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Research Paper

Weather based forewarning model for cotton pests using zero-inflated and hurdle regression models

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ABSTRACT

Early forewarning of crop pest based on weather variables provides lead time to manage impending pest attacks that minimize crop loss, decrease the cost of pesticides and enhance the crop yield. This paper is an attempt to forewarn incidence of Cotton pests using weather variables. The pest incidence data from 2015 to 2023 for Aphids, Jassids, Thrips, and Whiteflies has been used for the study. The pest incidence being count variable, different count regression models such as zero inflated Poisson & negative binomial, hurdle Poisson & negative binomial, negative binomial and generalized Poisson regression models have been developed for forewarning of pests. Results indicated that zero inflated Poisson regression model outperformed the other models with improved performance of nearly 30 to 75%. Thus, the zero inflated Poisson regression model is a reliable tool in prediction of cotton pests, thereby aiding towards better pest management strategies.

Keywords: Pest Management, Climate Change, Forecasting, Crop Yield, Regression.

Agriculture is the pillar of the Indian economy that contributes 50% to the survival of Indian population. Cotton is an important commercial crop in India, contributing over 30% of the foreign exchange of the country (Aggarwal *et al.,* 2007). India ranks first in cotton area cultivation among all other countries in the world. Even though it ranks first in area, it ranks 39th in yield. The low yield of cotton is caused by some serious constraints, particularly lack of timely crop protection measures leading to the serious pest outbreaks (Aggarwal *et al.,* 2007). Several farmers use excess amounts of pesticides to control the crop pests as plan protection measures. In this process, the quality of the soil tends to degrade after a certain period (Kapoor *et al.,* 2025). So, proper prediction of crop pests can help farmers to decide the amount of pesticide to use on the soil, which helps to maintain the soil quality. By forewarning the pest, one can take preventive measures to control the occurrence of pests and improve crop yield. Climate variables like temperature, humidity, rainfall, *etc.* are the major factors for the growth, development and multiplication of pests. The development of a proper forewarning model using weather variables can help to prevent the outbreaks of pests and improve the crop yield. Various researchers have developed weather-based forecasting models for the crop disease (Garain *et al.,* 2021; Vaidheki *et al.,* 2023; Johnson and Chandrakumar, 2024) and population dynamics of crop pest (Sarkar *et al.,* 2023; Singh *et al.,* 2024; Manikandan and Rengalakshmi, 2024).

Pest incidence is usually a count variable. In analysing count dependent variables, count regression models like negative binomial, generalized Poisson, zero-inflated and hurdle models are used commonly. Researchers have used and compared zero inflated, hurdle and negative binomial regression models in different fields like modelling butterfly count (Jamil *et al.,* 2017), modelling malaria incidence in three endemic regions (Diao *et al.,* 2023). The present study uses count regression models for forewarning the pest incidence, which overcomes the drawbacks of linear regression that is commonly used.

MATERIALS AND METHODS

Data description

To develop the forewarning model, data of population dynamics of Cotton pests such as Aphid, Jassid, Thrips and Whitefly have been used. Standard weekly data on the incidences (number per three leaves) of Coimbatore from 2016-17 to 2022-23

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for Aphids and from year 2015-16 to 2022-23 for Jassids, Thrips, Whiteflies were collected from various reports of the All India Coordinated Research Project (AICRP) of Cotton and used for the study. Since crop pests are influenced by weather, weekly weather data of variables such as minimum temperature (°C), maximum temperature (°C), relative humidity morning (%), relative humidity evening (%) and rainfall (mm) were used as independent variables for the development of forewarning models.

Sinusoidal and spline terms in regression models

The pest incidence contains complexity like non-stationarity and non-linearity. A widely used technique to transform non stationary data into stationary is differencing. But the disadvantage of differencing is after differencing, it may contain negative integers. Negative integer terms cannot be used for count regression model. A suitable alternative method of modelling non stationary data is to add trend and seasonal component as independent variables to the regression model. The trend data is fitted by time polynomial and seasonal component is fitted by Fourier terms including sine and cosine (Box *et al.,* 2003). The formula to be included in regression model is as follows (Stolwijk *et al.,* 1999),

$$f(t) = \sin\left(\frac{2\pi t}{T}\right) + \cos\left(\frac{2\pi t}{T}\right) \qquad (1)$$

where, T is total number of time periods (18 weeks), t is time period (1st week, 2nd week, …, 18th week)

Table 1 gives the description of variables including time and seasonal terms used for the development of model.

The nonlinearity in the data is captured by spline function using B-splines. Hence, the regression model using cubic spline with one knot will be in the form;

$$y = \beta_0 + \beta_{11}X_1 + \beta_{21}X_1^2 + \beta_{31}X_1^3 + \beta_{12}X_2 + \beta_{22}X_2^2 + \beta_{32}X_2^3 + \beta_{13}X_3 + \beta_{23}X_3^2 + \beta_{33}X_3^3 + \beta_{14}X_4 + \beta_{24}X_4^2 + \beta_{34}X_4^3 + \beta_{15}X_5 + \beta_{25}X_5^2 + \beta_{35}X_5^3 + \beta_t \times time + \beta_s \times season + \epsilon \qquad (2)$$

Hence, count regression model is developed using these functions for forewarning pest incidence.

Zero inflated and hurdle regression models

For modelling count data, linear regression model is not suitable because the residuals are neither normally distributed nor homoscedastic (Martin, 2021). So, use of count regression model would be more suitable for modelling pest data. Poisson regression model is known as a benchmark model for modelling count dependent variable (Jamil *et al.,* 2017). Poisson regression which follows Poisson distribution has a property called equidispersion where the mean and variance are the same. But in many real-life data, often the variance is larger than mean which is known as overdispersion. For modelling overdispersion data, negative binomial and generalized Poisson regression would be a good alternative. If our data has large number of zeros, those models would not perform well. Modelling dependent variables with excess zeros is more complicated, which cannot be achieved by ordinary count models. So, models like zero-inflated and hurdle models are used for modelling data with excess zero. The zero-inflated model contains two parts; one predicts structural zeros and other predicts the remaining counts (Martin, 2021). The count part is modelled with Poisson or negative binomial distribution and zero data is modelled using logistic regression. Zero-inflated Poisson models are defined as:

$$P(Y_i = 0) = p_i + (1 - p_i)\exp(-\mu_i) \qquad (3)$$

$$P(Y_i = k) = \frac{(1-p_i)\exp(-\mu_i)\mu_i^k}{k!}, k \geq 1 \qquad (4)$$

Equation (3) and (4) gives the probability distribution for zero and count data respectively. In hurdle model, the count data is modelled using zero-truncated Poisson or negative binomial distribution and the zeros are modelled using logistic regression. The hurdle Poisson regression model is defined as;

$$P(Y_i = 0) = 1 - \pi \qquad (5)$$

$$P(Y_i = k) = \frac{\pi_i \mu_i^k}{k!(e^{\mu_i} - 1)}, k \geq 1 \qquad (6)$$

Similar to ZIP, equation (5) and (6) defines the probability distribution of zero and count data respectively.

Goodness of fit measures

To evaluate the performance of the models, goodness of fit measures like Root mean squared error (RMSE), Mean squared error (MSE), Mean absolute error (MAE), Predicted residual error sum of square (PRESS) are used.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad (7)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (8)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (9)$$

$$\text{PRESS Statistic} = \sum_{i=1}^{n}[y_i - \hat{y}_i]^2 \qquad (10)$$

where, n- number of observations y_i – actual value and $\hat{y}_i$ – predicted value

Table 1: Description of independent variables

Notation	Variable	Units
Y	Pest incidence	Pest no. /3 leaves
X_1	Rainfall	mm
X_2	Minimum temperature	°C
X_3	Maximum temperature	°C
X_4	Relative humidity morning	%
X_5	Relative humidity evening	%
X_t	Time	week
X_s	Season	week

RESULTS AND DISCUSSION

Summary statistics

Table 2 gives the summary statistics for pest incidence of sucking pests. The 0.00 value in minimum signifies that many

Table 2: Summary statistics of pest incidence

Statistics	Aphids	Jassids	Thrips	Whiteflies
Mean	5.08	5.45	3.29	0.76
Variance	28.31	25.36	16.45	0.86
Minimum	0.00	0.00	0.00	0.00
Maximum	28.60 (2022-45)	18.64 (2017-2)	14.94 (2020-45)	4.37 (2020-45)

Note: Numbers in the bracket indicates the year and SMW

weeks has no influence of sucking pests in the crop. Here, variance of all pests is larger than mean. This phenomenon is called as overdispersion. The major assumption of Poisson regression is that mean and variance are equal. Therefore, alternative models like zero inflated models, hurdle models and generalised Poisson, negative binomial regression can be used for predicting overdispersion count data.

To further prove that many weeks has 0 counts, histogram for the pest incidence is presented in Fig. 1. From histogram it is clear that the pest incidence data has many zero values. Since the data is count data and have many 0 values, zero inflated and hurdle models would be suitable for modelling the pest incidence data.

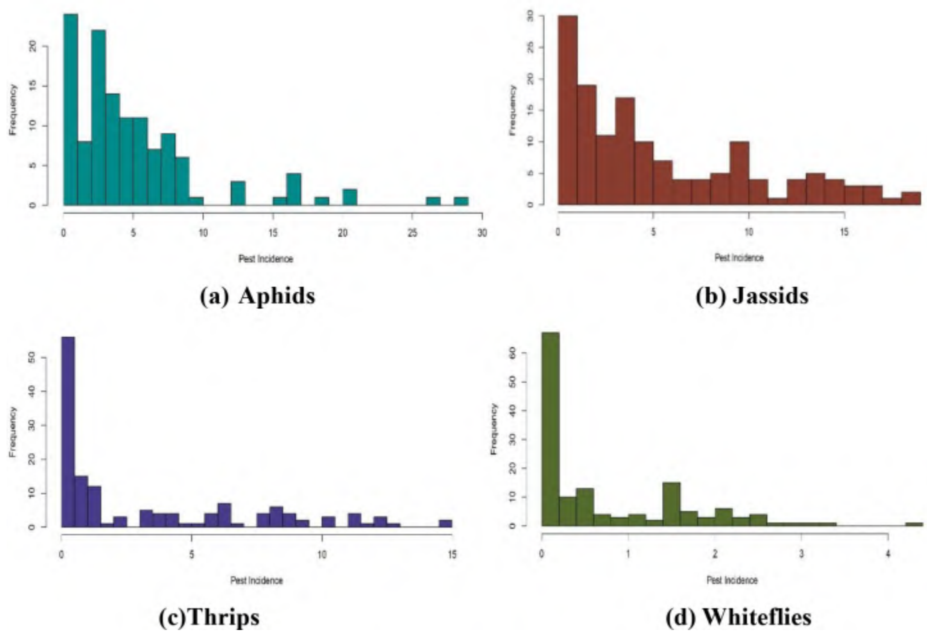

Fig. 1: Histogram plot for All Pests

Count regression model and goodness of fit measures

Utilizing count regression models described in the materials and methods, the forewarning model for pest incidence is developed using weather variables, time, and season as independent variables with spline functions. To assess the performance of models, goodness of fit measures like RMSE, MSE, MAE and PRESS Statistic are used. The estimated parameter of models along with the goodness of fit measures for Aphids, Jassids, Thrips and Whiteflies are presented in Tables 3, 4, 5, and 6 respectively.

From the estimated parameters, log(μ) gives the equation of model for count data, which is modelled by negative binomial (NB), generalized Poisson (GP), zero inflated Poisson (ZIP), zero inflated negative binomial (ZINB), hurdle Poisson (HP) and hurdle negative binomial (HNB) regression. Since zero inflated and hurdle models also have zero data, the model for zero data is given as logit(π), which is modelled using logistic regression. To assess the performance of count models, it is compared with linear regression using spline terms (SR). Since the regression equation is in the form of log, the exponential of the coefficients is calculated known as incidence ratio rate (IRR). The IRR is interpreted as the rate of change in the predicted number of outcome events for a one-unit variation in the predictor. From the regression equation it is clear that the independent variables like minimum, maximum temperature, time and seasonal term influence the pest incidence. Time and seasonal components are the major cause of prediction in zero data.

Low error metric values give the best model for forewarning. From the goodness of fit it is clear that zero inflated Poisson (ZIP) regression model have lower RMSE, MSE, MAE, PRESS values. Hence, it can be defined that ZIP model have performed better than other models in forewarning pest incidence for all pests. The percentage of improvement is computed in order to assess the ZIP model's performance.

Old model accuracy = 20.49, New model accuracy = 16.62

The improved percentage is = (Difference between old model and new model accuracy/old model accuracy) *100%

= [(20.49-16.62)/20.49] *100 = 18.88%

With this formula the percentage improvement of ZIP

Table 3: Estimated parameters and goodness of fit measures for aphids

Model	Equation	RMSE	MSE	MAE	PRESS
Spline terms (SR)	$Y_A=2.26+9.1X_1^{3*}+16.46X_2^{2*}+31.16X_4^*$	4.53	20.49	3.17	2581.8
Negative binomial (NB)	$\log(\boldsymbol{\mu}_A) = 1.2 + 8.03X_2^{2*}-0.04X_t^*-0.02X_s^*$	4.42	19.5	2.97	2457.5
Generalized Poisson (GP)	$\log(\boldsymbol{\mu}_A) = -1.62 +7.81X_2^{2*}+57.69X_4^*$	4.47	19.98	3.1	2518.7
Zero inflated Poisson (ZIP)	$\log(\boldsymbol{\mu}_A)= 1.31 - 0.86X_2^* +7.17X_2^{2*} + 3.35X_3^{2*} - 1.61X_5^{3**}$ $\text{logit}(\pi_A) = -8.37-0.65X_t^{**}+1.66X_s^{**}$	**4.07**	**16.62**	**2.76**	**2094.6**
Zero inflated negative binomial (ZINB)	$\log(\boldsymbol{\mu}_A) = 1.68+1.18X_1^{3*}-0.012X_t^{**}$ $\text{logit}(\pi_A) = - 0.008 - 0.091X_t^*+2.05X_s^*$	4.25	18.08	2.83	2279.3
Hurdle Poisson (HP)	$\log(\boldsymbol{\mu}_A) = 0.97+7.1X_2^{2*}+3.35X_3^{2*}-1.67X_5^{3**}$ $\text{logit}(\pi_A) = 8.3 + 0.044X_t^{**}-1.14X_s^*$	4.15	17.18	2.83	2164.62
Hurdle negative binomial (HNB)	$\log(\boldsymbol{\mu}_A) = 1.16+1.19X_3^{3*}-3.06X_5^*-0.013X_t^{**}$ $\text{logit}(\pi_A) = 8.3 + 0.04X_t^{**}-1.14X_t^*$	4.31	18.59	2.92	2342.82

Table 4: Estimated parameters and goodness of fit measures for jassids

Model	Equation	RMSE	MSE	MAE	PRESS
Spline terms (SR)	$Y_J=12.28- 42.64X_3^*-16.59X_4^{**}-11.82X_4^{3*} + 9.81X_5^{2*}+0.94X_s^*$	4.21	17.71	3.36	2549.9
Negative binomial (NB)	$\log(\boldsymbol{\mu}_J) = 1.88 + 2.09X_2^{2*}-15.43X_3^{**}-4.16X_5^* +2.12X_5^{2*}$	4.92	24.23	3.37	3485.3
Generalized Poisson (GP)	$\log(\boldsymbol{\mu}_J) = -1.62+2.74X_1^{2*}-1.59X_1^{3*}-15.79X_2^{**} - 3.31X_4^{3*}$	6.11	37.31	3.63	5373.2
Zero inflated Poisson (ZIP)	$\log(\boldsymbol{\mu}_J) = 0.46 - 0.72X_1^*+1.25X_1^{2*}-1.23X_1^{3*} +5.55X_2^{**}$ $\text{logit}(\pi_J) = -3.91 - 5.16X_1^{2*}+4.35X_2^*$	**4.15**	**17.33**	**3.16**	**2498.9**
Zero inflated negative binomial (ZINB)	$\log(\boldsymbol{\mu}_J) = 0.82 +7.99X_2^*-4.27X_t^*+0.02X_s^*$ $\text{logit}(\pi_J) = -0.0039 - 0.04X_t^*+0.75X_s^*$	4.48	20.11	3.22	2895.7
Hurdle Poisson (HP)	$\log(\boldsymbol{\mu}_J) = -3.1- 0.7X_1^*+1.3X_1^{2*}-1.3X_1^{3*}-7.7X_3^{**} -1.3X_3^{3**}$ $\text{logit}(\pi_J) = 3.88 - 0.026X_t^*$	4.17	17.37	3.18	2501.04
Hurdle negative binomial (HNB)	$\log(\boldsymbol{\mu}_J) = -5.101+11.56X_2^*-41.75X_4^*-4.19X_5^* + 0.21X_s^*$ $\text{logit}(\pi_J) = 3.88 - 0.026X_t^*$	4.38	19.18	3.27	2763.33

Table 5: Estimated parameters and goodness of fit measures for thrips

Model	Equation	RMSE	MSE	MAE	PRESS
Spline terms (SR)	$Y_T = -0.17+0.02X_t^*+0.84X_s^*$	3.41	11.61	2.57	1671.6
Negative binomial (NB)	$\log(\mu_T)= -3.88+0.02X_t^{**}+0.36X_s^*$	4.48	20.11	2.79	2895.4
Generalized Poisson (GP)	$\log(\mu_T)= -0.85+26.28X_2^*-6.66X_2^{2*}+0.44X_s^{**}$	3.35	10.94	2.67	1531.9
Zero inflated Poisson (ZIP)	$\log(\mu_T)= 3.16+1.15X_1^*-10.41X_5^{**}+4.22X_5^{2**}-14.13X_5^{3**}$ $\text{logit}(\pi_T) = -3.48 + 2.89X_t^{**}$	**3.24**	**10.51**	**2.21**	**1513.1**
Zero inflated negative binomial (ZINB)	$\log(\mu_T) = 3.16+1.33X_1^*-10.68X_5^*-14.91X_5^{3*}$ $\text{logit}(\pi_T) = -3.47 + 0.029X_t^{**}$	3.28	10.75	2.31	1547.6
Hurdle Poisson (HP)	$\log(\mu_T) = -5.81+1.03X_1^*-8.58X_5^{**}-11.47X_5^{3*}$ $\text{logit}(\pi_T) = 3.46+7.03X_5^{2*}+0.019X_t^*$	3.33	11.14	2.41	1604.08
Hurdle negative binomial (HNB)	$\log(\mu_T) = -7.93+1.16X_1^*-8.62X_5^*+0.33X_s^{**}$ $\text{logit}(\pi_T) = 3.46+7.03X_5^{2*}-0.019X_t^*$	3.38	11.48	2.41	1654.28

Table 6: Estimated parameters and goodness of fit measures for whiteflies

Model	Equation	RMSE	MSE	MAE	PRESS
Spline terms (SR)	$Y_w = -0.87 + 6.55 X_4{}^{*}$	0.89	0.79	0.67	114.82
Negative binomial (NB)	$\log(\boldsymbol{\mu}_w) = -31.87+1.52X_2{}^{2*}+11.71X_2{}^{2*}$	0.88	0.78	0.65	111.96
Generalized Poisson (GP)	$\log(\boldsymbol{\mu}_w) = -2.28 + 1.52X_1{}^{2*}+4.11X_4{}^{3*}$	0.88	0.77	0.65	111.94
Zero inflated Poisson (ZIP)	$\log(\boldsymbol{\mu}_w) = 4.19 - 0.011X_t{}^{**}-0.51X_s{}^{**}$ $\text{logit}(\pi_w) = 2.29 - 0.61X_t{}^{*}-7.88X_s{}^{*}$	**0.72**	**0.52**	**0.51**	**75.87**
Zero inflated negative binomial (ZINB)	$\log(\boldsymbol{\mu}_w) = -3.3 - 0.011X_t{}^{**}-0.511X_s{}^{**}$ $\text{logit}(\pi_w) = 2.98 - 0.42X_t{}^{*}-5.55X_s{}^{*}$	1.41	1.96	0.62	282.7
Hurdle Poisson (HP)	$\log(\boldsymbol{\mu}_w) = -2.21 +5.38X_2{}^{2*}-0.49X_s{}^{*}$ $\text{logit}(\pi_w) = -2.89+2.42X_2{}^{2*}-0.31X_s{}^{*}$	1.19	1.43	0.79	207.22
Hurdle negative binomial (HNB)	$\log(\boldsymbol{\mu}_w) = -1.79 +3.82X_5{}^{3*}-0.0012X_t{}^{*}$ $\text{logit}(\pi_w) = -2.89+2.42X_2{}^{2*}-0.32X_s{}^{*}$	1.17	1.37	0.79	197.29

* Significant at 5% level; ** Significant at 1% level

models compared to all models have been calculated. The result revealed that, ZIP model performs better than SR, NB, ZINB, HP, HNB and GP models by 18.88%, 14.76%, 8.07%, 3.25%, 10.59% and 16.81% respectively for pest incidence of aphids. For forewarning pest incidence of jassids, ZIP performed better than SR, NB, ZINB, HP, HNB and GP models by 2.14%, 28.36%, 13.82%, 0.23%, 9.8% and 53.55% respectively. In modelling pest incidence of thrips ZIP performed better than other models by 9.47%, 47.73%, 2.23%, 5.65%, 8.44% and 3.93%. For Whiteflies, ZIP model performs better than SR, NB, ZINB, HP, HNB and GP models by 34.17%, 33.33%, 73.46%, 63.63%, 62.04% and 32.46% respectively. From this percentage, it is clear that ZIP performed better than other models nearly 30 to 70%.

CONCLUSION

Weather-based forewarning models have been developed using count regression models. The study highlights the significant influence of weather variables like rainfall, minimum, maximum temperature and relative humidity morning and evening on the incidence of cotton pests such as aphids, jassids, thrips and whiteflies. Population dynamics of pests show a significant correlation to weather parameters like minimum and maximum temperature. Different count regression models are compared and the zero-inflated Poisson regression model outperformed other models by nearly 30 to 75% in efficiency of forewarning. Thus, the officials and government authorities in the agriculture department can make use of these weather-based forewarning models to help the farmers in effective pest management.

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