverse cropping systems play a significant role. Additionally, the study omits factors like interspecific interactions and pesticide use regimes, which are crucial to BC dynamics. These challenges underscore the need for continuous refinement of modeling approaches to better align with real-world complexities.

5. Conclusions

Overall, this study utilized multiple algorithms to propose a methodology to identify specific sites for deploying BC against FAW in Africa. The tool offers timely and reliable predictions of site-specific infested plants and environmentally friendly management strategies for FAW management. Consequently, this tool is expected to be enhanced and adapted to stimulate and accelerate the adoption of IPM management technologies at localised FAW hotspots. Moreover, the approach, which is driven by an understanding of pest biology rather than purely statistical regressions and accuracy metrics, can be generalized globally and applied to other IPM technologies.

CRediT authorship contribution statement

Komi Mensah Agboka: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Henri E.Z. Tonnang:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Elfatih M. Abdel-Rahman:** Conceptualization, Supervision, Writing – review & editing. **John Odindi:** Methodology, Supervision, Writing – review & editing. **Onisimo Mutanga:** Methodology, Supervision, Writing – review & editing. **Saliou Niassy:** Methodology, Supervision, 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.

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