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Research article

Steering conservation biocontrol at the frontlines: A fuzzy logic approach unleashing potentials of climate-smart intercropping as a component within the integrated management of fall armyworm in Africa

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ABSTRACT

This study introduces a computational index that employs fuzzy sets theory to identify potential deployment sites for push-pull as a component in the integrated management of Fall Armyworm (FAW) in Africa. The index, validated through known push-pull testing sites and informed by insights from field data and practical observations, is primarily based on companion plants (*Desmodium intortum* and *Brachiaria brizantha*), livestock, and maize as covariates. The study developed a set of rules linking each selected covariate to the output as membership functions, which are later combined using an algebraic operator. It identifies extensive maize farms across Africa potentially suitable for Push-Pull technology, although the suitability varies by region. Farms in the eastern and southern regions are predicted to be highly suitable, while the suitability of farms in West Africa is expected to improve over time due to the perennial nature and agronomic benefits of companion plants. The index is proposed as a metric for deploying push-pull technology, providing a roadmap for effective agronomic practices in Africa, and assisting farmers and decision-makers in the integrated management of FAW. Overall, our results indicate that the fuzzy-based computational index is an effective tool for identifying potential areas to maximise the benefits of push-pull technology as a key component of integrated FAW management. Our study identifies appropriate areas for application, allowing for the careful use of resources and increasing the likelihood of effective pest management. This approach will ultimately safeguard cereal crops, boost agricultural productivity, and aid in ensuring food security in Africa.

1. Introduction

The Fall Armyworm (FAW), scientifically known as Spodoptera frugiperda (J. E. Smith), constitutes a transboundary invasive insect

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pest that first emerged in Africa in 2016 [1]. Originating from South America, this pest has presented a substantial threat to cereal crops, with particular emphasis on maize [2]. As maize is a crucial staple food in Africa, ensuring food security [3], FAW substantially threatens regional food stability. Estimates suggest that crop losses attributable to FAW range from 8.3 million to 20.6 million tons, valued between US$ 2.481 billion and US$ 6.187 billion [4,5]. This scenario underscores the pressing need for effective control measures to be put in place to mitigate the impact of this invasive species. Considering the extensive threat posed by FAW invasions, the prevailing control strategy frequently employed involves the application of synthetic chemical insecticides. Nonetheless, these substances exhibit slow environmental degradation and tend to accumulate within the food chain, raising significant concerns [6].

Furthermore, these chemical agents could harm non-target organisms and beneficial insects, including bees and natural predators [7]. It is also imperative to acknowledge that there have been recorded instances of FAW developing resistance to multiple classes of insecticides [8]. Given the harmful implications associated with chemical controls on both the environment and human health, an increasing exigency exists for safer alternatives that could effectively and sustainably manage the menace posed by FAW.

In Africa, several environmentally sustainable management strategies have been advocated for the control of FAW, including the utilisation of biopesticides [9], the mass release of parasitoids [10], and the implementation of agroecological practices such as intercropping edible maize with legumes and climate-smart maize-legume intercropping, notably utilising push-pull technology [11]. In conjunction with the application of biopesticides and the mass release of parasitoids, the push-pull climate-smart intercropping system has emerged as a readily deployable solution in Africa, owing to its resilience against drought [12,13] and its alignment with the traditional intercropping practices employed by local farmers. Push-pull technology entails the cultivation of maize alongside the legume fodder *Desmodium* sp as a repellent crop (push) and the incorporation of fodder grasses (*Pennissetum* sp or *Brachiaria* sp) as attractant crops (pull). Numerous variants of the push-pull system exist; the climate-smart push-pull method utilises *Desmodium intortum* Urb. (Greenleaf) and *Brachiaria brizantha* cv Mulato II as intercrops and border crops, respectively. As a legume, *Desmodium* enriches the soil with nitrogen and safeguards it against erosion by functioning as a cover crop, consequently enhancing soil fertility, improving nutrient fixation, and increasing soil organic matter, which results in higher maize yields (ranging from two to three times higher) [14]. Moreover, the push-pull technology facilitates the production of valuable animal fodder from the harvest of companion crops, thereby promoting increased milk production and diversifying farmers' income streams [15,16]. Despite the numerous advantages presented by this push-pull approach including enhanced maize productivity, improved soil fertility, control of striga weed, and the integration of livestock management its adoption throughout Africa remains restricted. Of the approximately 380 million cereal farmers in Sub-Saharan Africa, only 300,000 have embraced this technology. Analogous to any other agroecological technique, the effective implementation of push-pull technology necessitates specific conditions, thus complicating prioritisation in regions characterised by diverse and fragmented agroecological landscapes. This study proposes applying fuzzy set theory as a potential methodology for addressing these complexities, particularly in managing FAW. By utilising this theory, we aim to elucidate the intricate decision-making processes integral to implementing and scaling such agroecological practices.

Informed by the preceding studies [17,18,19,20], which leverage the potential of fuzzy sets for insect pest management, our work presents an index, based on fuzzy sets theory, aimed at identifying the most favourable locations for deploying push-pull technology for FAW control across Africa. The primary objective of this study is to assess the feasibility of implementing push-pull technology. This endeavour is predicated on the assumption that the companion plants, *Desmodium intortum* and *Brachiaria brizantha*, which function as the 'push' and 'pull' components of this strategy, play a critical role in the prospective application of this technology. Furthermore, the presence of livestock may play a crucial role in enhancing the utilisation of push-pull technology, as these companion plants can serve as fodder crops. By establishing this index, we aspire to facilitate the broader integration of push-pull technology in conjunction with biopesticide application and the mass release of parasitoids across Africa. This tool will offer significant guidance to farmers and decision-makers, assisting them in identifying where the technology could be most effectively implemented within the framework of integrated management FAW.

2. Methods

2.1. Overview

The index to be developed must be easy to understand, yet reproducible in order to identify the most favourable areas for the optimal deployment of push-pull technology. The index does not measure how effective the technology is against FAW, but instead pinpoints locations where it can be implemented to provide the most significant benefit to farmers. The study follows a step-by-step approach to identify key factors (covariates) that would serve as indicators for the technology. Next, the contribution of each factor to the successful deployment of push-pull is assessed, and finally, the index is validated through ground data to ensure its accuracy and reliability.

2.1.1. Covariates that would serve as indicators of the technology

This study used several key factors, or covariates, to determine the best areas for deploying push-pull technology. These include companion plants (*D. intortum* and *B. brizantha*), livestock density, and maize cultivation. Companion plants are essential because they form the system's foundation, supporting pest control and the natural ecosystem. Livestock presence adds value, as these plants also serve as high-quality fodder, making the system more attractive to farmers who have livestock. Finally, maize cultivation is a critical factor since it is the primary host of the FAW, making it a central focus for push-pull interventions. Together, these covariates help us to identify areas where the technology can be most effective and beneficial for farmers.

2.1.1.1. Push-pull companion plants covariates: Desmodium and Brachiaria. Companion plants like *D. intortum* and *B. brizantha* are central to the push-pull technology because they are the backbone of the entire system [21,22,23,24]. These plants are not just additional components, but play a key role in ensuring the technology works effectively. They help to create the right conditions for managing pests naturally, while also improving the overall health of the farming ecosystem. *D. intortum* and *B. brizantha* boost the presence of beneficial organisms, improve soil quality, and help maintain moisture, contributing to healthier crops and reducing reliance on chemical pesticides.

The maximum entropy (MaxEnt) algorithm [25] was utilised to predict areas suitable for *D. intortum* and *B. brizantha*. The MaxEnt algorithm [25] was considered owing to its statistical robustness, adaptability to various environments, relatively small sample size requirement, and presence-only data [26]. The modelling data consisted of the species' *D. intortum* and *B. brizantha* occurrences and environmental variables. The species occurrence data were sourced from the Global Biodiversity Information Facility (GBIF) open-source biodiversity database (https://www.gbif.org). The occurrence data does not have a fixed spatial resolution. The data consists of individual species occurrence records, which include specific geographic coordinates (latitude and longitude) where the species was observed. Each occurrence point represents a location rather than a spatially gridded dataset.

The environmental variables (Table 1) considered in addition to the species occurrence records consisted of 19 bioclimatic variables downloaded from the Worldclim data portal (https://worldclim.org/), three edaphic variables downloaded from the international soil reference and information centre (ISRIC) data hub (https://data.isric.org), and one Landcover variable downloaded from European space agency portal (https://www.esa-landcover-cci.org/). Because the environmental variables cover the entire continent, the dataset is quite large; accordingly, we resampled these variables with different resolutions to 5 km to ensure consistency. This adjustment helps to manage the large dataset efficiently, allowing for smoother computing, while still keeping sufficient detail to visualise changes and patterns across the continent. This 5 km resolution strikes the right balance between processing power and maintaining a clear, accurate picture of the data.

Prior to running the MaxEnt model, we reduced the dimensionality in the predictor variables by reducing multicollinearity through using Pearson's collinearity test, performed on the entire environmental variables ($n = 22$, Table 1) to determine the least-correlated predictors suitable for model development. The exploration of the dendrogram (Fig. 1), generated using Pearson's correlation coefficient, led to the exemption of highly correlated variables and the selection of eleven variables (Bio2, Bio9, Bio10, Bio12, Bio15, Bio16, Bio17, Land use/land cover, soil nitrogen, soil organic and soil pH) for the companion plants' models.

The models were run and replicated three times by using the sub-sample method, and an ensemble of the three probability outputs was considered to determine the optimum suitability and performance of the models. We used 70 % of the respective species occurrence points for training, while 30 % were retained for testing the model performance. The outputs generated with higher accuracy (area under the curve (AUC) > 0. 9) at a 5 × 5 km resolution (Fig. 2) were saved in TIFF format to ensure they were ready for easy analysis and further processing. In the figure, the brackets "[" used at the lower bound means that the lower value is included in the range, while "]" at the upper bound means the upper value is included and vice versa.

2.1.1.2. Livestock covariate. A significant advantage of incorporating *D. intortum* and *B. brizantha* in the push-pull system is that both plants serve as high-quality fodder for livestock, giving farmers who have livestock an extra benefit [27]. These plants protect crops

Table 1
Environmental variables considered for modelling.

Variable	Description	Unit
Bio1	Annual mean temperature	°C
Bio2	Mean diurnal range (mean of monthly (max temp - min temp))	°C
Bio3	Isothermality (Bio2/ Bio7) (× 100)	NU
Bio4	Temperature seasonality (standard deviation × 100)	NU
Bio5	Max temperature of the warmest month	°C
Bio6	Min temperature of the coldest month	°C
Bio7	Temperature annual range (BIO5-BIO6)	°C
Bio8	The mean temperature of the wettest quarter	°C
Bio9	The mean temperature of the driest quarter	°C
Bio10	The mean temperature of the warmest quarter	°C
Bio11	The mean temperature of the coldest quarter	°C
Bio12	Annual precipitation	mm
Bio13	Precipitation of the wettest month	mm
Bio14	Precipitation of the driest month	mm
Bio15	Precipitation seasonality (coefficient of variation)	NU
Bio16	Precipitation of the wettest quarter	mm
Bio17	Precipitation of the driest quarter	mm
Bio18	Precipitation of the warmest quarter	mm
Bio19	Precipitation of the coldest quarter	mm
Soil nitrogen	Nitrogen content in the soil at 5–15 cm depth	cg/kg
Soil organic content	Organic content in the soil at 5–15 cm depth	dg/kg
Soil pH	The pH level of the soil at 5–15 cm depth	pH[a]10
Landuse/land cover	Land cover classes in the area	NU

[a] NU – No unit.

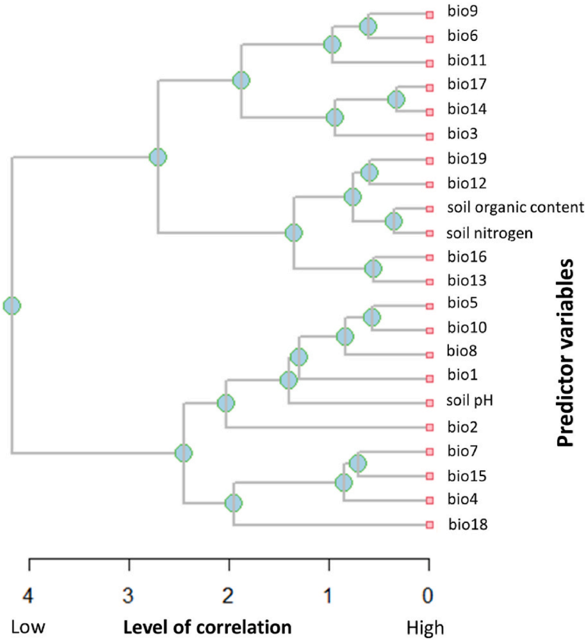

Fig. 1. Dendrogram of the intercorrelated variables. The length of the lines in the dendrogram visually indicates the degree of correlation.

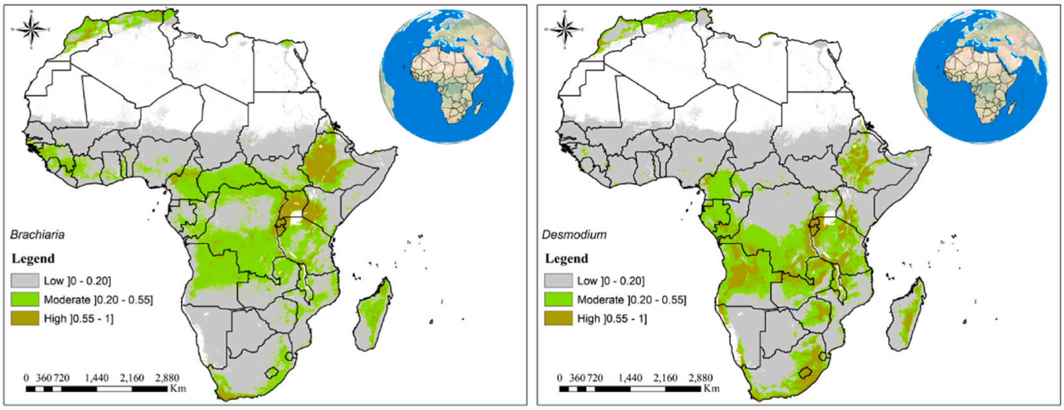

Fig. 2. Predicted potential habitat suitability of push-pull companion plants: *Brachiaria. brizantha* and *Desmodium intortum* in Africa.

from pests and provide nutritious animal feed, which is especially valuable for smallholder farmers who depend on crops and livestock. This dual-purpose system helps farmers to derive more value from their land by increasing crop yields while supporting healthy livestock, thus rendering the entire system more sustainable and economically viable.

By enhancing the overall ecosystem and offering practical benefits, these companion plants are crucial to the efficacy of push-pull technology, presenting a solution that extends beyond mere pest control to significantly augment overall farm productivity. To incorporate the livestock component into this analysis, we utilised global data concerning the distribution of ruminant livestock [28], obtained from https://dataverse.harvard.edu/ and resampled to a resolution of 5 km for consistency with other datasets.

2.1.1.3. Maize covariate. Maize, being significantly susceptible to the fall armyworm (FAW), assumes a vital role in determining the effectiveness of push-pull technology. Areas where maize is cultivated are particularly susceptible to pest damage, rendering them prime candidates for introducing this technology. Given that FAW has established itself in Africa, with maize serving as its principal host, it is essential to comprehend the distribution of maize cultivation for accurately mapping the potential for the deployment of push-pull technology [20,29]. To achieve this objective, maize distribution data was acquired from the MapSPAM data centre at a resolution of 10× 10 km (https://www.mapspam.info/data/) [30]. However, in order to ensure consistency with other datasets, such as the suitability data for Desmodium and Brachiaria, the maize layer was resampled to a resolution of 5 × 5 km through utilising QGIS software [31]. This harmonisation process appropriately aligned the maize data with the companion plant layers, employing them as a mask for consistency.

Furthermore, the maize variable was transformed into a binary format (0 or 1) using QGIS's "Raster Calculator" tool. Areas with maize cultivation were designated as '1' (maize present). In contrast, all other areas were indicated as '0' (maize absent). This pre-processing step guarantees that the data is clear, uniform, and prepared for subsequent analysis within the study.

2.1.2. Rule-based model for the successful deployment

The fuzzy model used in this study is inspired by the work of Garcia et al. [18]. Unlike traditional fuzzy sets, which require the defuzzification of linguistic outputs (i.e. converting them back to numerical values), this model is designed to produce numerical outputs directly, ranging from 0 to 1. The membership functions in this model outline the relationship between the inputs and outputs, thus providing a structured method for quantifying each input's contribution to the final result. This methodology improves the clarity of numerical results and streamlines the overall process. The rules established in this model produce numerical outputs that are synthesised through algebraic operators.

Furthermore, this simplified fuzzy model assumes an additive relationship between the impacts of various variables on the final output. The raster data was converted into a tabular format to facilitate computation with the extensive continental-scale raster data at a resolution of 5 km. A 5 km grid was created through using QGIS [31]; for each grid cell, we extracted values corresponding to the centroid for all the utilised variables, including *D. intortum* and *B. brizantha*, livestock, and the binary maize layer.

2.1.2.1. Model computing scheme. The first phase of the computational approach focuses on developing a set of rules that link each selected variable to the output, representing the membership functions. These membership functions are constructed as part of the fuzzy logic framework, defining the relationship between the variables (e.g. companion plants, livestock, and maize cultivation) and the suitability index score. The method consists of two main steps: defining arbitrary thresholds and iterating the model to match observed data (ground truthing).

Step 1. Defining initial thresholds

Each variable X_i (where i∈{1,2, 3} represents the number of variables) is assigned an initial threshold T_i, which defines its membership in the system. The membership function μ_{X_i} maps each variable X_i to a value in the range [0, 1], representing its contribution to the final index:

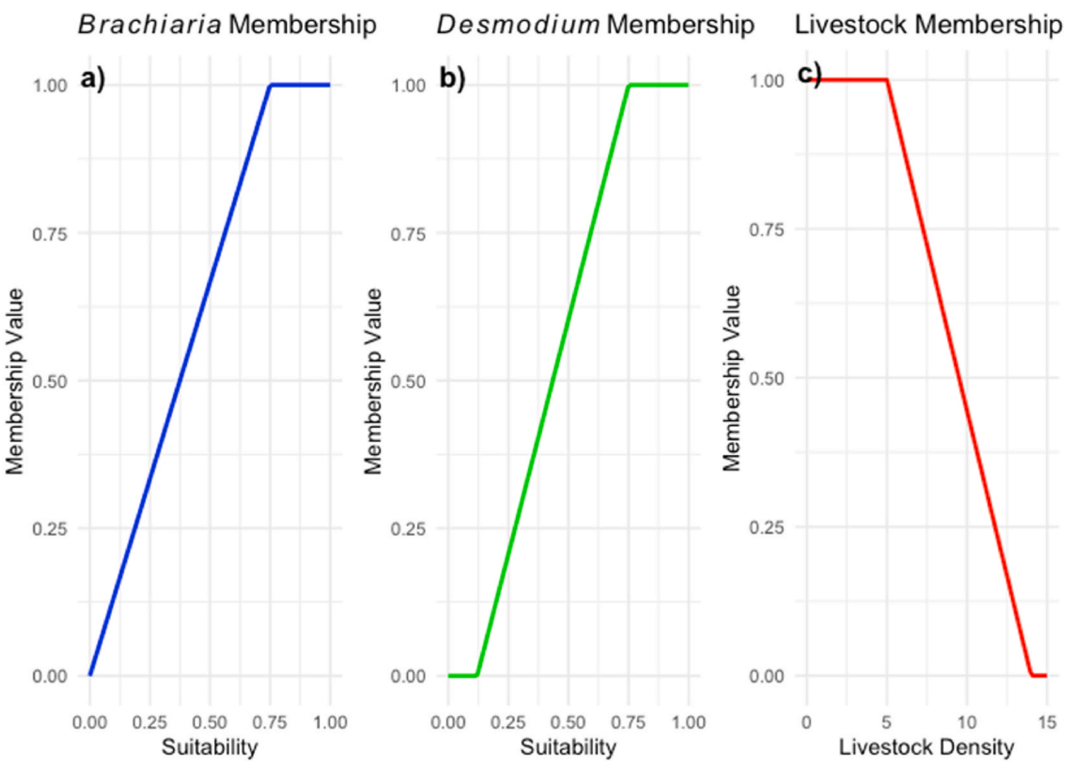

Fig. 3. Arbitrary Fuzzy membership functions for (a) *B. brizantha* suitability score, (b) *D. intortum* suitability score, and (c) livestock.

$$\mu_{X_i}(X_i) = \begin{cases} a \ if \ X_i \leq T_1 \\ b \ if \ T_1 \langle \ X_i \leq T_2 \\ c \ if \ T_2 \langle \ X_i \leq T_3 \\ d \ if \ X_i > \ T_3 \end{cases}$$

where $a, b, c, d \in [0,1]$ are the membership values corresponding to the predefined thresholds T_1, T_2, T_3.

This step is crucial for translating real-world variables into a structured fuzzy logic model. The variables, such as livestock density (Fig. 3c) or companion plant suitability (Fig. 3a and b), are linked to the index through these arbitrary thresholds (Fig. 3), which are subject to adjustment in the next step.

Step 2. Iterative refinement using ground truthing

The second step involves refining the initial thresholds through an iterative process. We extract data from areas in Kenya, Uganda, and Tanzania (Table 2), among other locations, where push-pull technology has been successfully tested.

This real-world data is used to adjust the membership function thresholds iteratively. The objective is to match the modelled suitability index $S(x)$ with the ground truth:

$$S(x) = \prod_{i=1}^{n} \mu_{X_i}(X)$$

where $S(x)$ is the suitability index score at location x_1, and $\mu_{X_i}(X)$ is the membership function of the i-th variable at x. The model is adjusted until $S(x) \geq 0.2$ for known areas of successful deployment.

The decision to set the index threshold at 0.2 is based on recent literature, where a probability of 0.3 indicates species presence [38, 39]. However, considering the high drought tolerance of the push-pull companion plants, we reduced the threshold to 0.2 to better represent their environmental resilience in arid conditions. This adjustment allows the model to account for areas where the technology could still be effective, despite less-than-ideal conditions.

2.1.2.2. Model outcome and validation. The final suitability index *S(x)* reflects the combined contribution of all selected variables through their membership functions. The algebraic product, a compensatory operator [17,40], was used to calculate the suitability score, but only in areas where maize is cultivated (maize layer = 1). The formula is expressed as:

$$S(x) = \begin{cases} \mu_{X_1}(X_1)^* \, \mu_{X_2}(X_2)^* \, \mu_{X_3}(X_3) \quad \text{if maize layer} = 1 \\ 0 \text{ if maize layer} = 0 \end{cases}$$

In this equation, $\mu_{X_1}(X_1)$, $\mu_{X_2}(X_2)$, and $\mu_{X_3}(X_3)$ represent the membership functions for companion plants and livestock density, respectively. The index is only calculated when maize is present (maize layer = 1). If maize is not cultivated, the suitability score is set to zero, as push-pull technology relies on it being part of the ecosystem.

This calculation was performed through using R statistical software [41]. This condition ensures that the model provides a realistic prediction of where push-pull technology could be effectively tested.

To validate the model, we followed a process similar to the calibration phase, applying it to the remaining countries where push-pull technology has been successfully tested (Table 2), excluding Kenya, Tanzania and Uganda, which were used earlier for calibration. The suitability index initially generated in a tabular format was interpolated using the processing toolbox in QGIS 3.10.9 [31] to create a more comprehensive visual representation of the suitability across Africa.

3. Results

Fig. 4 shows the final membership functions for the key variables after calibration. The three subplots illustrate the membership functions for companion plants (Fig. 4a), (Fig. 4b), and livestock density (Fig. 4c), which contribute to the overall index of push-pull

Table 2
References sites in Africa where push-pull technology was tested successfully used for calibration and validation.

Countries	Numbers of sites	References
Malawi	3	[32]
Rwanda	2	[33]
Ethiopia	3	[34]
Uganda	4	[12]
Kenya	6	[12]
Ghana	2	[35]
Senegal	1	[36]
Zambia	1	[37]
Zimbabwe	3	Unpublished
Tanzania	1	[12]

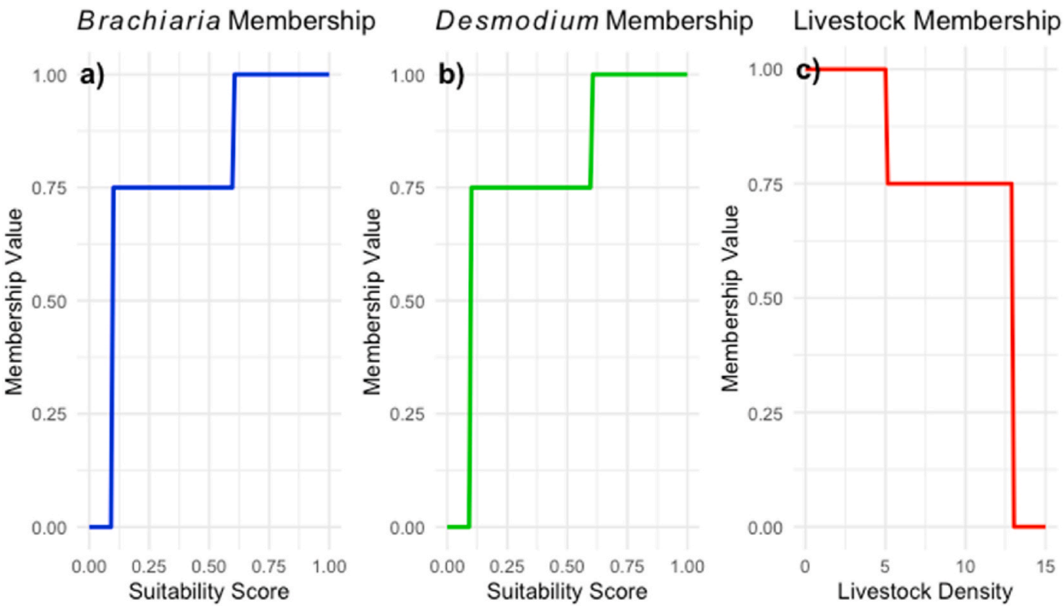

Fig. 4. Calibrated Fuzzy membership functions for (a) *B. brizantha* suitability score, (b) *D. intortum* suitability score , and (c) livestock.

technology. These membership functions, created after model calibration, define the final rules regulating how each variable contributes to the overall push-pull index.

Fig. 5 depicts the maps created by using interpolation to indicate the push-pull index score in African maize farms. Overall, the results suggest that push-pull technology would be suitable in many maize farms with varying probability. Specifically, vast regions in Tanzania, central Ethiopia, central and western Kenya, southern Uganda, Burundi, and Rwanda are conducive to successfully implementing push-pull technology in East Africa. The south-eastern region of South Africa, north and central Malawi, central Cameroon, eastern Zimbabwe, central Angola, northern Morocco, and Mauritania are also predicted to be highly suitable (>0.5) for the technology. Generally, the mountain ranges in Morocco, Mauritania, Madagascar and South Africa, as well as the rift valley escarpments of Ethiopia and Kenya, Tanzania, Uganda and Rwanda, have shown extreme suitability (>0.75) for the Push-Pull farming

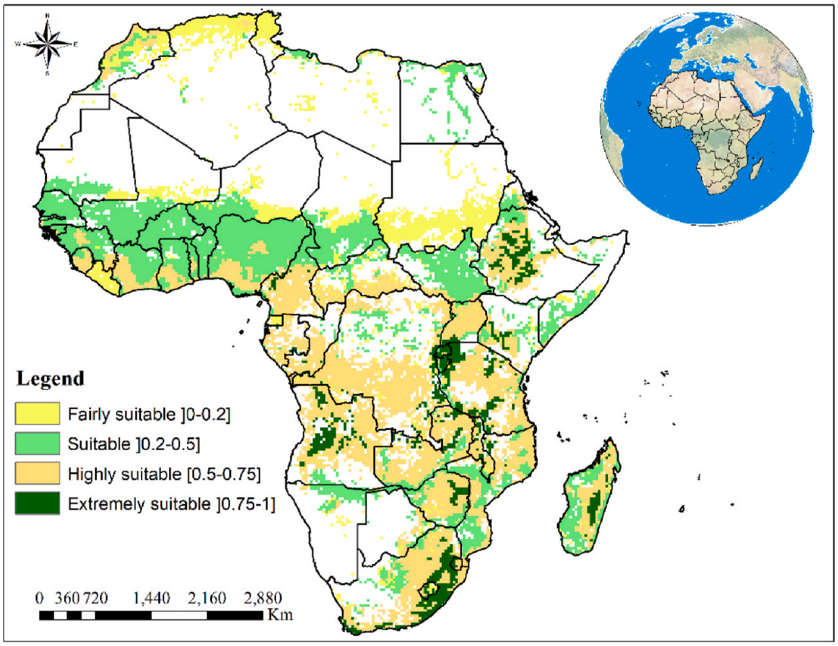

Fig. 5. Maps indicating push-pull index score across Africa. The index is classified into four categories: reasonably suitable]0.0, 0.2]), suitable]0.2, 0.5]), highly suitable (]0.5, 0.75]), and extremely suitable (]0.75, 1.0]).

system. Western African countries were also considered suitable, except Liberia and the Sahelian belts, where maize is not the main cultivated crop.

The validation results, shown in Fig. 6 below, demonstrate that the model's hypothesis and parametrisation are realistic and broadly capture the ecology of push-pull technology. The model consistently produced scores greater than 0.2 for all validation sites, reinforcing the robustness of the approach. Additionally, the validation highlights the variability in scores across different regions of Africa, reflecting the diverse landscape characteristics and pastoral practices.

4. Discussion

4.1. Fuzzy model for push-pull suitability interpolation

Push-pull is a nature-based solution that depends on various biological processes influenced by environmental and biological factors, such as climate, soil type of companion plants, and pest performance. The interpolation map showed a diverse range of suitability, which could be explained by the fact that the performance of push-pull relies on companion plants, which in turn depend on other biophysical (soil type, landscape) and biological factors (soil microbiota) [42,43]. The results of our model provide a solid foundation and critical information for guiding the upscaling of the technology at spatial scales within the FAW framework of integrated pest management (IPM).

Furthermore, it substantiates Garcia al [18]. in using and applying fuzzy sets to develop a realistic suitability index regarding the integrated management of insect pests. As a result, this index can aid policymakers and other developmental organisations or the private sector in identifying optimum sites for disseminating sustainable farming practices, such as push-pull technology within FAW IPM packages to increase food security across Africa. Because no precise information about the system is required, the model's flexibility and simplicity reduce its vulnerability to uncertainty [44] and offer a methodology for describing complex systems that are time-varying, nonlinear and adaptive, such as those found in biological and agricultural processes [45].

Moreover, even though push-pull technology was established over two decades ago, the scaling process across Africa has always been slow. While push-pull technology was initially developed to tackle striga and stemborer, the invasion of FAW has made it essential to scale up its use [12,46]. When combined with other environmentally friendly approaches under an IPM strategy, it can significantly reduce or even replace the reliance on synthetic pesticides, thus providing a more sustainable and effective solution for managing pests like FAW.

Our study is the first attempt to provide a decision-making tool through using a knowledge discovery algorithm to guide the effective scaling of push-pull technology.

4.2. Push-pull performance at scale

The variability in the performance of push-pull technology across agroecological regions has also been previously reported [32,35]. Several factors account for variations in suitability, including soil fertility, rainfall, and pest incidence. Additionally, it is important to note that Greenleaf Desmodium (*D. intortum*), used in climate-smart push-pull systems, originates from the highlands of South America. It is a summer-growing perennial plant with an optimal temperature range of 25–30 °C, which grows best at altitudes between 500 and 2500 m in the tropics, where annual rainfall exceeds 900 mm and can reach 3000, and in a variety of soils as long as they are not too acidic (pH above 4.5–5) or saline [47]. *Brachiaria brizantha*, the other companion plant, is native to tropical Sub-Saharan Africa and is now widely naturalised in the humid and sub-humid tropics. It is a warm-season lowlands grass, growing from sea level to 2000 m in the tropics and 1000 m in higher latitudes. The ideal temperature for its growth is 30–35 °C with an average annual rainfall of 1500–3500 mm. It can perform in conditions of low soil nitrogen [48], and a wide range of soil nutrients and a pH (4–8) [47]. These attributes make *B. brizantha* suitable for a broader range of agroecologies. Therefore, the existing climatic conditions and soil fertility significantly affect both companion plants, which outcome aligns with the predicted push-pull index score. Regional variations in agroecology explain the fluctuation in the push-pull technology suitability index across Africa. However, the technology is anticipated to be quite suitable in the major maize-growing areas of the continent.

Furthermore, considering the climatic variations across the continent, eastern Africa has a higher altitude and cooler temperatures than western Africa has. We could speculate that the weather conditions and soil in the western and northern regions may be less conducive to the extensive growth of companion plants, as compared with eastern Africa, but this would require further study. However, we predict that push-pull technology would be suitable for western Africa. In areas where push-pull is reasonably suitable, we anticipated that its suitability would increase in the coming years, considering that the companion plants are perennial and can enhance soil health through nitrogen fixation [49], improvement of soil organic matter, moisture retention [50], erosion prevention, and low pest infestation [12]. However, it is important to consider the potential impact of climate change on the long-term suitability of these areas. Changes in rainfall patterns, temperature fluctuations, and the increased frequency of extreme weather events could alter the growth and performance of the companion plants, as well as affect soil moisture retention and pest dynamics. While the perennial nature of these plants offers some resilience, climate-induced changes may influence their overall effectiveness and, subsequently, the long-term sustainability of the push-pull system in certain regions. Therefore, continuous monitoring of these climate factors is essential to ensure the adaptability and success of the technology under future climate scenarios.

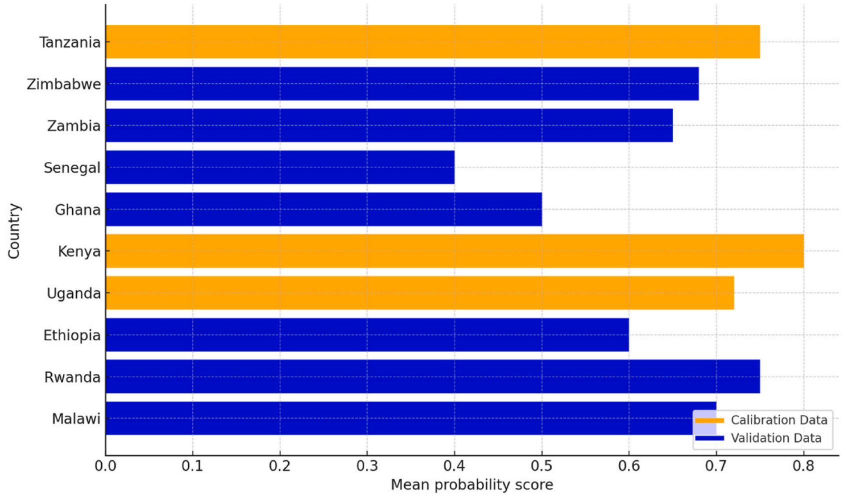

Fig. 6. Mean probability score of the push-pull index by country. This figure shows the mean probability scores for the validity of the push-pull technology index across various countries. Countries marked in orange (Kenya, Tanzania, and Uganda) represent calibration data, while countries marked in blue represent validation data.

4.3. Validation and limitation

This study finds that large areas of maize farms in Africa could be potentially viable for using the technology, although with varying degrees of suitability. The validation results confirm that the model accurately captures the potential for deploying Push-Pull technology, with all validation sites scoring above 0.2. The strong correlation reinforces the model's reliability in assessing regional suitability. The observed variability across Africa reflects differences in landscapes and pastoral practices, emphasising the importance of regional factors in determining where Push-Pull could be most effective. Eastern and Southern Africa are predicted to be mostly favourable for Push-Pull technology, while vast parts of Western Africa are expected to be reasonably favourable.

Despite the successful validation observed in this study, there are important limitations to acknowledge. First, the validation data is somewhat limited, making it difficult to fully confirm the real-world accuracy of the results. A more comprehensive validation should encompass areas where the push-pull technology has been unsuccessful, but we currently lack this data. Another limitation is the assumption of additivity in the model, which simplifies the process but may not fully capture the complex interactions among variables. For example, the combined effects of companion plants, livestock, and maize on the push-pull index score might involve more complex dynamics than an additive model can capture. Consequently, this simplification might result in an incomplete understanding of how these factors interact to influence the push-pull index.

5. Conclusion

This study developed a computational index to identify potential areas for successfully deploying push-pull technology. Based on the informative results and successful validation, the developed index could also improve the deployment of complementary technologies to push-pull technology (other agronomic practices) within the FAW IPM packages. The index can be easily adapted to other case studies and has the potential to support the campaign of upscaling sustainable control programmes, helping policy- and decision-makers to quickly identify suitable sites for the optimum tailoring of appropriate technological intervention.

Integrating studies on the socio-economic factors that influence the adoption of push-pull technology is essential, as farmers' perceptions and social behaviour are key drivers of technology uptake. For instance, the motivation might involve integrating high-value vegetable crops that contribute to household nutrition, striga control, soil fertility management, or access to high-quality fodder.

Push-pull strategies can be integrated with other pest management practices as part of the IPM approach within the One Health concept to achieve effective FAW control. This integration includes soil management practices and helps to ensure a more resilient farming system [51].

CRediT authorship contribution statement

Komi Mensah Agboka: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **HenriE.Z. Tonnang:** Writing – review & editing, Validation, Supervision. **Emily Kimathi:** Writing – review & editing, Data curation. **Elfatih M. Abdel-Rahman:** Validation, Supervision. **John Odindi:** Writing – review & editing, Validation, Supervision. **Onisimo Mutanga:** Validation, Supervision. **Saliou Niassy:** Writing – review & editing, Validation, Supervision, Conceptualization.

Data availability statement

All data generated or analysed during this study are included in this published article. The codes that support the findings of this study are available permanently and freely online through the following link: https://github.com/komimensah/Fuzzy-index/blob/main/Codes.

Submission declaration

The work described has not been published previously except in the form of a preprint, an abstract, a published lecture or academic thesis. The article is not under consideration for publication elsewhere. The article's publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out. If accepted, the article will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

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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