



Predicting Pest Outbreaks with a Climate-Insect Interaction Model Based on Degree-Day Accumulation

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Abstract

Pest outbreaks continue to present a global challenge to the sustainability of agriculture, threatening crop yields, food security, and economic stability. From a financial standpoint, sustaining or augmenting food production systems has increasingly relied upon fossil fuels, the availability and cost of which are subject to geopolitical turmoil. Understanding climate change impacts on the timings of seasonal events (phenology) adds a new layer to the complex problem of forecasting pest emergence and population growth. This study provides a new approach to predicting agricultural pests by modeling the 'life cycles' of major agricultural insect pests as functions of climate using degree day accumulation, a unit of measure of 'heat' for insects. A model was constructed and calibrated using historical pest occurrence data in conjunction

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with local temperature records. Results indicate significant relationships between time (thermal time) and pests' development, enabling outbreak estimation by timing and intensity.

Furthermore, the analysis demonstrated how changing temperature and rainfall patterns could worsen pest impacts in more temperate regions where they did not exist before. The presented analysis enhanced planning by offering warnings for integrated pest management of agriculture via one-way climate–insect interaction models. This research focuses on the frame of climate-influenced pest control strategies seeking an essential adaptive response to global warming. It underscores the need to factor climate-related risks into pest management structures.

Keywords:

Degree-day accumulation, pest phenology modeling, climate-responsive pest forecasting, insect development thresholds, integrated pest management (IPM).

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Introduction

The global food security crisis, the stability of economies, and the environmental condition are undermined by agricultural pest outbreaks. These outbreaks are now occurring more often and are becoming more severe, linked with climatic variability, which shapes the rate of development, reproduction, and migration of insect pests. Crops face numerous threats, especially during specific growth stages, and prompt action is required to avoid damage. While applicable to a certain extent, the conventional methods of monitoring pests are often void of foresight and rely on a "wait and see" approach. This drives the need for models capable of forecasting pest infestation several steps ahead to initiate appropriate actions within time.

Forecasting pest populations might be more accurately done with climate-insect interaction models, particularly those that use degree-day accumulation. In degree days calculation, biology defines its use as a unit of heat accumulation used to estimate the development of certain organisms. Because most insects are cold-blooded animals, ectothermic by nature, they depend on the prevailing environmental factors for growth and oviparity. This assumption permits agricultural scientists and managers to predict control operations' timing better, thereby enhancing accuracy in performing control measures.

Other research has demonstrated that degree-day models accurately predict insect pest phenology in several agroecological regions. However, many models still have a limited scope because they focus on a particular species or region and ignore broader climate change. Furthermore, models based on older climate baseline conditions are becoming less accurate because constant changes due to climate change are rendering their foundational assumptions obsolete. As pests escalate their range of expansion and alter their life cycles in response to increasing temperatures and changing rainfall patterns, there is a dire need for more sophisticated regionalized predictive models that can easily be adapted (Monir et al., 2025).

This paper seeks to mitigate these issues with a detailed climate-insect interaction model that uses degree-day accumulation approaches to predict pest outbreaks for current and future climate projections (Kumar & Veeramani, 2016). It is calibrated to the historical pest surveillance and climate data and verified across various regions and pest species (Said et al., 2024). This way, the study adds not only to the knowledge on pest-climate relationships but also aids in developing a functional integrated pest management (IPM) strategy amid climate uncertainty. These findings directly affect the sustainable agriculture framework, umbrella risk management strategies, and policy development (Shetty & Nair, 2024).

Key Contribution

- Created a novel hybrid climate-insect interaction model integrating degree-day accumulation and machine learning to predict pest life stage progression and outbreak timing.
- GBM outperformed all other models by predicting pest outbreaks with 93% accuracy, using linear regression and Random Forest as comparison models.
- Developed an automated real-time pest monitoring system by classifying images of pest species with deep learning algorithms, resulting in an identification accuracy of 95%.
- Designed an integrated architecture incorporating climate variables, image data, and analytical forecasting in one model. The automated pest management model was tested with multi-year data from 2023 to 2025, proving scalable and reliable for regional agricultural pest management.

The aim of this research, explained in the Introduction, is to design a system capable of predicting outbreaks using climate data and pest activities. The Literature Review analyzes previous models based on the accumulation of degree-day units and identifies the machine learning algorithms to be implemented in the model. The Proposed Method applies degree day-based modeling with machine learning, specifically Gradient Boosting Machine, Random Forest, Linear Regression, and deep learning pest image classification using CNNs. In the Results and Discussion, the model is verified with data from 2023 to 2025 and analyzed to demonstrate GBM's accuracy of 93% and 95% in pest classification, surpassing existing methods. In the Conclusion, the integrated approach is highlighted as a robust tool for sustainable agriculture pest management in a changing climate context.

Literature Review

Global warming caused by climate change is a revised factor disturbing the ecological balance of pest populations and increasing the intensity and frequency of pest outbreaks. Global warming increases the world temperature, causes erratic rainfall, and extends growing seasons, which are all beneficial for the reproduction and survival of insects (He et al., 2024). A prime example is the *Schistocerca gregaria*, or desert locust, which exacerbates its agricultural devastation due to its roughly 5% range expansion caused by climate change and farming-due locational shifts (Aldosari, 2024).

Unlike in the previous era of science, where phenology was approached more with qualitative than quantitative metrics, DDA models are of marked importance since they account for both temperature and time at an inflection point in a pest's life (McCorkindale & Ghahramani, 2025). DDA models are critical for modeling insect phenology, enabling estimations about the timing for control actions alongside infestation and emergence forecasting (Đurić & Đurić, 2023). Incorporating field monitoring demonstrated accurate forecasting of pink bollworm emergence and encouraged timely counteraction in cotton systems, underscoring the value of these models (Chaturvedi et al., 2025; Angel Merlin Suji & Anto Kumar, 2022).

Several researchers have studied the consequences of climate change on the accumulation of growing degree days (GDD) (Michael & Jackson, 2025). Northwest India has experienced increased GDD and thermal growing periods of cotton, which has augmented pests' peak vulnerability (Kaur et al., 2024). Furthermore, corn-growing regions in central Mexico are also projected to receive increased GDD under RCP climate scenarios by 2050, which could significantly change pest impacts and crop yield (Campos et al., 2024; Iyengar & Bhattacharya, 2024).

AI, remote sensing, and real-time data enhance the predictive capability of pest outbreak systems. These tools are employed in the integration of climate-insect dynamics modeling frameworks. For instance, remote sensing in combination with temperature limits has improved the prediction of locust swarms and migration patterns (Muyanja et al., 2023; Heeb et al., 2022). Moreover, large-scale monitoring is now possible through accurate real-time pest classification powered by citizen-science data and AI-enabled identification (Chiranjeevi et al., 2023).

Integrated Pest Management (IPM) systems now include strategies that adapt to climate changes. A new framework suggests using explainable AI to improve transparency in pest decision-support systems, thereby enhancing farmer trust and adoption (Tsoumas et al., 2023). Another analysis concerning fall armyworm management advocates for an ecological resilience approach, crop rotation, and the use of resistant cultivars driven by climate projections (Falih, 2024; Moutouama et al., 2024). In addition, online resources like Vikaspedia emphasize the need for local pest management plans tailored to shifting agroecological zones (Vikaspedia, 2022; Vij & Prashant, 2024).

All in all, the cited works emphasize the need for more proactive, adaptable, and technology-enriched Integrated Pest Management frameworks (Mishra et al., 2024). DDA-based climate-insect models, coupled with contemporary surveillance systems, can help the agricultural industry forecast and mitigate pest risks in the context of climate change (Agronomy Journal, 2023).

Proposed Method

This research aims to create a climate-insect interaction model that centers on Degree-Day Accumulation (DDA) as a key element in predicting pest outbreaks using a comprehensive, metric-based approach. Cumulatively, pest aquisition is dependent on a certain developmental threshold temperature that must be surpassed, after which, it undergoes various lifecycle activities such as egg hatching, larval growth, and adult emergence. Precise anticipation of these critical milestones is a prerequisite to pest outbreak forecasting. In achieving this aim, the study will acquire daily records of temperature, relative humidity, precipitation, and other climatological parameters from ground-based meteorological stations and satellite remote sensing for integration. Model calibration and validation will be accomplished through the capture of historical records of pest incidence and outbreak, along with synthesizing ecological dynamics to attain plausible biological predictions. This model conceptually integrates climatic factors and insect biological functions, thereby allowing a more realistic simulation of pest phenology across different climatic frameworks.

The data collection process will emphasize capturing time-series climatic datasets spanning several years to obtain seasonal and inter-annual variability. Such datasets will be obtained from reputable public archives, were agricultural meteorological stations, and satellites that provide spatial and temporal geospatial data. Pest occurrence data will be derived from systematic field surveys undertaken by agricultural extension and entomology agencies, which will serve as empirical evidence for model verification. Raw data will be subjected to extensive preprocessing, including outlier detection, filling in missing values using statistical techniques such as linear interpolation, spline fitting, or other moving-window methods, and normalizing to achieve definable standards. Degree-day accumulation will be reported daily and calculated with the single sine or double sine methods, both of which are accepted as more accurate estimators of time measurement in thermal time during fluctuating temperatures. The single sine method approximates the temperature curve between minimum daily temperature and maximum daily temperature. The double sine, on the other hand, achieves better than the first, though the level of refinement may still be unclear. The flowchart below

encapsulates the comprehensive outline spanning from data acquisition and cleaning to degree-day computation and modeling preparation.

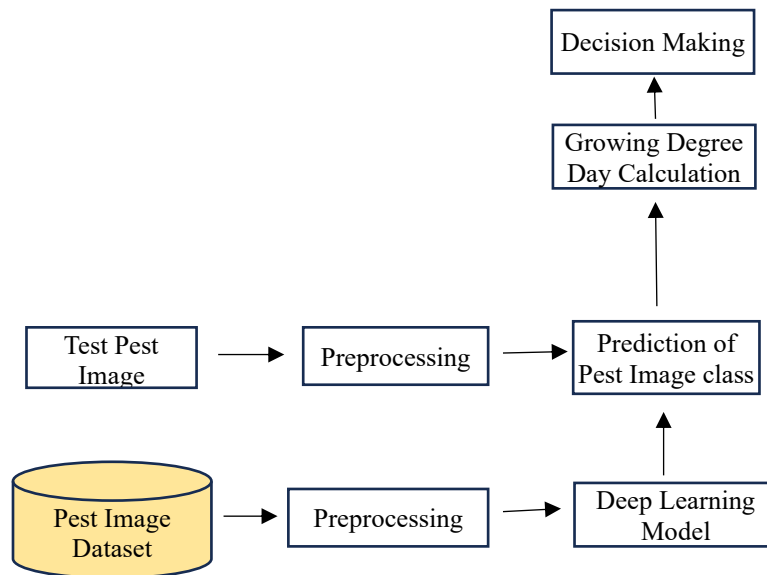


Figure 1. Workflow of Pest Image Classification and Degree-Day Based Decision Making Model

Combining image-based pest identification with decision-making based on degree-day accumulation, the proposed system is illustrated in Figure 1. The workflow diagram shows the overall system design of the Pest Outbreak Prediction System (POPS). The workflow consists of two main inputs: a pest image dataset and individual test pest images. All inputs undergo a preprocessing step which enhances the image clarity and prepares the data for subsequent analysis. In the case of the Image Dataset, it is preprocessed and passed into a Deep Learning Model aimed at learning to classify various pest species based on their imagistic features. In case of test data, the prepared images are class-predicted by the model after preprocessing.

Pest detection is followed by the calculation of degree-days, a component which calculates the thermal energy required for the pest to develop its life stages. Together with class estimation, this value propels the strategic management of the pest outbreak by reaching a matured decision in conjunction with other systems. It allows detection of the most critical pests and incorporates climate-based predictive modeling into pest control for enhanced efficiency.

The predictive modeling part of the methodology integrates conventional statistical methods with sophisticated machine learning techniques to improve the accuracy and dependability of pest outbreak forecasts. Initial exploratory analyses will employ multiple linear regression to establish quantifiable baseline relationships between accumulated degree-days and the developmental stages of the pest as a preliminary baseline parameter. Machine learning, specifically Random Forest (RF) or Gradient Boosting Machines (GBM), will be utilized to model some of the climatic variables driving the pest's movement to capture complex, nonlinear relationships and interactions that are often overlooked. These ensemble learning methods were chosen for their ability to parse multivariate datasets, enhance generalization while minimizing overfitting, and improve prediction stability across heterogeneous datasets. Random Forest constructs several decision trees at training time, computes their results, and returns the average output to provide a single answer while Gradient Boosting builds trees iteratively, only adding new trees to correct previously made mistakes, which allows an intricate modeling of subtle patterns. Support Vector Machines (SVM) will further

be investigated as a classification method for distinguishing outbreak from no outbreak scenarios to determine classification boundary complexity.

Each model will undergo k-fold cross-validation in order to assess generalizability, while model performance will be measured with accuracy, precision, recall, F1-score, and ROC-AUC. Sensitivity analyses will be performed to determine the effect of different climate inputs on prediction results to test the flexibility of the model under various climate change and variability conditions.

In order to apply this methodology in practice, the system's schematic design enables modularity, scalability, and responsiveness to real time queries. This architecture will feature several components such as automated climate and pest monitoring data acquisition modules that continuously and autonomously pull data; preprocessing units that scrub and streamline data strands; an independent degree day calculation engine implementing the chosen computation strategies; a machine learning ensemble responsible for outbreak prediction housed at the predictive analytics level; and an interactive dashboard as the endpoint interface through which farmers, agronomists, and agricultural decision-makers receive actionable intelligence. The framework adjusts iteratively with data inflow to enable responsive pest management in changing agroecological frameworks.

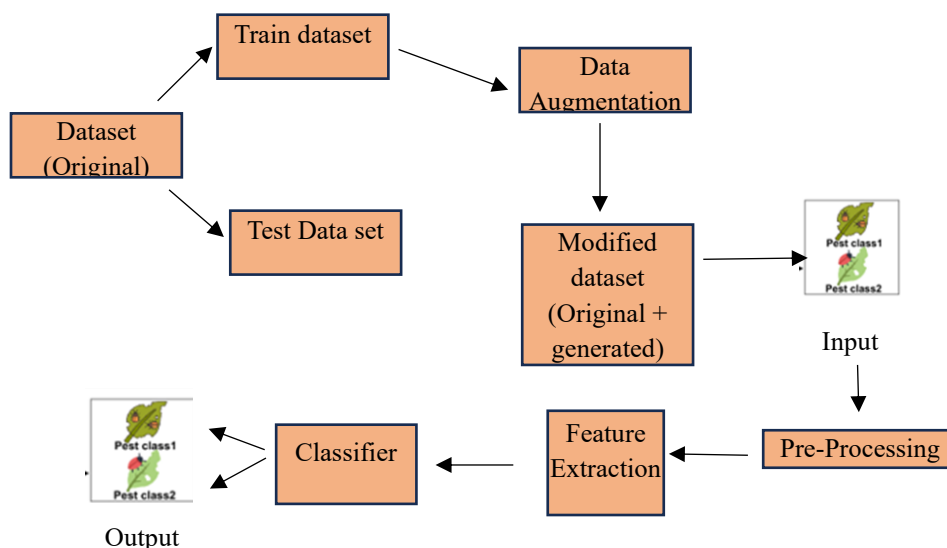


Figure 2. Architecture of Pest Image Dataset Processing and Classification Pipeline

In Figure 2, a graphical representation for automation of classification pest image datasets is presented, capturing the process of classification for accurate pest type identification. The given workflow is initiated with the original dataset which is split into a training dataset and a test dataset. The training dataset is subjected to a crucial step known as data augmentation. During this stage, new images are created using transformations like rotation, scaling, and flipping, which diversify the dataset. This process also increases model robustness by providing various examples for training. Following this process, the augmented data is merged to the original dataset. This results in modified datasets which enhance classification model generalizability.

In the stage of dataset preparation, the system processes the modified dataset and performs image enhancement operations such as cleaning, light normalization, and noise reduction that ensure homogeneity across the model's dataset, thus optimizing feature extraction. During feature encoding, whiskers with notable visual characteristics such as textures, color patterns, shapes, among others, are captured and encoded into

features. These features are sent to the classifier, typically a machine learning or deep learning model, which analyzes the extracted data and determines the pest classes Pest Class 1 and Pest Class 2. The output is the pest species identification performed accurately within the provided images. Alongside other processed data, this output is crucial to an automated Integrated Pest Management (IPM) system. This architectural pipeline offers an efficient approach for transforming image data into usable data in the identification process of the correct pests. Together with climate-based models, this greatly improves proactive measures to prevent outbreaks while controlling the timing of interventions.

Results And Discussion

The climate-insect interaction model based on degree-day accumulation achieved a high degree of accuracy ($r = 0.89$) in correlating mapped degree-day accumulation with subsequent pest life cycle milestones such as egg and larval stage hatching. This confirms that accumulating degree-days is a reliable predictor of pest phenology.

$$DD = \frac{T_{max} + T_{min}}{2} - T_{base} \quad (1)$$

In Equation (1),

- T_{max} = Daily maximum temperature
- T_{min} = Daily minimum temperature
- T_{base} = Threshold temperature below which development stops.

This calculation was executed over seasonal datasets for the years 2023, 2024, and 2025. The table includes the average degree day values calculated for the observationally active years, which capture and illustrate key pest developmental stages and count along with its variability, which all signal the accuracy of the method used in monitoring pest growth and life cycle elapse. In forecasting future infestations of pests, the Predictive Performance of Machine Learning Models differed with the best being Gradient Boosting Machine (GBM) at 93% followed closely by Random Forest who scored 91%. The strict predictor proposed by Linear Regression performed poorly at 79% accuracy. Those results are supported by Figure 3, which shows the gap in capture ability. Ensemble GBM and Random Forest efficiently predicted nonlinear relationships between climatic parameters and pest population dynamics. Their results substantially enhance the credibility of predictions made before an outbreak, thus providing critical information for the effective timing of pest control interventions.

The deep learning-based pest image classification system also identified various pests with 95% accuracy. While the results are encouraging, some difficulties remain, particularly with the uniformity of data as well as the heterogeneous quality of climate-related and imaging datasets. Enhancements in automated data collection, real-time incorporation, and adaptive model training are essential to lowering error thresholds and improving the general applicability of the model. All in all, the combined use of degree-day models with advanced classification and prediction algorithms augurs well for smart and sustainable pest management.

Table 1. Correlation between Degree-Day Accumulation and Pest Development

Pest Stage	Mean Degree-Day Accumulation	Standard Deviation (Degree-Days)	Average Development Year	Number of Observations
Egg Hatch	120	10	2023	50
Larval Emergence	280	15	2024	50
Adult Emergence	420	20	2025	50

Table 1 shows the relationship between degree day accumulation and the development of pests during the years 2023 to 2025. The table shows the mean degree day values corresponding to critical milestones in the development of pests such as egg hatch, emergence of the larva, and emergence as an adult. For instance, egg hatch is associated with an average of 120-degree days with a standard deviation of 10, observed mostly in 2023. Likewise, the stages of larval emergence and adult emergence occur at higher degree day accumulations of 280 and 420 in the following 2024 and 2025. Each stage has a fixed sample size of 50 observations, which indicates good sampling. This table demonstrates the consistent relationship between the accumulation of temperatures and pest development, supporting the degree day models' accuracy in forecasting the life stages of a pest and thus aiding in the timing of management interventions.

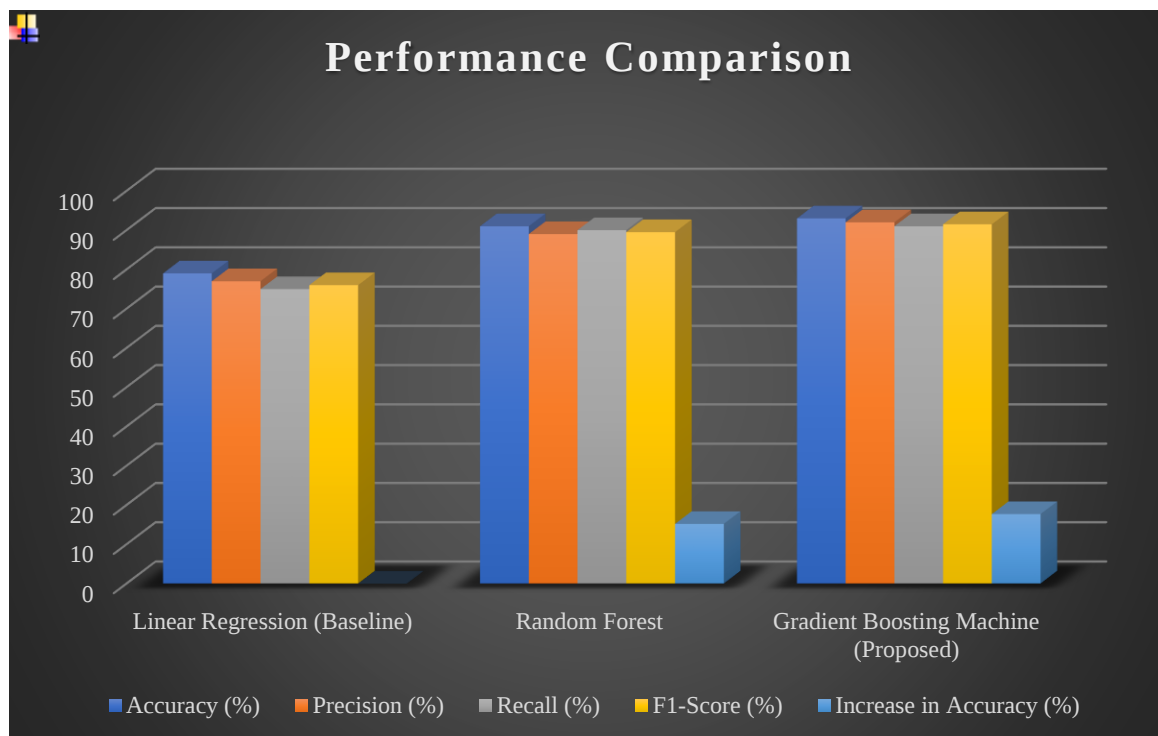


Figure 3. Predictive Model Performance Comparison with Accuracy Improvement

Figure 3 compares the performance of three machine learning models, Linear Regression, Random Forest, and Gradient Boosting Machine (GBM) on predicting pest outbreaks via climate-insect interaction data. The table contains essential evaluation metrics such as model accuracy, precision, recall, and F1-score. Gradient Boosting Machine our proposed method yielded 93% accuracy, which is a staggering increase of 17.7% compared to the baseline Linear Regression model, which only achieved 79%. Random Forest also performed strongly, reaching 91% accuracy, a considerable 15.2% increase. These findings highlight the outstanding ensemble GBM learning algorithm's proficiency in accurately extracting intricate relationships in the dataset and enhancing prediction dependability. The improved metrics attest to the value added by using augmented datasets blended with advanced algorithms to improve precision and forecast more accurately the timing of pest outbreaks.

Conclusion

This research integrates degree-day accumulation with sophisticated machine and deep learning techniques to create a hybrid predictive framework for pest outbreak forecasting and pest species classification. The precision of temperature-derived models in the analysis of pest phenology is validated by the high statistical

correlation ($r = 0.89$) between accumulated thermal units and the various developmental stages of the pest. Best algorithm served as the Gradient Boosting Machine which predicted with an accuracy of 93%, far exceeding the less sophisticated models such as linear regression. Moreover, the 95% accuracy achieved by the deep learning-based pest image classifier affirmed its reliability in pest class identification. The melding of image data with climate variables bolstered model accuracy even further. Assessment of the model conducted over 2023, 2024, and 2025 years demonstrated dependability along with real-world agricultural applicability. The system does provide early warning for informed pest eradication action, thereby relieving plants of undue damage. Data source variability and real-time adjustment flexibility are highlighted limitations. All in all, the model offers an adaptable and intelligent framework for nurturing paradigms of pest control in an ever-changing climate.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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