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Big Data Analytics for Predictive Pest Modelling

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Abstract

Big data analytics is revolutionizing predictive pest modelling by enhancing the accuracy and timeliness of pest management strategies. This paper explores the integration of big data techniques with various pest modelling approaches, including phenology models, life table models, pest simulation models and mathematical models. Phenology models leverage large datasets to predict the timing of pest life stages, facilitating proactive control measures. Life table models utilize extensive demographic data to understand pest population dynamics and inform sustainable management practices. Pest simulation models, powered by big data, simulate complex interactions within ecosystems, offering insights into potential pest outbreaks under different environmental scenarios. Additionally, mathematical models provide a robust framework for quantifying pest behaviour and predicting future infestations. By harnessing the power of big data analytics, these models can significantly improve the precision and effectiveness of pest management, ensuring better crop protection and yield optimization.

Keywords Big data, Models, Pest management, Prediction

1. Introduction

Insect pests in agriculture cause significant crop damage, especially in tropical regions where they can lead to losses up to 60-70% (Thomas, 1999). These pests, which damage crops, livestock and human health, negatively impact agricultural production, market access and the environment. The unpredictable weather and biotic stresses further threaten crop yields, leading to substantial economic and societal losses. To address the growing food demand, precision agriculture using big data offers a solution. Big data can develop accurate forecasting models, optimizing crop production. Predictive analytics, in particular, helps extract trends and insights from data to enhance agricultural outcomes.

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Big data refers to vast sets of information that surpass the capabilities of current tools for effective analysis. It is characterized by its size and complexity. Size is determined by the number of data sources; while complexity involves the relationships and arrangements within the data. Big data analytics involves multiple steps. First, define the data requirements, which outline the purpose of acquiring the data. Second, collect the data through experiments or from publicly available sources. Third, process the data into a presentable format. Fourth, perform extrapolative or interpolative trend analysis to predict trends within and beyond the data range. Finally, model the data to create a general formula or relationship.

Big data analytics has revolutionized pest management by enabling the development of predictive models that forecast pest outbreaks (Balduque-Gil *et al.*, 2023), pest generations (Swarupa Rani and Jyothi, 2020), population dynamics (Feng *et al.*, 2010), decision making in managing pests (Rao *et al.*, 2021), damage/impacts caused by pests, *etc.* (Donatelli *et al.*, 2017). Big Data Analytics for Predictive Pest Modelling involves the use of advanced data analytics techniques to predict pest outbreaks and their potential impact on crops. By analysing vast amounts of data from various sources, including weather patterns, soil conditions, crop health and pest behaviour, researchers and farmers can make informed decisions to manage and mitigate pest-related risks effectively. This chapter highlights the importance of big data, its collection, analytics and finally how it helps in forming a model that helps in predicting the insect-pests and discusses about previously established models that are being used around the world to monitor the insect-pests.

2. Big Data Analytics

An important aspect of big data analytics is the computation of predetermined algorithms in order to solve certain types of problems. In recent years, artificial intelligence has been widely used in various agricultural applications. In this field, artificial intelligence (AI) is used to enable machines to think and make decisions without human assistance. Machine Learning (ML) is also a part of AI. It makes use of the algorithms that use statistical learning and construct systems that are capable of learning and improving without any further programming.

Deep learning (DL) is an advanced subset of machine learning (ML) that mimics the human brain's processing of information with artificial neural networks, which mimic the anatomy of human brains. By learning from examples, DL enables computer models to sift through vast datasets to classify and predict information. Techniques such as big data analytics, digital methods and climate and weather informatics are crucial in enhancing agricultural production (Ramesh *et al.*, 2020).

3. Structure of Big Data Analytics in Agriculture

Across the globe, big data is increasingly being utilized in the agriculture sector, although it has historically lagged behind other industries in adopting big data analytics. Farm equipment is generating vast quantities of data that includes climatic, edaphic and crop information, thanks to the integration of GPS, sensors and Internet of Things (IoT). In today's world, mobile and sensor technologies are transforming traditional practices through the use of digital information and big data analytics.Public and private organizations are leveraging historical agricultural data to develop precise crop management strategies that enhance input efficiency, crop productivity and economic profitability. As a result of these efforts, Decision Support Systems (DSS) tools are being developed that use data analytics and IoT in order to optimize farming inputs and maximize profits. The CGIAR consortium, alongside platforms like *Agritask*, exemplifies this push towards data-driven agriculture by providing actionable insights through the integration of various data sources.

Climate-related risks in agriculture can be understood and mitigated through big data analytics. For instance, in rainfed farming, where 80% of production variability is due to rainfall fluctuations, big data can augment traditional weather forecasts and climate projections, helping to reduce risks from insect-pests and severe climatic factors, thereby benefiting the farming sector.

Big data analytics in agriculture necessitate expertise from various fields, including agronomy, climate science, digital design and human-computer interaction (Van De Gevel *et al.*, 2020). The three most important characteristics of big data are its volume, velocity and variety. The volume concept refers to data sets that are so large that conventional database tools cannot handle them, especially as IoT and sensor data sizes increase, from terabytes to petabytes. As the term implies, velocity refers to the ability to acquire, process and interpret data in real time, driven by advancements in mobile broadband, high-resolution agricultural data and affordable computing power. These developments have sparked interest in using Big Data for improving productivity and managing risks in agriculture.

4. Data Acquisition

Acquiring high-quality, real-time and diverse data (including weather, soil, data on insect-pests and crop information) is essential for leveraging AI in agriculture. The methods for obtaining this data include:

4.1. Field Data Collection

Field data collection involves gathering data from research undertaken areas, farmers' fields by researchers and progressive farmers. These extensive datasets, often held by public organizations, can also come from state and private sector surveys. However, they can be structured or unstructured and accessibility varies. Challenges for Big Data analysis include data quality issues, lack of protocols for sharing data and limited incentives to share. The lack of geo-referencing, discontinuity and difficulty in extracting historical datasets make it necessary for data scientists to develop methods for preparing historical datasets for analysis. Despite the difficulties, this effort is crucial for validating models created using other methods of data acquisition.

4.2. Sensors

A variety of sensors can be integrated into farm equipment such as tractors, handheld devices and field installations, forming part of a digitally-integrated farm system. These sensors, including e-kisan tablets, tiny needle-like sensors and polymer-based sensors, require extensive evaluation under field conditions to ensure their effectiveness.

4.3. Multispectral Data from Satellites and Unmanned Air Vehicle

The use of remote sensing in agriculture is widely spread because it provides valuable information about land features. It is useful for identifying crops, estimating acreage, determining planting dates, identifying pests and diseases and assessing crop conditions. Farmers can maximize productivity and efficiency by using remote sensing data in conjunction with historical data. According to the FAO, pests and diseases cause 20-40% of global crop yield losses annually. Agrichemical use can be reduced by precision pest targeting with technologies like robotics and drones.

5. Big Data Analytics in Predictive Pest Modelling

As insects are exothermic, they are incapable of regulating their internal temperature, making their development dependent on their surrounding environment. Researchers often study insect population dynamics by modelling temperature-dependent growth. Such models can be modelled effectively with rate summation (Stinner *et al.*, 1974). Degree-day summation is the most common model for predicting development rates assumes a linear relationship between development rate and temperature, which is highly effective at optimum temperature levels (Allen, 1976). The linear model posits that rates are proportional to temperature, so the amount of development is the integral of temperature (or a linear function of it) over time, measured in degree-days. Additionally, insects can be modelled by using developmental time to predict temperature-related development. Traditional development models are based on biochemical and biophysical properties, but utilizing rate rather than time can bring complications.

Earlier models often overlooked the variation in development rates among individual insects, which influences the spread of pest activity. Significant models now consider mean rate versus temperature relationships and the distribution of development times. Rather than treating rate summation as deterministic, stochastic approaches view rates as random variables. These models differ in the random variable chosen and the form of the frequency distribution applied. Rate distribution coefficients seem relatively temperature-independent, meaning that one distribution can describe development rates across 113 insect and mite species in 80% of the data sets (Shaffer, 1983). The Monte Carlo simulation model can be used for insects that undergo diapause or aestivation during its life cycle (Phelps *et al.*, 1993).

Biological development of insect-pests must not be linearly correlated with temperature, since extreme temperatures can be lethal to some organisms. In order to describe inhibition at high and low temperatures, as well as both extremes, non-linear development rate functions based on enzyme kinetics were developed (Sharpe and DeMichele, 1977). Stinner *et al.* (1974) produced another nonlinear model based on an inverted sigmoid curve above the optimal temperature and they modified it for asymmetric properties. Schoolfield *et al.* (1981) enhanced the Sharpe and DeMichele model for better utility and simpler parameter estimation. It was noted that nonlinear development and cyclical temperatures could cause deviations from linear models, especially at extreme temperatures (Worner, 1992). The Stinner's model was found to be the best match for Russian wheat aphid development rates (Ma and Bechinski, 2008). However, According to Ma (2010), Russian wheat aphid development is influenced by temperature and stage of plant growth as per the results provided by survival analysis model.

6. Phenology Models

Crop pest phenology models are useful for predicting their development and emergence. These models are based on the principle that the growth and development of insects are influenced by environmental factors, primarily temperature. By tracking cumulative heat units, often expressed as degree days, phenology models can forecast the timing of various life stages of pests, such as oviposition period, larval or nymphal development, nature of pupation and emergence of adult insects. Phenology models are essential for predicting insect development events, aiding in the understanding of pest population dynamics in various environmental conditions. Accurate predictions depend on precise temperature recordings and development durations (Danks, 2000). The degree-day model has long been used to make decisions about when to spray and when to scout for pests in decision support systems. In addition to predicting exotic pest establishment, these models have also been used in risk analysis (Jarvis and Baker, 2001). Another model, CLIMEX which isn't a complete phenology model, provides a framework to assess risks based on development. Using another model known as NAPPFAST, phytosanitary risk maps can be customized using climate data and biological models. Resources such as the Crop Protection Compendium provide comprehensive insect development summaries. Additionally, the University of California State-wide IPM program offers detailed development data for insects on their website, which can be utilized in degree-day models. In vineyards, phenology models based on degree days are used to predict the emergence and development of grape berry moths, allowing for targeted application of insecticides and mating disruption techniques (Balduque-Gil *et al.*, 2023).

Dal and Arora (2019) identified lower threshold temperatures for various life stages of *H. armigera* on tomatoes, aiding in predicting phenology and potential outbreaks for timely control. They used two linear models for development prediction of damage causing larval stages. They developed a

Simple Linear Model (SLM), Y = a+bT, which calculates lower development threshold temperature (T_o) and degree-days (DD) accumulated. 'Y' in equation represents the development rate of test insect, 'T' indicates mean temperature, a depicts development rate when temperature is at 0 °C and slope value is indicated by 'b'. Another model, Ikemoto-Takai Model (ITM) also calculates T_o and DD. Using equations 1 and 2, they calculated the standard error of means for T_o and DD, respectively (Kontodimas *et al.*, 2004).

$$SE_{To} = \frac{r}{b}\sqrt{\frac{s^2}{N.r^2} + \left[\frac{SE_b}{b}\right]^2} \quad \text{.........................} \ (1)$$

$$SE_{DD} = \frac{SE_b}{b^2} \quad \text{.........................} \ (2)$$

Where, s^2 = residual mean square of r; r = mean of the sample; N = size of the sample; b = linear equation's coefficient. In addition to the development rates and their respective mean temperatures, a nonlinear model developed by Kontodimas was developed whose mathematical equation is shown below.

$$\frac{1}{D} = a \times (temp - t_{min})^2 \times (t_{max} - temp) \quad \text{.........................} \ (3)$$

Where, 1/D= rate of the development of insect; D = larval and pupal period of *H. armigera* at specific mean temperature; temp = mean temperature; t_{max} = maximum threshold temperature; t_{min} = minimum threshold temperature; a = coefficient.

Results from the experiment conducted by Dal and Arora (2019) found that the Ikemoto-Takai model estimated lower threshold temperatures for the egg, larva and pupa stages of *H. armigera* at 9.9 °C, 7.8 °C and 12.3 °C, respectively, indicating that daily mean temperatures below these values are likely fatal. The Kontodimas nonlinear model predicted maximum threshold temperatures of 32.5 °C for eggs and 37.8 °C for larvae. These findings help inform timely, need-based control measures for *H. armigera*. The mathematical model, equations, algorithms vary depending on crop, pest's nature, variables, *etc*.

While phenology models are powerful tools, they are based on historical weather data and specific developmental thresholds, which may vary geographically and with changing climate conditions. Therefore, local calibration and validation are essential to ensure accuracy. Additionally, integrating phenology models with other pest management tools, such as pheromone traps and remote sensing, can enhance their predictive power and reliability. In conclusion, phenology models play a crucial role in integrated pest management by providing predictive insights into insect pest development and aiding in the optimization of control strategies. By accurately forecasting pest life cycles, these models help mitigate crop damage and improve agricultural productivity.

7. Population Models and Life Tables

Life table models are vital tools in entomology and pest management that track the survival, development and reproduction of insect populations. By providing a detailed breakdown of the life cycle stages and mortality factors affecting a pest population, these models offer valuable insights for predicting population dynamics and informing control strategies. Ecological life tables are essential tools for examining the population dynamics of insects with discrete generations. They involve recording sequential measurements to track changes in the insect's population throughout its life cycle in their habitat (Morris and Miller, 1954). They systematically present survival and mortality data for a known cohort. Long-term, carefully planned population studies with accurate measurements of all relevant factors are crucial for constructing realistic population models.

Life-table analysis establishes models that mimic reality by identifying and measuring factors that cause mortality which includes both density-dependent and density-independent factors. Multiple regressions are used to examine interactions between different age intervals within a survival model. It is possible to predict the average insect population level or changes in the insect population density based on the equations derived from the results. There are, however, limitations to these methods when dealing with insects that have overlapping generations. Life table analysis has been used to assess survival, development and distribution of the aphid species, *Diuraphisnoxia* Kurdjumov (Ma andBechinski, 2008). Many ecological studies cannot provide reliable population peaks predictions due to gaps in ecological databases, such as dispersal patterns, overwintering, colonization patterns and interspecies competition. Zalucki *et al.* (2017) used the DYMEX modelling package to study the effects of climate on the population dynamics of an age-structured diamondback moth (DBM) population. Their results showed a strong climate influence on DBM population changes, with natural enemies significantly reducing pest pressure. The severity of the pest problem varied notably with cropping practices; large-scale production units that implement production breaks and maintain strict post-harvest hygiene experienced lower pest pressure.

8. Pest Simulation Models and Decision Support Systems

Pest simulation models are sophisticated tools that predict the behavior, population dynamics and impacts of insect pests on crops. These models integrate various factors, including environmental conditions, pest biology and crop phenology, to simulate potential pest outbreaks and inform management decisions. The use of mathematical models to simulate environmental influences on biological data can be applied to many different situations and environments. These models, supported by computer programs, enhance understanding of population dynamics and facilitate timely pest management decisions. They can be tested, refined, sensitivity analyzed and validated across a variety of environmental conditions. In order to understand pest-plant interactions, detailed descriptions of cropping systems are essential (Colbach, 2010).

The use of systems models or prediction schemes helps assess control, sustainability and risks as well as management actions (Strand, 2000). For example, the HEAPS model (*Helicoverpa armigera* and *Punctigera* Simulation) in Australia integrates habitat structure and pest population dynamics, simulating movement of adults within a local cropping ecosystem. An estimation of populations within a grid is based on the movement of adults, the oviposition of females, their development, their survival and the phenology of hosts provided by this model. Originally developed by the Australian cotton industry from 1976 to 1993, EntomoLOGIC, a decision support tool for insect control, reduced risks associated with chemical pest management. Developed by CSIRO and the University of Western Sydney, it has evolved into CottonLOGIC, now available on Palm OS handhelds that is being used by the farmers growing cotton in Australia.

The MORPH suite of predictive computer models, developed at Horticulture Research International in the UK, is used for fruits and vegetable crops. The ECAMON model, for example, explains 70% of the variation in critical growth phases of crops based on daily weather parameters (Trnka *et al.*, 2007). It accurately predicted European corn borer's presence based on characteristic symptoms in the Czech Republic from 1961-1990 and explained increased damage during warm periods of 1991-2000, predicting an expansion of this niche in the next 20-30 years. The RICEPEST model, developed by the International Rice Research Institute (IRRI), Philippines, simulates yield losses due to insect-pests of rice in tropical regions of Asian continent and has shown promising results in field experiments (Willocquet *et al.*, 2002). Thus, models that can be accessed *via* the web and decision support systems are becoming increasingly important in IPM.

Mesoscale modelling techniques are used by US and Dutch commercial firms to forecast insect development on farms and for regional pest management. A decision-support system which forecasts black bean aphid outbreaks in spring-sown beans considers regional forecasts and specific field and crop characteristics, including a module for aphicide use and economic calculations. SOPRA, a pest management tool is used in Switzerland and southern Germany to effectively control eight of the most important insects that attack fruit trees, predicting crucial management events based on local weather data (Hohn *et al.*, 2007). The SIMLEP forecasting model is being used to forecast Colorado potato beetle, *Leptinotarsa decemlineata* Say in many European countries, has significantly improved pest control measures (Kos *et al.*, 2009).

CIPRA (Computer Centre for Agricultural Pest Forecasting), developed in the mid-1990s, provides real-time weather data to forecast pests and diseases for apple crops (Figure 1). These bioclimatic models range from simple degree-days approaches to detailed epidemiological models, aiding field specialists in managing the pests of apple (Bourgeois *et al.*, 2008). Kranthi and Kranthi (2004) developed a stochastic model, '*Bt*-Adapt,' to simulate the resistance development of *Helicoverpa armigera* to Cry1Ac toxin in Bt-cotton under Indian conditions. Simulations predicted resistance could develop in 11 to 54 years based on *Bt*-cotton use and pest control practices. The study recommends strategies to delay resistance, including reducing surviving pest populations on *Bt*-cotton and using alternate host crops as refuges to prolong the effectiveness of *Bt*-cotton.

Let's take another example. Kumari *et al.* (2013) worked on forecasting productivity and pod damage by *H. armigera* in pigeonpea (*Cajanus cajan*) using an Artificial Neural Network (ANN) model. This model was developed using time series data from 1985-86 to 2011-12, collected from multiple centres in the North East Plain Zone (NEPZ) of India. The performance of the model was validated using mean squared error (Equation-4) and multiple correlation coefficients, showing a good fit between observed and predicted values, thereby demonstrating the model's reliability in forecasting pest impact on pigeonpea crop. In order to develop neural network architectures, Levenberg Marquardt (LM) Algorithm was used as a training algorithm of weight matrixes.

$$E\,(x,w)= \frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e^2\, p.m \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

Where, 'P' = number of patterns; 'M' = number of outputs; '$e_{p,m}$' = training error at output m when applying pattern 'p'; $e_{p,m} = d_{p,m} - o_{p,m}$; 'd' is the desired output vector and 'o' is the actual output vector. The results indicated that the ANN model successfully forecasted pod damage and productivity for the 2012-13 period with values of 26.29% and 1137.40 kg ha^{-1}, respectively.

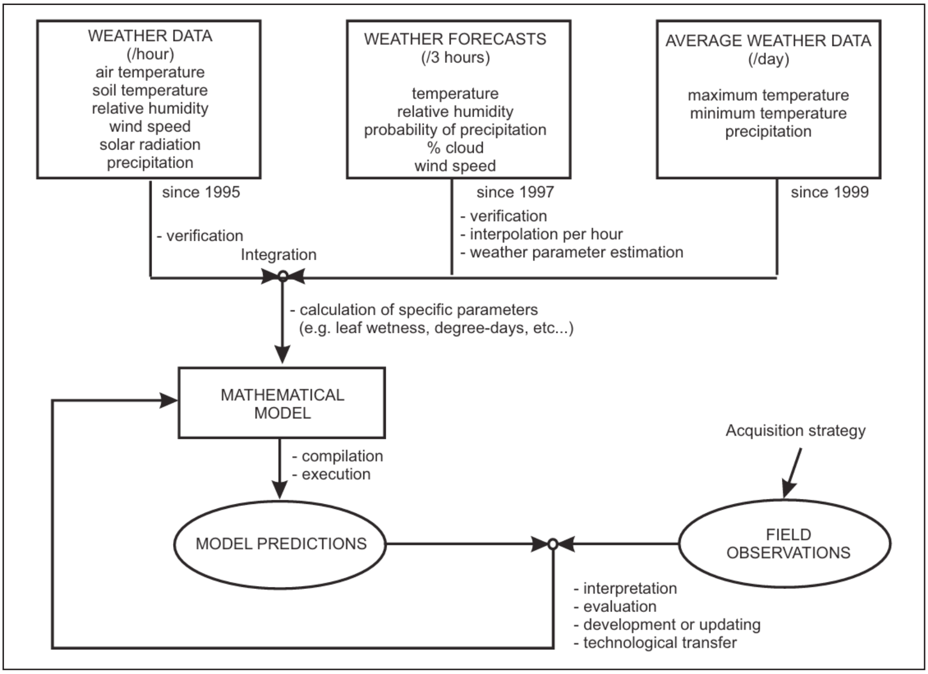

Figure 1: Overview on the working pattern of CIPRA model (Bourgeois *et al.*, 2008)

Table 1: Recent case studies pertaining to predictive pest modelling using big data analytics

Sl. No.	Application	Algorithm	Factors involved	Outcomes	References
1.	To ascertain population dynamics of *Bactrocera dorsalis* and *Ceratitis* spp. in Avocado	Fuzzy Neural Network	Weekly pest counts, rainfall, average temperature, relative humidity, and avocado plant physiological stages	The FNN models demonstrated satisfactory predictive capabilities, with most achieving R^2 values greater than 0.85	Ibrahim *et al.* (2022)
2.	To predict infestation of litchi stink bugs	Machine learning models like KNN, SVM	Environmental data, on-site pest surveys	Used to predict infestation of Litchi stink bugs on longan plantations with an accuracy rate of 85%	Chen *et al.* (2022)
3.	Impact of environmental factors on rice diseases and insect pests (DIP) using big data analytics	Principal component analysis	Terrain, temperature, precipitation, and light	Predicted DIP occurrence and trends, noting that higher temperatures and changing precipitation patterns promote pest and disease proliferation.	Chen and Wang (2020)
4.	To predict the population of the yellow stem borer (YSB) in rice fields	Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) neural networks	Light-trap data and weather parameters	LSTM model proved to be a more robust tool for developing an early warning system for YSB outbreaks, aiding in timely pest management and protecting rice crops from significant yield losses	Bapatla *et al.* (2024)

Sl. No.	Application	Algorithm	Factors involved	Outcomes	References
5.	Big data analytics to analyze FAW density and distribution in sub-Saharan Africa	Big data analytics (Data mining)	Temperature, rainfall, wind speed	The study found FAW density to be highly sensitive to climate and host vegetation. Predictive models achieved 53% overall accuracy	Guimapi *et al.* (2022)
6.	Predicting pest generations under varying climate conditions using big data mining	*MarkSim* climate generator, REP tree classification	Weather conditions, Data on insect-pest	Emphasized the value of combining data mining, classification, and prediction techniques to forecast pest generations	Rani and Jyothi (2020)
7.	To predict the population of the yellow stem borer (YSB) in rice fields	Long Short-Term Memory (LSTM) neural networks	Data on dead hearts and white heads and climatic data	Efficiently predict rice stem borer damage	Wahyono *et al.* (2020)
8.	Predictions of population dynamics of *Tribolium-confusum* and *Callosobruchus chinensis*	Ricker's classic equation	Temperature and humidity	Indicated significant changes in pest status during 2071-2100 under IPCC's A2 and B2 climate change scenarios	Estay *et al.* (2008)
9.	Predictive models to manage greenhouse whitefly populations	ARIMA and ARIMAX models	Whitefly count and environmental variables	ARIMAX to be superior in predicting normal and moderate levels of daily increase in whitefly count	Chiu *et al.* (2019)
10.	Prediction of rice gall midge populations	Machine learning models (ANN, SVR)	Insect count and climatological factors	ANN with exogenous variables (ANNX) model significantly outperformed the SVR model in predicting gall midge population	Rathod *et al.* (2022)

9. Conclusion

In conclusion, the application of big data analytics for predictive pest modelling represents a significant advancement in agricultural pest management. By leveraging vast datasets and sophisticated analytical techniques, one can achieve more accurate and timely predictions of pest outbreaks which are showcased by recent publications that have come up with pest prediction models using big data (Table 1). This proactive approach not only enhances crop protection but also optimizes resource use and minimizes environmental impact. As technology continues to evolve, integrating big data analytics into pest management strategies will become increasingly essential, fostering sustainable agriculture and ensuring food security in the face of growing global challenges.

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