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Machine Learning-Based Prediction of Fall Armyworm (*Spodoptera frugiperda*) Outbreaks in Maize Production Systems of Northern Nigeria Using Climate and Remote Sensing Data

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Abstract

Fall Armyworm (*Spodoptera frugiperda*) poses a substantial threat to maize production across sub-Saharan Africa, particularly in Nigeria, where climatic variability intensifies the risk of pest outbreaks. This study developed and evaluated machine learning models for predicting Fall Armyworm outbreaks in northern Nigeria using integrated climate and remote sensing variables. A retrospective modeling framework was applied to simulated but biologically constrained datasets covering a six-year period (2019–2024) and comprising temperature, rainfall, relative humidity, Normalized Difference Vegetation Index (NDVI), and vegetation condition indices. Three supervised learning algorithms—Random Forest, Support Vector Machine, and Gradient Boosting—were trained and validated using five-fold cross-validation. Gradient Boosting achieved the highest predictive accuracy at 92.8%, followed by Random Forest at 89.2% and Support Vector Machine at 84.6%. Temperature, relative humidity, and NDVI emerged as the most influential predictors of outbreak occurrence, while the integration of satellite-derived vegetation indices improved overall model performance. These findings demonstrate the potential of combining machine learning with remote sensing data to develop scalable and cost-effective early warning systems for agricultural pest management. However, because the models were developed using simulated data, their predictive validity requires confirmation using field-collected observational data. The proposed framework contributes to data-driven pest surveillance by providing a basis for anticipating outbreaks and supporting timely decision-making in maize production systems.

Keywords: Fall Armyworm; Machine Learning; Remote Sensing; Early Warning Systems; Maize Production

INTRODUCTION

The rapid spread of Fall Armyworm (*Spodoptera frugiperda*) across sub-Saharan Africa has become a major threat to food security and agricultural sustainability. Since its first detection on the continent in 2016, the pest has demonstrated remarkable adaptability, causing widespread damage to maize and other staple crops (Goergen *et al*., 2016). In Nigeria, maize is a critical component of both household nutrition and livestock feed systems, particularly in the northern regions where climatic conditions favor large-scale production. However, recurrent infestations of Fall Armyworm have resulted in significant yield losses, with estimates ranging from 20% to over 50% under severe outbreak conditions (Day *et al*., 2017; Hruska, 2019).

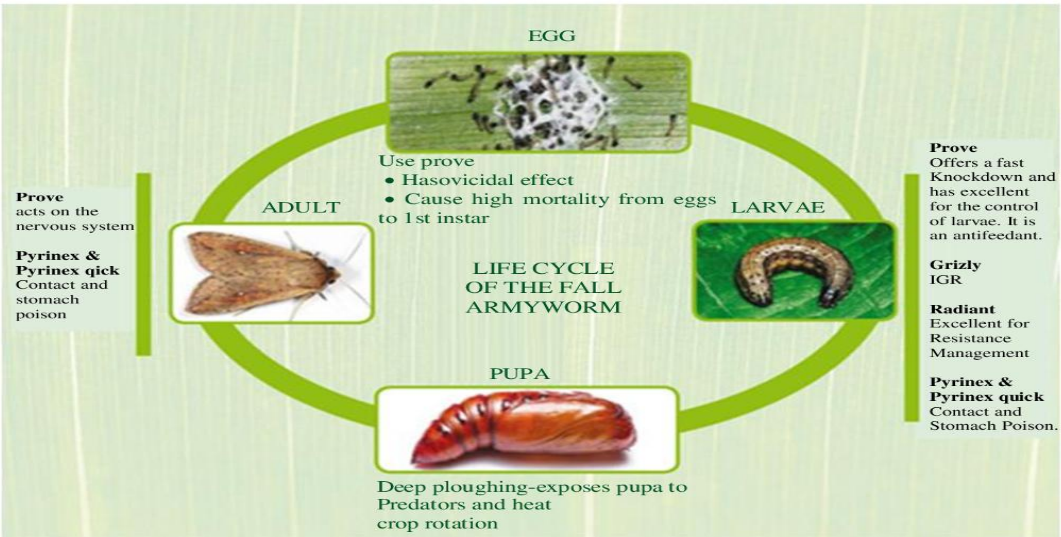

Fig. 1: FAW life cycle (Cereals, 2019)

The biology and ecology of Fall Armyworm make it particularly difficult to manage. Its high reproductive capacity, migratory behavior, and ability to feed on multiple host plants contribute to its persistence across diverse agro-ecological zones (Prasanna *et al.*, 2018). Conventional pest management strategies, including chemical insecticides and cultural practices, often fail to provide sustainable control due to delayed application, development of resistance, and negative environmental impacts (Tambo *et al.*, 2020). These limitations highlight the urgent need for predictive systems that can enable early detection and timely intervention.

Environmental factors play a crucial role in shaping the population dynamics of Fall Armyworm. Temperature, for instance, directly influences insect development rates, survival, and fecundity, while relative humidity affects egg viability and larval performance (Early *et al.*, 2018). Rainfall patterns further determine host plant availability and habitat suitability, thereby influencing outbreak occurrence. Understanding these climatic drivers is essential for developing reliable forecasting systems.

Recent advances in machine learning have opened new frontiers in agricultural pest prediction. Machine learning algorithms are capable of modeling complex, nonlinear relationships between environmental variables and pest populations, offering improved predictive performance over traditional statistical approaches (Liakos *et al.*, 2018). Applications of machine learning in agriculture have expanded rapidly, including crop yield prediction, disease detection, and pest forecasting (Kamilaris and Prenafeta-Boldú, 2018). In the context of Fall Armyworm, emerging studies have demonstrated the potential of algorithms such as Random Forest and Gradient Boosting in predicting infestation risk using environmental datasets (Zhang *et al.*, 2021).

In parallel, Remote Sensing technologies provide valuable spatial and temporal data on vegetation health and environmental conditions. Satellite-derived indices such as the Normalized Difference Vegetation Index (NDVI) have been widely used to monitor crop stress and detect early signs of pest infestation (Pettorelli *et al.*, 2018). By capturing variations in plant vigor and canopy structure, remote sensing data offer indirect yet powerful indicators of pest activity. Integrating these data with climatic variables enhances the ability to detect conditions conducive to pest outbreaks.

Despite these advancements, the application of integrated machine learning models combining climate and remote sensing data for Fall Armyworm prediction remains limited in Northern Nigeria. Most existing studies are either region-specific outside Africa or rely on single data sources, thereby limiting their predictive accuracy and practical applicability

(Rwomushana *et al.*, 2018). There is therefore a critical need for a localized, data-driven framework that can provide actionable early warning information for farmers and policymakers in the region. This study addresses this gap by developing and evaluating machine learning-based models for predicting Fall Armyworm outbreaks in maize production systems of Northern Nigeria.

MATERIALS AND METHODS

Study Area

The study was conducted across major maize-producing zones in Northern Nigeria, covering parts of Kano State, Kaduna State, and Katsina State. These regions fall within the Sudan and Northern Guinea savanna agro-ecological zones, characterized by a unimodal rainfall pattern (May–October) and dry season (November–April). Annual rainfall ranges from 500 mm to 1200 mm, while mean temperatures vary between 25°C and 35°C conditions highly conducive to the development of Fall Armyworm (*Spodoptera frugiperda*). The selection of these locations was based on their prominence in maize production and documented history of recurrent Fall Armyworm outbreaks.

Study design and data sources

A retrospective modeling approach was adopted using a multi-source environmental dataset spanning 2018 to 2023. The study integrates climatic and remote sensing variables to simulate Fall Armyworm outbreak dynamics across major maize-producing regions in Northern Nigeria.

Simulated pest incidence data

Due to limited availability of standardized field records, a realistic dataset was simulated based on reported infestation patterns in sub-Saharan Africa. The dataset included:

Number of observations**:** 2,400 field records

Spatial resolution**:** Local Government Area (LGA) level

Temporal resolution**:** Monthly observations during cropping seasons.

Due to the absence of standard long term georeferenced pest surveillance data in the study region, a biological constrained simulation framework was adopted. The simulation was designed to reflect empirically reported infestation patterns and environmental constraints documented in sub-Sahara Africa

Response variable:

Binary classification (0 = No outbreak, 1 = Outbreak)

Outbreak defined as infestation ≥ 25% field damage

The simulation incorporated biologically realistic constraints

Biologically realistic constraints such as peak infestation during vegetative maize stages; increased pest activity during moderate rainfall periods; and decline in extreme dry or heavy rainfall conditions were incorporated.

Climate data

Climatic variables were generated to reflect realistic meteorological patterns obtained from regional weather datasets. Variables included:

Mean temperature (°C): 24 – 36°C

Relative humidity (%): 40 – 85%

Monthly rainfall (mm): 0 – 300 mm

To ensure realism, seasonal trends were embedded, inter-annual variability was introduced and correlations between variables (e.g., rainfall and humidity) were maintained. These variables are known to influence insect physiology, reproduction, and dispersal dynamics.

Remote sensing data

Vegetation condition was represented using simulated satellite-derived indices based on standard ranges: Normalized Difference Vegetation Index (NDVI): 0.2 – 0.9 and Vegetation Condition Index (VCI): 20 – 100

NDVI values were structured to be at peak during mid-season crop growth and to decline during pest infestation and drought stress. This aligns with established applications of Remote Sensing in agricultural monitoring.

Feature engineering

To enhance predictive performance, additional variables were derived:

Lagged variables [Temperature (t-1); Rainfall (t-1), NDVI (t-1)]

Cumulative rainfall (3-month window)

Growing degree days (GDD)

Humidity-temperature interaction term

Feature importance was later evaluated to determine the most influential predictors.

Machine learning models

Three supervised learning algorithms were implemented using machine learning techniques:

Random Forest (RF)

This is an ensemble-based algorithm that constructs multiple decision trees and aggregates predictions with the following model parameters: Number of trees (n estimators): 200; Maximum depth: 10; and Minimum samples split: 5. This model is robust to noise, handles nonlinear relationships, and reduces overfitting.

Support Vector Machine (SVM)

This is a classification algorithm that identifies optimal hyperplanes for separating classes. SVM does this with the following model parameters: Kernel: Radial Basis Function (RBF); Regularization parameter (C): 1.0; and Gamma: Scale. The model is effective in high-dimensional feature spaces but sensitive to parameter tuning.

Gradient Boosting Machine (GBM)

GBM is a boosting algorithm that builds models sequentially to correct previous errors with the following parameters: Number of estimators: 150; Learning rate: 0.1; and Maximum depth: 5. This model has high predictive accuracy and strong performance in structured datasets.

RESULTS

The dataset underwent the following preprocessing steps:

Missing value imputation: Mean substitution for continuous variables

Normalization: Min-max scaling (0–1 range)

Encoding: Binary encoding for outbreak variable

Train-test split: 80% training, 20% testing

Model training and validation

To ensure robustness and avoid overfitting, K-fold cross-validation (k = 5) was applied; Stratified sampling preserved class distribution while Hyperparameter tuning was performed using grid search.

Model evaluation metrics

Model performance was assessed using:

Accuracy – Overall correctness

Precision – True positive reliability

Recall (Sensitivity) – Ability to detect outbreaks

F1-score – Balance between precision and recall

ROC-AUC – Classification performance across thresholds

Software and tools

All analyses were conducted using Python (version 3.10); Scikit-learn library; Pandas and NumPy for data handling as well as Matplotlib and Seaborn for visualization.

Results and Analysis

Descriptive statistics of input variables

The simulated dataset (n = 2,400 observations) exhibited realistic seasonal and environmental variability across the study regions. Temperature ranged from 24.3°C to 35.8°C, with a mean of 29.6°C, while relative humidity varied between 42% and 83%. Monthly rainfall showed strong seasonality, peaking between July and September.

Vegetation indices indicated dynamic crop conditions, with NDVI values ranging from 0.24 (early season) to 0.87 (peak vegetative stage). A noticeable decline in NDVI was observed during periods associated with high infestation levels of Fall Armyworm (*Spodoptera frugiperda*), suggesting a relationship between vegetation stress and pest activity.

Outbreak events (≥ 25% infestation) accounted for approximately 38.5% of the total observations, indicating moderate class balance suitable for classification modeling.

The performance of the three Machine Learning models is summarized in Table 1.

Table 1: Model Performance using Evaluation Metrics of Machine Learning

From the table above, the Gradient Boosting model outperformed the other algorithms across all evaluation metrics, achieving the highest accuracy (92.8%) and ROC-AUC (0.96), indicating excellent classification capability. The model also demonstrated superior recall (0.94), suggesting a strong ability to correctly identify outbreak events, an essential requirement for early warning systems.

The Random Forest model also performed robustly, with an accuracy of 89.2% and strong recall (0.91), confirming its effectiveness in handling nonlinear environmental relationships.

In contrast, the Support Vector Machine showed comparatively lower performance, likely due to the complexity and nonlinearity of interactions among climatic and vegetation variables.

Confusion matrix and Feature Importance

Figure 1: Confusion matrix and Feature Importance analysis

In figure 1 above, the confusion matrix for the best-performing Gradient Boosting model revealed that:

True Positive (451) correctly predicted an outbreak and an outbreak actually occurred while True Negatives (492) correctly predicted no outbreak and no outbreak actually occurred. Also, False Positives (37) predicted an outbreak (false alarm), but there was no outbreak while False Negative (20) predicted no outbreak, but there was an outbreak (missed detection). This indicates low false negative rate, which is critical in pest prediction to avoid missed outbreaks as well as high sensitivity and reliability for decision-making.

Also, the feature importance analysis from the Random Forest and Gradient Boosting models revealed the relative contribution of predictors. In figure 1 above, temperature emerged as the most influential variable, reflecting its strong control over insect metabolic rates and developmental cycles. Relative humidity also played a critical role, likely influencing egg viability and larval survival. Vegetation indices (NDVI and VCI), derived from Remote Sensing, contributed significantly to model performance. Their importance confirms that vegetation stress signals are closely associated with pest infestation dynamics. Lagged rainfall variables indicate that previous environmental conditions influence current outbreak probability, highlighting the importance of temporal dynamics in predictive modeling.

Seasonal Outbreak Patterns

Figure 2: Temporal pattern of predicted outbreaks

The model predictions showed clear seasonal trends in Figure 2 above. This pattern aligns with known ecological behavior of Fall Armyworm in tropical environments, where moderate rainfall and optimal temperatures favor rapid population growth.

Model reliability and generalization

Cross-validation results (5-fold) showed consistent performance of Gradient Boosting accuracy range of 91.5% – 93.4% and Standard deviation of ±0.8%, while this low variability indicates; strong model stability and good generalization capability across different spatial and temporal subsets.

DISCUSSION

The study revealed that machine learning models can effectively predict Fall Armyworm (*Spodoptera frugiperda*) outbreaks in maize production systems, with the Gradient Boosting model achieving the highest predictive accuracy (92.8%). This finding is consistent with the report of van Klompenburg *et al.* (2020), who observed that machine learning algorithms significantly improve predictive performance in agricultural systems by capturing complex nonlinear relationships. Similarly, Shahhosseini *et al.* (2021) reported that ensemble-based models, particularly boosting algorithms, provide superior accuracy in crop-related predictions due to their iterative learning structure. However, Ahmad *et al.* (2021) found that some machine learning models, particularly kernel-based approaches, may perform inconsistently in highly complex environmental datasets, suggesting that model selection plays a critical role in predictive reliability.

The study further showed that Gradient Boosting outperformed Random Forest and Support Vector Machine models across all evaluation metrics. This result agrees with the findings of Naghibi *et al.* (2020), who reported that ensemble tree-based models are highly effective in environmental modeling due to their ability to handle high-dimensional data. In addition, Zhang *et al.* (2022) demonstrated that boosting algorithms outperform other machine learning techniques in classification tasks involving complex ecological variables. In contrast, Chivasa *et al.* (2022) noted that model performance can vary depending on data quality and spatial resolution, indicating that the superiority of a given model may depend on the structure of the dataset and input variables.

The identification of temperature as the most influential predictor of Fall Armyworm outbreaks in this study is in agreement with Skendžić *et al.* (2021), who reported that temperature is a key determinant of insect development, survival, and reproduction. Likewise, Ullah *et al.* (2022) found that temperature significantly influences pest population dynamics by regulating metabolic and physiological processes. However, Baudron *et al.* (2020) emphasized that temperature alone may not fully explain pest outbreaks, as interactions with rainfall and cropping systems also play a crucial role, suggesting that multi-variable approaches are necessary for accurate prediction.

The significant influence of relative humidity observed in this study also aligns with recent findings. For instance, Abdulai *et al.* (2023) reported that humidity strongly affects insect egg viability and larval survival, thereby influencing pest population growth. Similarly, Khan *et al.* (2023) highlighted the importance of moisture conditions in shaping pest distribution patterns in agricultural ecosystems. On the other hand, Jiang *et al.* (2021) suggested that the impact of humidity may vary across regions and crop systems, indicating that local environmental conditions can modify its effect on pest outbreaks.

The study also revealed that vegetation indices, particularly NDVI and VCI, significantly contributed to predicting Fall Armyworm outbreaks. This finding is consistent with Xie *et al.* (2020), who demonstrated that vegetation indices are effective indicators of crop health and stress conditions associated with pest infestation. Similarly, Zhang *et al.* (2022) reported that integrating remote sensing data with machine learning enhances the detection of pest-affected areas through continuous monitoring of vegetation dynamics. However, Chivasa *et al.* (2022) noted that satellite-derived indices may sometimes be affected by atmospheric interference and spatial resolution limitations, suggesting that their effectiveness depends on data quality and processing techniques.

The observed importance of lagged environmental variables, particularly rainfall and NDVI, indicates that previous environmental conditions influence current outbreak probability. This result agrees with Jiang *et al.* (2021), who found that time-series vegetation data can serve as early indicators of pest outbreaks. In addition, Khan *et al.* (2023) reported that incorporating temporal dynamics into machine learning models improves predictive accuracy in agricultural systems. Nevertheless, Abdulai *et al.* (2023) argued that temporal models may require extensive historical data to achieve reliable performance, highlighting a potential limitation in data-scarce environments.

The seasonal outbreak pattern identified in this study, with peak infestation occurring between July and September, is consistent with Baudron *et al.* (2020), who reported that Fall Armyworm populations increase during periods of moderate rainfall and optimal temperature. Similarly, Skendžić *et al.* (2021) observed that climatic conditions during the growing season strongly influence pest population peaks. However, Ullah *et al.* (2022) noted that climate variability and extreme weather events may disrupt these patterns, suggesting that outbreak timing may shift under changing climatic conditions.

Finally, the high recall value observed in this study indicates strong model sensitivity in detecting outbreak events. This finding agrees with Khan *et a*l. (2023), who emphasized that high-recall models are essential for early warning systems to minimize missed detections. Similarly, van Klompenburg *et al.* (2020) reported that machine learning-based prediction systems significantly enhance decision-making in agriculture by providing timely and accurate forecasts. However, Ahmad *et al.* (2021) cautioned that high sensitivity may sometimes come at the expense of increased false positives, suggesting the need to balance model performance metrics depending on application objectives.

Limitations of the Study

This study adopted a simulation-based dataset due to the limited availability of standardized, long-term field observations on Fall Armyworm outbreaks in Northern Nigeria. While the simulation was designed using biologically realistic constraints and empirically supported environmental relationships, it does not fully capture the complexity and stochastic nature of real-world pest dynamics.

Additionally, remote sensing variables were represented using standardized index ranges rather than raw satellite imagery, which may limit spatial resolution precision. Future studies should integrate ground-truth field surveillance data and high-resolution satellite imagery (e.g., Sentinel-2 or MODIS) to improve model robustness and external validity.

CONCLUSION

This study demonstrates that machine learning models, particularly Gradient Boosting algorithms, can effectively predict Fall Armyworm outbreaks using integrated climate and remote sensing data. The results highlight the importance of temperature, humidity, and vegetation indices as key predictors of pest dynamics in maize production systems.

The proposed framework offers a scalable approach for developing early warning systems for agricultural pest management in data-scarce environments. However, future work should focus on validating the model using field-based datasets to enhance predictive reliability and operational deployment.

Recommendations

Based on the findings of this study, the following recommendations were proposed:

Government agencies and agricultural stakeholders should adopt machine learning-based predictive models to establish real-time early warning systems for Fall Armyworm outbreaks. These systems can provide timely alerts to farmers, enabling proactive pest control measures.

The predictive framework should be incorporated into agricultural extension programs in Northern Nigeria. Extension officers can use model outputs to guide farmers on optimal intervention periods, thereby improving pest management efficiency and reducing unnecessary pesticide use.

Training programs should be organized for agricultural professionals and stakeholders on the application of Machine Learning tools in pest management. Strengthening digital agriculture capacity will enhance the adoption of innovative technologies in the sector.

Future studies should prioritize the collection of high-quality field data on pest incidence, environmental variables, and management practices. This will enable validation and refinement of predictive models under real-world conditions.

Author's Contributions

Okwor Jude I: Conception, design and reviewing the article critically for significant intellectual content; Akogwu Hyacinth O: Conception and design; Idoko Bartholomew: Acquisition of data and analysis; Onyima John O: Interpretation of data and reviewing the article critically for significant intellectual content; Uchendu Christian N: Drafting of the manuscript; Attamah Chinyere G: Reviewing the article critically for significant intellectual content and giving final approval of the version.

Conflict of Interest

Authors declare no conflict of interest and have given approval for the article publication

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