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Forecasting Model For Decision Making On IPM

KishoreS.M[1], KatlaSowmya[2], MekaAvanija[3] and A.Krishnaveni[4]
[1]-Keladi Shivappa NayakaUniversity of Agricultural & Horticultural Sciences-Shivamogga
[2,3,4]–Professor Jayashankar Telangana State Agriculture University-HYD
Correspondingauthor-kp464751@gmail.com

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Abstract

The host-parasitoid ratio, initial densities, parasitoid release schedules, pesticide dosages and timings, and parasitism and host-feeding levels are just a few of the variables that affect the effectiveness of integrated pest management (IPM) control programmes. Pest management experts have made an effort to apply mathematical theories of population dynamics to assist in the process of developing techniques for suppressing pest populations.

A model is an abstract depiction of a real-world system that exhibits characteristics of the real-world system, according to Manetsch and Park. In the context of pest control, modelling not only aids in population forecasts but also provides solutions for issues pertaining to strategy, tactics, and state selection. FRUTFLY is one such model that has been effective in forecasting the emergence of fruit flies.

This article examines the concepts of simulation, systems, and models and how they relate to managing insect pests. The appropriate emphasis has also been placed on the classification of modelling provided by Jeffers (1978) that works effectively in a pest management scenario.

Introduction

In pest forecasting, a number of the insects' inherent characteristics as well as the variables that determine the environment and host must be taken into account. The phenology of the herbivore and its host is considered in the majority of pest forecast models. Early detection of an imminent pest build-up is made possible in both space and time by the combination of near real-time pest incidence data, remote sensing, and GIS tools. Additionally, gathering and examining meteorological data from regions impacted by pests is crucial for model development. Decision support systems, which are covered in the following sections, facilitate the real-world implementation of model outputs.

Mathematical models specifically created for the purpose of forecasting have produced extremely accurate predictions of pest incidence. By using pesticides only when necessary, preventing resistance, resurgence, and residue, and generating high-quality food products, this can provide excellent outcomes in terms of effective pest management during the most vulnerable stage of the insect life cycle.

Modelling is a powerful mathematical tool that may support management decision-making and be used to build suitable control measures (Tang and Cheke 2008). Pest management experts have tried to apply mathematical theories of population dynamics to assist in the process of developing strategies for the control of pest populations (Plant and Mangel, 1987).

Model and System

A system is something that has parts called units or components that are interdependent and interact with one another, and it has a set of characteristics common to all systems, according to Manetsch and Park (1982). A model is an abstract representation of a real-world system that behaves like the real-world system in certain respects (Miller and Miller 1984). The link between these components is used to build a suitable mathematical expression once these components have been stated in mathematical functions. Because of this, these models

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are dependable resources for forecasting and making decisions.

Modeling in Insect Pest Management

The ability of mathematics to model the pest population is sufficient. Insect pests must be treated on time in agricultural crops, which are regarded as managed ecosystems. To help them in their work, pest control professionals have appropriately emphasised the mathematical theories of population dynamics (Plant and Mangel, 1987).

In practical application, state estimations, tactics selection, and strategy selection are all actually related to the same problem. Thus, any combination of chemical control and the sterile insect approach for the purpose of suppressing or eliminating an insect population is highly effective when choosing a strategy. In a similar vein, choosing the right time to apply a pesticide is considered while discussing strategies selection. Ultimately, the two instances can help to clarify state estimation. Estimating a pest species' population in a given field is the first step, and quickly determining the degree of an invasive pest's infestation is the second.

Strategy Selection

The integrated pest management (IPM) plan is typically the framework in which the IPM concept and strategy selection are carried out. First, the main concepts are that chemical control ought to be applied in conjunction with biological and cultural control, not in lieu of them, and that no control measure ought to be implemented until the degree of insect pest infestation reaches an economic threshold, above which the expense of treatment becomes reasonable.

Not only does mathematical analysis indicate when this approach is suitable, but it also illustrates the optimal combination of chemical controls. A seminal work on eradication or control using sterile insect technique (SIT) was published in 1955 by E. F. Knipling (Knipling, 1955). Choosing a strategy: The pesticide application schedule The farmer must first choose the specific plan of action for controlling an insect pest, then decide the strategies to employ to carry it out.

Pest Forecasting

Farmers can avoid the potential of applying pesticides indiscriminately, minimise their usage, and still achieve effective pesticide effects by using pest forecasting to guide them on the timing of pest incidence (Mahal et al., 2011). The use of statistical techniques such as ANOVA, factorial analysis, regression, and multiple regression is included in these forecasts, and pest forecasting models are particularly helpful in them.

Mahal et al. (2011) discuss the prerequisites needed to construct pest forecasting models, which include the following fundamental data.

- Quantitative seasonal studies entail population sampling and seasonal abundance.
- The subjects of life history and pest biology include feeding, intrinsic growth rate in the lab and field, life span, and survival rate.
- The life cycle of the pest is studied in ecological studies, which are crucial for comprehending the establishment of pest populations, natural mortality factors, and critical stages.
- Crop phenology is influenced by various factors such as plant spacing, irrigation, fertiliser doses, and crop cultivars.
- Natural enemies refer to the population of natural enemies that are present in the crop at different times.
- An agro-ecosystem that incorporates crop diversification and varying cropping patterns with a variety of crops in various age groups provides an appropriate niche for Helicoverpagrowth.

Pest forecasting Models Mustardaphid

The use of the agrometeorological Journal of Entomology and Zoology was assessed in Ludhiana, Punjab, by Dhaliwal et al. (2005) between the years 1988–89 to 1997–98. investigates indicators for Brassica juncea Raya mustard aphid forecasts. The weekly aphid population and humid-thermal ration were shown to be correlated with a formula. With aphid populations ranging from 700 to 1300 aphids/plant, the years 1992–1993 and 1996–1997 were marked by heavy infestation. Every year starting on December 1st, the rising degree days were accumulated.

MOTHZV-Computer based Simulation Model

The population dynamics of Helicoverpa species are predicted by the computer-based simulation model MOTHZV (Witz et al., 1985). The number of eggs, larvae, or adults in the early season is used by the model to predict the size and timing of a later, possibly harmful population. The ability to measure the early season population of adult Helicoverpa has been made possible by pheromone traps. The MOTHZV model uses this trap data, crop phenology, and climate variability to forecast when future Helicoverpa generations will occur.

Degree Day Model of Helicover Paarmigera

Dalal (2014) experimented on Helicoverpaarmigera at diverse temperatures that alternated between 25: 10 and 30: 16 ˚C in order to determine the precise timing of the development of the insect's egg, larval, and pupal stages. This experiment recorded observations about the developmental times of several immature stages. It was discovered that the mean development temperature had an inverse relationship with the development of immature phases. Given that the experiment was carried out under a changing temperature regime.
Step1involvedthecalculationofmeanvalueoftemperaturewhichutilizedformulae.

Mean Temperature

[(maximumtemperature xNo.ofhrs) +(minimumtemperaturexNo. ofhrs)]/24
Step2involvedthecalculationofdevelopmentthresholdtemperatureinwhichlinearregressionequation(y=a+bx) isformedforeveryimmaturestageofinsect,whichisarelationship between development rate(y) and temperature (x) which estimate developmentthreshold temperature for different immature stage. The values for lower threshold temperaturecan be estimated as per the equation by Campbell et al. (1974). Dalal and Arora (2016) haspredictedmorefoodconsumption byH.armigeraon tomatocrop leading tomoredamage.

FRUFLY Model

The whole life cycle of the fruit fly, Ceratitis capitata, is represented by the dynamic population model FRUFLY (Messousiet al., 2008). The model establishes the best possible behaviour for each component of the system across its life cycle, adjusting for limiting factors such as humidity, temperature, parasitism, and predation. Using the FRUFLY degree day model, the dynamics of the population were examined by examining the impact of temperature on the immature stage developmental times of the medfly, Ceratitis capitata. Para-pheromone traps were used to study flight activity in order to evaluate the model in the field.The FRUFLY model simulations predict the appearance of successive adult generations over time and agree with experimental data results of the insect obtained using para-pheromone traps. A useful technique for estimating the size of insect pest populations and figuring out when to implement treatment measures is FRUFLY simulation modelling.

Area Wide Pest Management(AWPM)

The term "area-wide insect control programme" refers to a long-term planned campaign aimed at lowering the population of nuisance insects in a reasonably large pre-specified area to a non-economic status, as described by Lindquist (2001).

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Models To Be Followed For Awpm

Two primary scenarios were taken into consideration during the development of the prototype model, which serves as the foundation for a decision-support tool to determine the minimal size of an intervention area necessary for the creation of a pest-free area:

:Two things are happening in the control area

(it is growing in accordance with the "Rolling-carpet principle" as stated in (Barclay *et al.,* 2011 (1)

.it is fixed in size (fixed-area model) and there is no extending pest control front (2)

Various Pest forecasting models around the world

Forecasting Models	Insect	Parameters	Country
Ordinal logistic Model	Whitefly, Pyrilla and Fruit fly	Max temp, Min temp. and RH	India
CLIMAX	*.Helicoverpa sp*	Temperature and humidity	Australia
SOPRA	*Dysaphisplantaginea and Grapholithalobarzeweskii*	Air and soil temperature	Switzerland
FLYPAST	*Aphis fabae*	Suction trap data	UK
NAPPFAST	*Scirtothrips dorsalis*	Degree days and cold temp. survival	USA

Monitoring and Forecasting

Crop challenges like nutrient deficiencies, pest infestations, disease developmentand drought monitoring can all be identified with the help of remote sensing technology. Numerous responses, such as leaf curling, wilting, chlorosis or necrosis of photosynthetic plant parts, stunted development, and, in certain situations, a decrease in leaf area due to severe defoliation, are possible responses of plants to pest and disease stress. The quantity and quality of electromagnetic radiation reflected from plant canopies will be impacted by various plant responses, even if many of them are challenging to measure visually with reasonable degrees of accuracy, precision, and speed.

It will take improved aerial imagery standardisation and consideration of disruptive environmental conditions to enable the use of remote sensing techniques for early pest detection.

(2009) Luedelinget al. Furthermore, due to the high expenses associated with airborne data collecting, only a small number of high-value crops are able to benefit from it.

Conclusions

The basis for the creation and verification of pest forecast models, decision support systems, and early warning systemsall essential for the planning and execution of effective integrated pest management (IPM) programsis pest monitoring. The information and understanding now available on the population dynamics of pests in agroecosystems and natural environments can be combined using models. The establishment of agro-meteorological networks for particular crop sectors is imperative in developing nations, with the primary goal being the use of models and decision support systems for pest forecasting.

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References

Agrawal R, Mehta SC. Weather Based Forecasting of Crop Yields, Pests and DiseasesIASRIModelsJournal Indian SocietyAgricultural Statistics2007; 61:255-263

Dhaliwal LK, Hundal SS, Kular JS. Use of agrometeorological indices for forecasting ofMustardaphid (Lipaphiserysimi). Journal Agrometerology. 2005; 7:304-306.

Joshi LM, Srivastava KD, Singh DV. Monitoring of wheat rusts in the Indian sub-continent.Proceedings: Plant Sciences, 1985; 94(2-3): 387-406.

Knight JD, Tatchell GM, Norton G, Harrington R. FLYPAST: an information managementsystemforRothamstedAohidDatabasetoaidpestcontrolresearchandadvice.CropProtection.1992;11:419-26.

Knipling EF. Possibilities of insect control or eradication through the use of sexually sterilemales.Journal of EconomicEntomology.1955; 48:459-62.

Kumar M, Gupta A. Effect of weather variables on white fly (Bemisiatabaci Gennadius)population in development of potato apical leaf curl virus disease. Journal Agrometerology.2016;18(2):288-291.

Lactin DJ, Holliday N, Johnson D, Craigen R. Improved rate of model of temperature-dependentdevelopmentby arthropods.Environmental Entomology.1995;24:68-75.

Manetsch TJ, Park GL. System Analysis and Simulation with Application to Economic andSocialSystems.EngineeringLibrary,MichiganStateUniversity,EastLansing,Michigan.1982, 52

Miller GG, Miller JL. The earth as a system. In: Richardson, J. (ed.) Models of RealityShaping T Plant RE, Mangel K. Modeling and simulation in agricultural pest management.SIAMRevolution. 1987; 29:235-261.

Rehman, Ateeq Ur, Sobia Chohan, Syed Hasnain Abbas. Bacterial leaf blight of rice: adiseaseforecastingmodelbasedonmeteorologicalfactorsinmultan,pakistan.JournalAgriculturalResearch. 54(4): 707-718.