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The use of interval censored data to assess the timing of early field infestation of fall armyworm, *Spodoptera frugiperda* (J. E. Smith) (Lepidoptera, Noctuidae) in maize fields

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ABSTRACT

The fall armyworm, *Spodoptera frugiperda*, situation in Africa remains a priority threat despite significant efforts made since the first outbreaks in 2016 to control the pest and thereby reduce yield losses. Field surveys in Benin and Mali reported that approximately one-week post-emergence of maize plants, the presence of fall armyworm (egg/neonates) could be observed in the field. Scouting for fall armyworm eggs and neonates is, however, difficult and time consuming. In this study, we therefore hypothesized that the optimum timeframe for the fall armyworm female arriving to lay eggs in sown maize fields could be predicted. We did this by back-calculating from interval censored data of egg and neonates collected in emerging maize seedlings at young leaf developmental stage. Early time of ovipositing fall armyworm after sowing was recorded in field experiments. By using temperature-based models to predict phenological development for maize and fall armyworm, combined with analytical approaches for time-to-event data with censored status, we estimated that about 210 accumulated Degree Days (DD) is needed for early detection of neonate larvae in the field. This work is meant to provide new insights on timely pest detection and to guide for precise timing of control measures.

1. Introduction

Maize is the most important cereal crop in sub-Saharan Africa and the third most produced cash crop in Africa after cassava and sugar cane (FAOSTAT, 2022). It accounts for 30–50% of low-income household expenditures in Africa and more than 300 million Africans rely on maize as their main subsistence crop (Badu-Apraku and Fakorede, 2017). Maize is, however, subject to attacks from various pest insect which include lepidopteran stem borers, *Busseola fusca* (Fuller) (Noctuidae), *Chilo partellus* Swinhoe (Crambidae) and fall armyworm (FAW), *Spodoptera frugiperda* (J. E. Smith) (Noctuidae).

FAW has caused significant losses in maize production across Africa (Baudron et al., 2019; Kansiime et al., 2023). Since its first report in West Africa in 2016 (Goergen et al., 2016), it has spread throughout nearly the entire African continent (Kenis et al., 2023; Palli et al., 2023). The level of FAW field infestation in Africa remains worrying despite significant efforts made since the invasion to understand its dynamics and reduce crop damage (De Groote et al., 2020). FAW is a polyphagous pest that can feed on the leaves, stems and reproductive parts of several hundred hosts plants, but maize, sorghum and wheat are among the preferred hosts (Montezano et al., 2018). The adult female lays 100–200 eggs on the underside of the leaves, which hatch after a few days into larvae (neonates) that feed on the plants through six larval instars (Rwomushana, 2019). The sixth larval instars then pupate in the soil and develop into adults. The complete life cycle can take 23–27 days under suitable temperature conditions ranging from 26 to 30 °C (Tian et al., 2022). The final larval instar is reported to be the most damaging stage to the plants (causing up to 77% of the damage) (Day et al., 2017). Interruption of FAW early in its developmental cycle (eggs or young instar larvae) by timely application of low-risk pesticides, or by other means, could reduce plant damage and be a good solution for integrated pest management (IPM) of FAW. This will give farmers the tools to

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handle FAW while reducing the side effects of extensive pesticide use on human health and the environment. Further, for the application of biological control agents against a pest to be successful, it is important to time the application to target a specific developmental stage of the pest insect and to also apply it when weather conditions are optimal (Schulz et al., 2019; Shapiro-Ilan et al., 2012).

A survey for early detection of FAW by Blanco et al. (2014) in 10 different maize-growing regions across Mexico showed that larvae were always found at the V2 (BBCH [Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie]-scale = 14) growth stage (Blanco et al., 2014). Westbrook et al. (2016) also detected FAW larvae early in maize (between V2 and V4, BBCH = 14 to BBCH = 16) in a study of its seasonal migration in Texas, and more recently a similar pattern were confirmed in Nigeria (Olusegun et al., 2022). In an initial field survey in Benin and Mali, we found that approximately one week after the emergence of maize plants, FAW eggs or larvae could be observed on maize plants in the field (unpublished data). Although Mali and Benin are both located in West Africa, they have different climatic and agro-ecological characteristics. Mali is a Sahelian country characterized by a climate prone to severe drought, which is arid in the north and subtropical in the southern part of the country, with annual rainfall ranging from 127 mm to 1400 mm (Dale et al., 2017; Frappart et al., 2009). Benin, however, is a coastal country locate on the equator, with a tropical climate warm all year round and with consistently high humidity levels. Annual rainfall are characterized by two rainy season (April to July and September and October) and two dry seasons (November to March and August) with rainfall varying between 700 mm and 1400 mm (Obada et al., 2021).

We hypothesized that following sowing of maize, the risk of FAW ovipositing in a maize field at a certain number of Degree Days (DD) could be predicted using concepts inspired from reliability analysis. Reliability analysis, or more generally time-to-event analysis, refers to a measure of reliability or the assurance that a system might perform successfully as expected over a period of time under specific conditions (Shelemyahu, 2011). An agroecosystem could be characterized as a good example of such a system because food production results from various biotic and abiotic interactions. The reliability of a system is expected to be very high at the start of the studied process and decrease over time, with two key concepts which are time and stress (influence from external components of the system). Indeed, an element of the system has to endure a certain level of stress from other components of the system over a certain period of time before the event of interest occurs (Kiran, 2017). In the context of insect invasion as in our study, the crop in a field is subject to the stress from e.g., weather, soil, water and nitrogen status, other living organisms, and human activity (farming practice) until the invasion by the pest.

Time-to-event data and related analytical approaches are widely used for risk assessment in many fields such as petroleum industry (Edwin et al., 2016; Le-Rademacher and Wang, 2021), management of human factors and behavior in process industries (Scaife, 2016), analysis of earth slopes (Metya et al., 2017), and national security and defense (Grzeskowiak, 2017). Time-to event analysis relies particularly on data with censoring status, meaning that the status of the endpoint of the observed event in the experiment remains unknown (Le-Rademacher and Wang, 2021). The analytics and statistical processes performed on data with censored status is mostly known in the field of biology and health care research as survival analysis (Kartsonaki, 2016; Prinja et al., 2010). It has been used to explore topics such as the risk of repetitive attempt of suicide (Christiansen and Frank Jensen, 2007), the duration from the detection of a lethal disease until death (Eloranta et al., 2021; Nezhad et al., 2019), and the response time to an administered drug (Magura et al., 1998; Pazdur, 2008). Time-to-event data are characterised by four important elements: time of origin, duration, target event, and description of how the observed items exit the study. In this study, the time of origin refers to the date of sowing, the duration refers to scouting every two days for three weeks, the target event refers to detected eggs or larvae in the field, and the exit refers to the confirmation of FAW infestation.

Depending on the purpose of the study and the experimental design, data subjected to reliability analysis can be presented in four different formats, which are (i) complete data: when exact time of occurrence of the target event is known for all items in the dataset, (ii) right censored data: the target event happened after the end of the period of the experiment, (iii) left censored data: when the target event happened before the time of origin, and (iv) interval censored data: when the exact time for the occurrence of the event is unknown but a lower and upper boundary of an interval around the occurrence are known.

The present study aimed at using the interval censored data approach to investigate the early oviposition patterns of FAW in maize in Mali and Benin with a subsequent goal to develop a model for use in a farmer-oriented app for decision support.

2. Materials and methods

2.1. Study area

Field experiments and data collection were performed in the localities of Abomey-Calavi (Lon:2.355; Lat:6.448; Altitude: 13m), Aplahoue (Lon:1.683; Lat:6.933; Altitude: 122m), Djakotomey (Lon:1.716; Lat:6.90; Altitude:132) in Benin; and Koulikoro (Lon: 7.438; Lat:13.801; Altitude: 350m), Bamako (Lon: 8.002; Lat:12.639; Altitude:326), Baguinera (Lon: 7.776; Lat:12.615; Altitude:323m) in Mali (Fig. 1). Although these two territories have Burkina Faso and Niger as neighbouring countries, they are characterised by different climatic and agroecological conditions (IFPRI, 2009). Pilot field scouting experiments as part of developing the Farmer Interface Application (FIA) have been carried out in the two countries (Tepa-Yotto et al., 2021) and this study draws on those experiments. Mali has wide automatic weather station coverage and allows easy access of accurate weather information close to the experimental sites.

2.2. Field experiment and data collection

Field experiments were done to identify when the eggs hatched in the maize fields. Disregarding whether the FAW populations are stationary or not, early detection to limit the impact of initial attacks on maize and assess the associated weather requirements for their arrival are fundamental.

The surveys were done during the maize cropping season. In Benin, the cropping season starts early March in the Couffo district and two sites were selected: Aplahoue (10 fields approximately 300 m apart) and Djakotomey (7 fields approximately 300 m apart and 3 fields 100 m apart from each other) at the International Institute of Tropical Agriculture (IITA-Benin) station. In Mali, the maize cropping season starts in May and two sites were selected in the Koulikoro district (17 fields approximately 500 m apart and 3 fields 100 m apart from each other) at the Institut d'Economie Rurale (IER-Mali) station. The most produced maize varieties in the region were the targeted varieties, i.e. Brico in Mali and possibly BEMA10 B-05 in Benin, though accurate information from the Beninese farmers was not possible to obtain.

Scouting (Fig. 2) was done in accordance with the procedure recommended by FIA's scouting tool, developed by IITA and partners to assist farmers to scout their fields using a simple approach for early FAW detection and timely intervention (Tepa-Yotto et al., 2021). The FIA scouting protocol is built on a diagonal transects model which is deemed simple for a tool intended to be used by low-literacy farmers. Following the FIA scouting protocol, scouting started 2–3 days post-emergence of maize to identify the plants to be inspected in the field. Six plants were thus selected and marked on each of five sampling stations on each of two transects, totaling 60 plants per field. The maize plants were observed every second day and the following data were recorded from each plant: (i) number of leaves, (ii) number of unhatched FAW egg

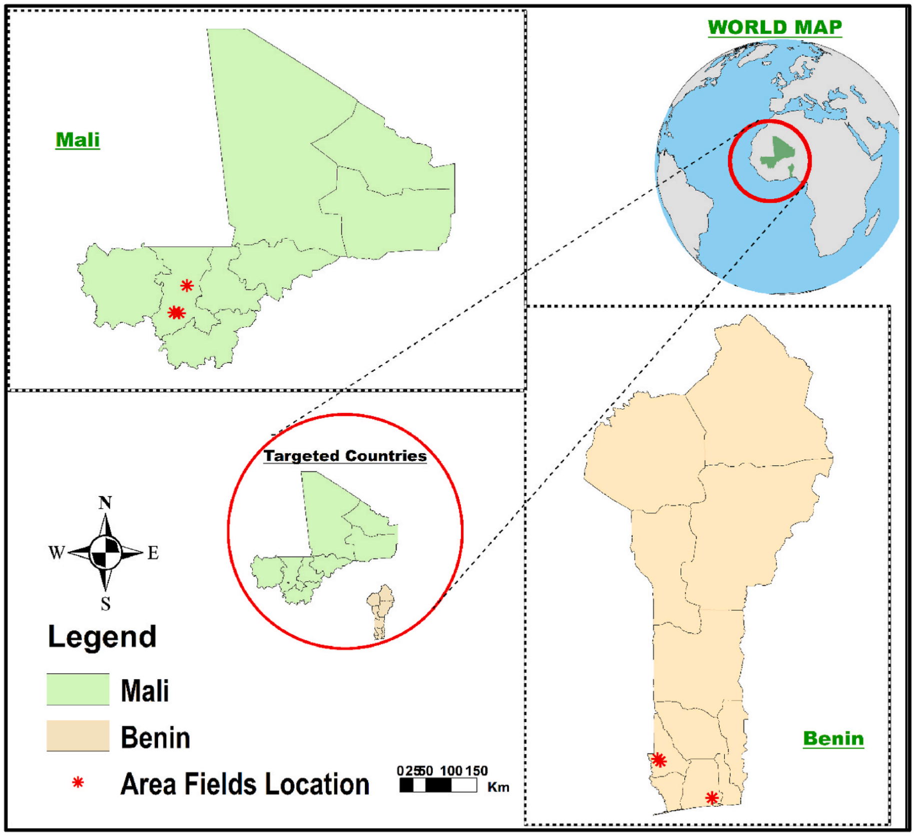

Fig. 1. Study field locations (red start) in Mali (green map) and Benin (beige map).

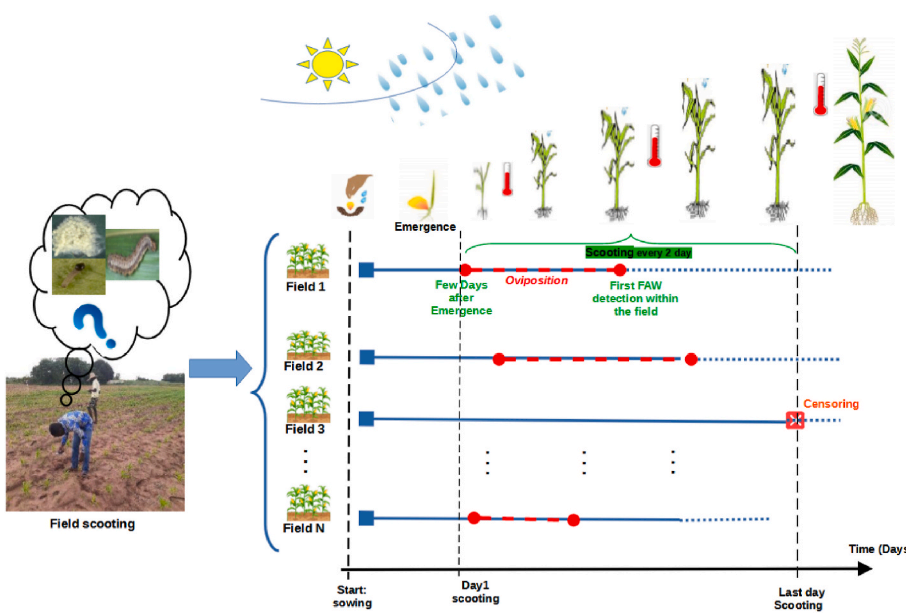

Fig. 2. Illustration of the field collection of the time-to-event data.

masses (iii) number of hatching FAW egg masses; (iii) presence of either 1st, 2nd or 3rd instar FAW larvae. Observations ended after 3 weeks, which also represents the end date for the early detection of FAW, defined based on both the pattern of FAW field monitoring across Africa and the previous study by Jaramillo-Barrios et al. (2020) suggesting that the first action thresholds against FAW should occur within 20 days (three weeks) after maize emergence. The data were recorded using either Android tablets or data sheets and uploaded to the cloud.

Weather information related to each field was provided by the closest automatic weather station to the location of the field. In Mali, weather data were sourced from the wide network of online weather stations provided by the Trans-African Hydrometeorological Observatory (TAHMO: https://tahmo.org/). In Benin, only the station from IITA was available to collect weather data and it was therefore used for all the fields under the assumption that the average climatic conditions were similar at the different field locations. All weather data were obtained in JSON (JavaScript Object Notation) format and covered the entire growing season. The recorded weather data included hourly records of temperature (minimum, maximum, mean), relative humidity (RH), rainfall and solar radiation, but only temperature was used in the analyses, as temperature is reported as the main factor affecting the physiological development of both maize and FAW (Du Plessis et al., 2020; Sokame et al., 2020).

2.3. Descriptive and statistical analysis

Interval censored data were collected, justified by the fact that oviposition occurs at a certain time between maize emergence and when eggs or larvae are found in the field. For simplicity and to reduce bias, the sowing date of maize was used as the time of origin of the process while for the date FAW eggs or neonates were reported in the maize field, we assumed that the reported developmental stage was reached that day. From the collected field data, FAW egg or larval developmental stage was defined as the latest developmental stage detected within the maize field. For example, if FAW larval instars (L1, L2, L3) were reported simultaneously or the latter two (L2, L3) in the field, the status of field infestation was set to L3. In the case where only one developmental stage was found that corresponding stage was used to set the field status of infestation.

The DD requirement for FAW to complete a specific developmental stage is set based on laboratory work done by Du Plessis et al. (2020). These values correspond to 35.68 DD for eggs; 82.82 DD for neonates (first instar larvae, L1), 104.4 DD for L2, and 125.98 DD for L3, respectively (Du Plessis et al., 2020). From the date of first detection of FAW larvae in a field, the hatching date was approximated by calculating the daily DD backwards. This was done recursively until we reached the value below the required threshold for the egg developmental stage. The estimated date was assumed to be the approximated FAW oviposition date in the field. The daily backward DD accumulation was estimated as the Growing Degree Days (GDD) model from Zhou and Wang (2018), using hourly temperature data obtained from local weather stations close to the location of the fields (Zhou and Wang, 2018). The estimation was done for every field and ended by determining a date that approximately corresponded to the day that the eggs were laid.

The GDD is given by the cumulative daily thermal time (DTT):

$$GDD = \sum DTT,$$

where DTT is calculated as the mean daily hourly thermal time (HTT):

$$DTT = \frac{\sum_{i=1}^{24} HTT_i}{24}.$$

Furthermore, HTT is calculated as a beta-distributed function of temperature, given by:

$$HTT = \begin{cases} 0 \quad T_h < T_b \\ \left(\frac{T_h - T_b}{T_{opt} - T_b}\right)\left(\frac{T_u - T_h}{T_u - T_{opt}}\right)^{\frac{T_u - T_{opt}}{T_{opt} - T_b}} \left(T_{opt} - T_b\right) \; T_b \le T_h \le T_u \\ 0 \quad T_u < T_h \end{cases}$$

Here, T_h is the hourly mean temperature obtained from the nearby weather stations, $T_b = 12.15$ °C is the base temperature, $T_u = 34.70$ °C is the upper temperature threshold and $T_{opt} = 28.10$ °C is the optimum temperature for the development of FAW.

Once the egg hatching date ($Date_{EggH}$) was estimated for each field, the amount of heat accumulated by the maize ($H_{sumMaiz}$) from the sowing date ($Date_{MaizP}$) until the hatching date can be estimated. This was done using the daily minimum ($T_{\min}$) and maximum ($T_{\max}$) air temperatures obtained from the local weather station based on the formula below.

$$H_{sumMaiz} = \sum_{Date_{MaizP}}^{Date_{EggH}} max\left(\frac{T_{min} - T_{max}}{2} - T_b, 0\right),$$

where $T_b = 10$ °C: base temperature for maize development.

Once the value of heat accumulated by the maize was calculated for each field, we had the necessary information that can be formatted into interval censored data using the maize sowing date as the origin of event. The following step was then performed on the time-to-event data to estimate the optimum amount of DD to be accumulated by maize when FAW eggs were expected to be laid in the field starting with the maize sowing date (see Fig. 3).

2.4. Analysis of censored data

2.4.1. Exploratory analysis

Prior to carrying out the time-to-event analysis, we checked the potential effect of the field experimental design on the time it takes for the event to occur. The purpose was to compare the dataset obtained independently from the two countries (20 fields per country) and explore the possibility to merge the data into one dataset. Thus, for each field, the recorded variables included heat accumulated by the maize from the sowing date until the FAW eggs were hatched, the country where the farm was located, the geographical location of the field, the maize variety and the sowing date. A linear mixed-effect model was used with country as fixed effect and maize variety, planting date and field location within the countries and their interactions as random effects on the accumulated maize heat sum (expressed in DD). The output summary was then used to decide whether the collected field data could be merged into one single dataset, and we ended up not merging the data, as we found a significant effect of country (Appendix 1). The statistical analysis was done with R 4.2 using the function from the R-Packages ggplot2 (Wickham, 2022) and lme4 (Bates et al., 2015).

2.4.2. Time to event analysis

The time-to-event analysis was used to estimate the accumulated heat threshold value (DD) that would be useful for decision support systems, providing notifications about the potential presence of FAW eggs in a maize field.

From the collected field data and subsequent exploratory analysis and data formatting, we obtained interval censored data. There are various modelling approaches suitable for analysing interval censored data, with each of them having their pros and cons depending on the objective of the study. The most popular and commonly used techniques for estimating the survival time function are Cox proportional hazards (PH) model, log-rank test and the Kaplan-Meier estimator (Schober and Vetter, 2018). The Kaplan-Meier estimator was adopted as the most suitable in the context of this study due to its ability to handle censored data. It is a non-parametric method used to determine the survival probability function over a given time point while considering the censoring status of the data (Goel et al., 2010). It is also named the "product limit estimate" and can be used to determine at a giving point of time the probability of occurrence of an event (Goel et al., 2010). The estimated curve that displays the survival probability function against the variable of interest (accumulated DD in this case) is a step function where each vertical depth characterizes the manifestation of one of multiple events. The curve is usually plotted within the estimated confidence interval bands that inform on the range of potential value of the survival probability. The R-function survfit (-) from the R-package "survival" was used to estimate the survival probability using the Kaplan-Meier estimator.

3. Results

No freshly oviposited FAW egg masses (unhatched) were ever found

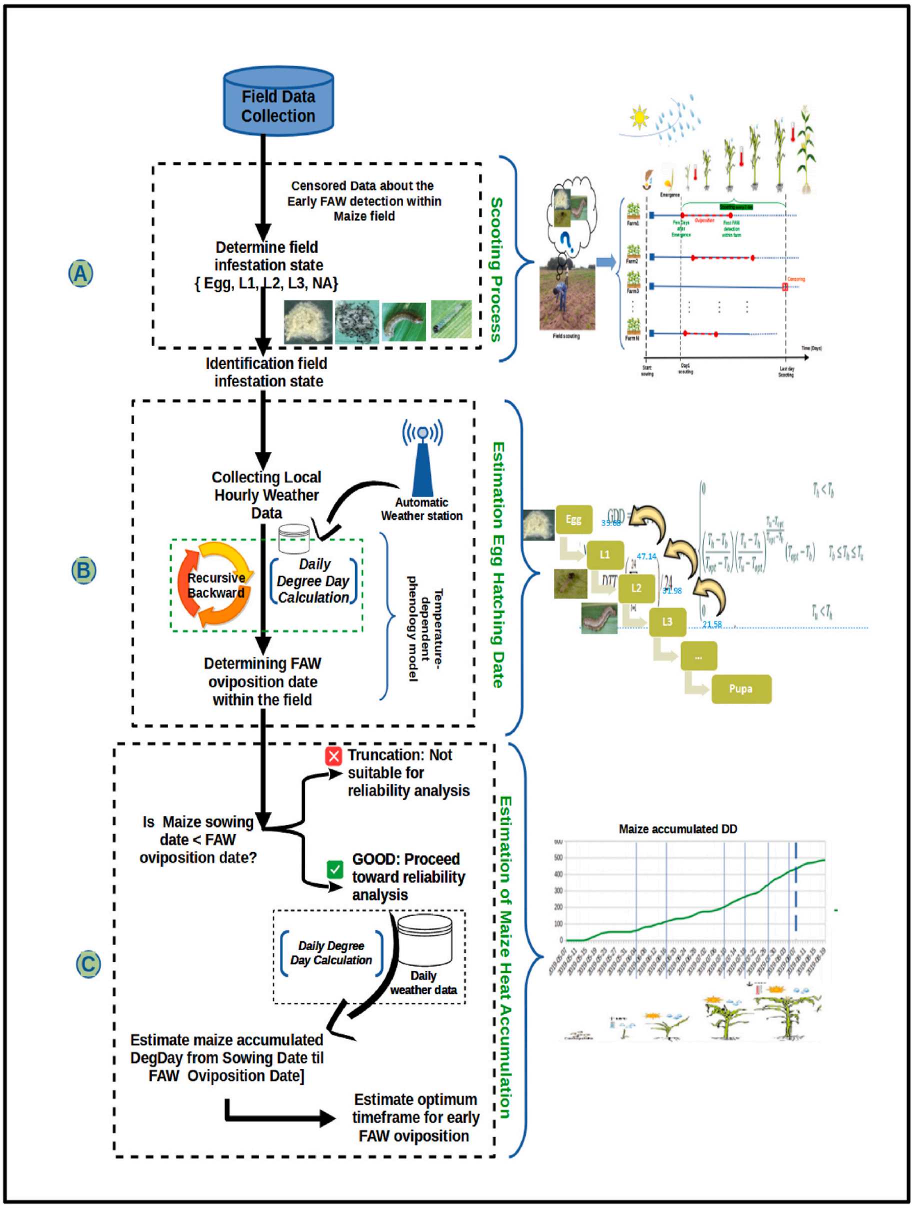

Fig. 3. Graphic illustration describing the process of estimating the maize heat accumulation from maize sowing until early detection of FAW.

in any of the maize fields before finding FAW larvae.

The linear mixed model analysis (Appendix 1) confirmed that the phenological developmental stage of the maize at early FAW detection in field, characterized by the accumulated DD, is greatly affected by the field location, subject to random source of variability of the sowing date and the maize variety (Fig. 4). The main effect of the country on the field was statistically significant ($P < 0.05$). The DD of maize from sowing until early detection of FAW eggs was significantly higher (95%) in Benin (237.3–346.3 DD) compared with Mali (145.9–254.8 DD). The variability of the accumulated DD varied among field locations within the same country Benin (red) and Mali (cyan) as shown in Fig. 4. Thus, the two datasets were not pooled.

The probability of early dectection of FAW in the maize field as a function of accumulated DD from sowing is given by the Kaplan-Meier estimate and is presented in Fig. 5. The point on the x-axis where the horizontal dashed red line at a survival probability of 0.5 intersects the curve represents the estimated median accumulated DD for early detection of FAW in maize in Mali and Benin. The estimated value corresponds to 210 ($\pm$ 49) DD.

4. Discussion

To optimize the time of scouting to detect FAW neonates, this study investigated the pattern of oviposition and field invasion of FAW in Mali and Benin. The Kaplan-Meier estimator was used to estimate the optimum amount of accumulated DD from maize sowing to detect early FAW neonates with the aim for future integration and use into Decision Support Systems (DSS) for an improved management of pests in Mali, Benin and potentially other African countries sharing similar agroecosystems.

Weather conditions, especially the temperature and rainfall metrics, are quite different between Mali and Benin (Ahokpossi, 2018; Quenum et al., 2021), but both allow the development of FAW during the maize cropping season. In this study, egg masses were not found during scouting in the field before finding larvae (see appendix 2), despite sampling every two days for over a month. This exemplifies how extremely difficult it is to monitor this critical phase and how important it is to implement a robust protocol for early detection. It is, however, important to note that unhatched egg masses can easily be found in

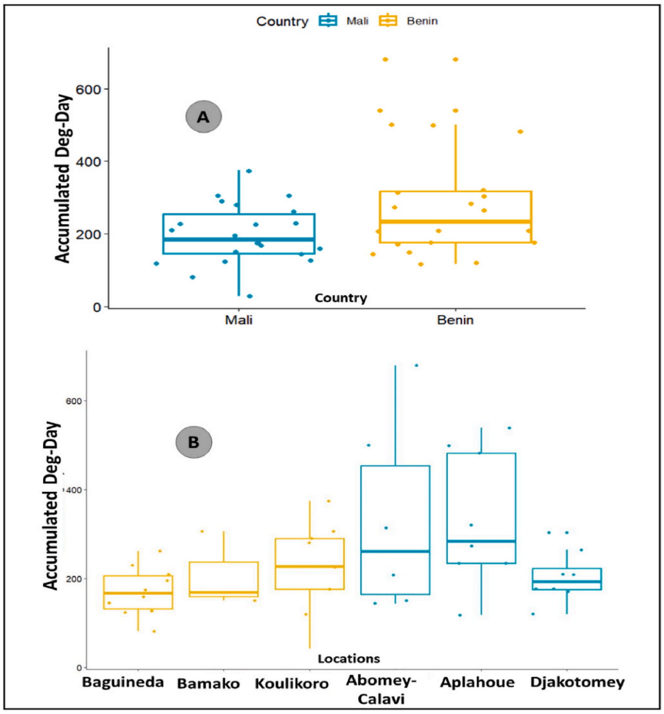

Fig. 4. Boxplot representing the variability of the accumulated Degree Days (DD) per (A) country and (B) location from the date maize was sown back calculated until early detection of FAW eggs in maize fields.

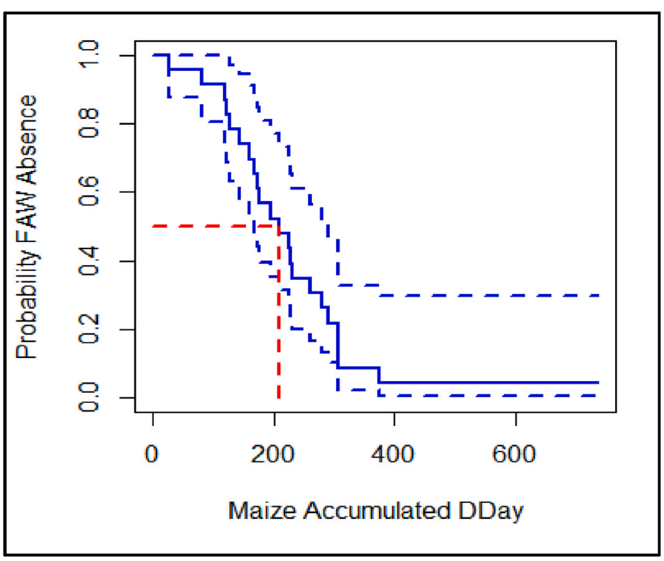

Fig. 5. Kaplan-Meier estimate showing the probability of early detection of FAW eggs in maize. The blue line represents the Kaplan-Meier estimate, the dashed blue lines are the 95% confidence interval. The red dashed line represents the estimated median of accumulated DD at a survival probability of 0.5.

maize fields when the field is highly infested (Winsou, 2022).

Unlike traditional and commonly used statistical methods such as logistic and linear regression which are not suited to deal with censored data, the time-to-event analysis is appropriate to handle censored data. The particularity of time-to-event data is that we are not only interested in knowing whether the studied event occurred or not, but also when it occurred. For adoption of effective measures against FAW in maize fields, it is more of interest for example to know when the field will be invaded rather than if it will be. The Kaplan-Meier estimator improves other traditional estimators such as the life-table analysis method by addressing their limitation of not being suitable for handling variable length of discrete time interval for the studied event (Rai et al., 2021).

Despite the Kaplan-Meier estimator being the most popular and commonly used method to handle time-to-events data, one significant drawback of this method is that it cannot be used to perform multivariate analytics on collected data (Rai et al., 2021). The log-rank test method is another popular approach to deal with such data, but is more suitable when there is a need to compare the outcome between groups (Rai et al., 2021). For example, if we were interested specifically in comparing the early detection of FAW between two or more different maize varieties or different cropping systems, the log-rank test would have been best suited to explore that comparison. In the context of insect pest management, the Kaplan-Meier estimator has been useful to analyze the effect of an insecticide used to control the soybean pest *Anticarsia gemmatalis* Hübner (Lepidoptera: Noctuidae) on its natural enemy (de Castro et al., 2013). The estimator was also useful to analyze the effect of irradiation on pupa and adult mosquitoes *Aedes aegypti* and *A. albopictus* ability to survive, reproduce and fly (Bond et al., 2019), and to study arthropod resistance development to insecticides (Brevik et al., 2018). The present work is innovative by the successful attempt to apply censoring statistics to estimate an action threshold for insect pest control.

In a recent study by Lowry et al. (2022) done in Zambia, they proposed a solution to improve the control strategy of FAW by modelling early and late larval instar development in relation to the physiological time from maize sowing date. Their study suggested that the accumulated DD needed to initiate control operations against FAW early instars (1–3) was 186.3 (±29 CI) DD after sowing. Our results in Fig. 4, that is based on back calculating to the FAW egg stage, show threshold values of 182.8 (±37.6 CI) DD in Mali and 201.03 (±43.5) DD in Benin. The Mali accumulated DD for the egg stage in our study is like the findings of Lowry et al. (2022) for FAW early instars (1–3) in Zambia; our Benin accumulated for the egg stage was only marginally higher if taking the higher ±SE into account. Different threshold values may need to be estimated for different regions with specific climatic conditions and maize growing systems throughout Africa. Although this might be required for different regions and maize varieties, the process for establishing a threshold for a selected maize variety in a specific region needs to be done only once. The time from a sowing date to reach that threshold will then vary among fields and season based on temperature fluctuations.

The time of origin for the event of interest needs to be defined when using censored data. Although the estimated threshold was obtained using the sowing date as the origin, the analysis was performed on interval censored data delimited by the last scouting date before FAW was detected. This time frame was chosen to narrow the window of the threshold for early detection of FAW. The physiological time to detect FAW neonates early, estimated in DD, is then ready to be implemented and used for action threshold strategies in any DSS platform. The value from Lowry et al. (2022) (186.3 (±29 CI) DD) is comparable to the value estimated for Mali (182.8 (±37.6 CI) DD) in this study, and thus provides a realistic basis toward the integration of the model into a the DSS, implemented in the VIPS (Plant Pest Early Warning System) platform (https://www.vips-landbruk.no/) and then integrated with the FIA (Farmer Interface App) application (Tepa-Yotto et al., 2021) for providing farmers with appropriate guidelines for timely management decisions.

The DSS in question for implementing the model developed here is characterized by combining the features of the Farmer Interface App, FIA (Tepa-Yotto et al., 2021) and the Plant Pest Early Warning system VIPS (https://www.vips-landbruk.no/information/). The FAW temperature-dependent development rate and senescence model obtained from the FAW phenology model (Malekera et al., 2022) have recently been added to the VIPS platform. FIA is then able to extract weather and pest forecasts from VIPS to provide farmers with guidelines for timely management decisions against FAW neonates. What remains, however, is to validate the model by ground-truthing our findings through several cropping season of maize in Mali. Given this final step, we will be able to determine when the damage caused by FAW neonates will reach an epidemic level under the prevailing climatic conditions, i. e. surpass the threshold. The time frame estimated to narrow the window of the threshold for early detection of FAW thus provides a realistic applicable basis that could be used to optimize the timing of management actions such as biocontrol strategies and other low risk pesticides against FAW on the target developmental stage.

CRediT authorship contribution statement

Ritter A. Guimapi: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Berit Nordskog:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization. **Anne-Grete Roer Hjelkrem:** Writing – review & editing, Resources, Methodology, Formal analysis, Conceptualization. **Ingeborg Klingen:** Writing – review & editing, Supervision, Resources, Investigation, Formal analysis. **Ghislain T. Tepa-Yotto:** Writing – review & editing, Resources, Project administration, Methodology, Funding acquisition. **Manuele Tamò:** Writing – review & editing, Resources, Project administration, Formal analysis. **Karl H. Thunes:** Writing – review & editing, Resources, Project administration, Funding acquisition, Formal analysis.

Declaration of competing interest

The author(s) declare no competing interests.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cropro.2024.106843.

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