Modelling the relationship between weather variables and Yellow Stem Borer population: A count data modelling approach

Abstract

Aim: This study was conducted to model the relationship between discrete dependent variable (yellow stem borer population) and continuous weather variables

Data description: The yellow stem borer (YSB) population and standard meteorological week (SMW) wise weather variables (temperature, relative humidity, rainfall and sunshine hours) data of Warangal centre (Telangana state) generated under All India Co-Ordinated Rice Improvement Project (AICRIP) from 2013-2021 were considered for the study. The YSB population were recorded daily using light trap with an incandescent bulb and are counted as weekly cumulative catches.

Methodology: The weekly cumulative trapped YSB populations and weekly averages of climatological data were considered as inputs to the models under consideration. In this study the classical linear regression i.e. step-wise multiple linear regression and count regression models such as Poisson, negative binomial, zero inflated Poisson and zero inflated negative binomial regression models were employed.

Result: The empirical results revealed that the zero inflated count regression models viz., zero inflated Poisson regression and zero inflated negative binomial regression models performed better compared to the classical linear regression, Poisson and negative binomial regression models, further the negative binomial regression model outperformed all models which as it provides lowest mean square error (MSE) and highest R^2 values.

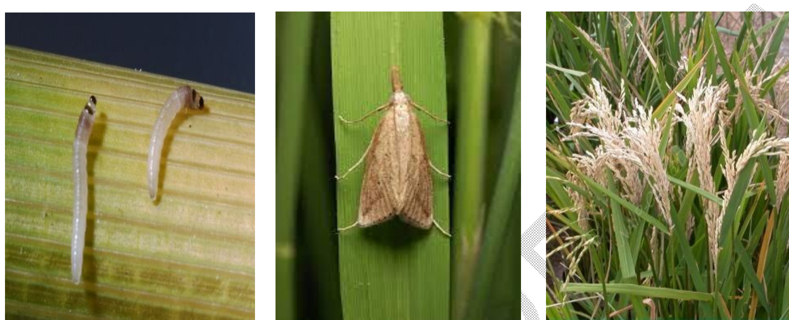
Conclusion: Based on the results obtained in this study, it is concluded that the zero inflated models performs better compared to classical models as they are unable to handle the presence of excess zeroes, as a result provides more prediction error and lower R^2 values. Further, the models developed in this study will be of great assistance in identifying the factors influencing occurrence of YSB population in rice.

Keywords: Yellow stem borer; light trap catches; weather variables; linear regression, count regression models; zero inflated count regression models

1. INTRODUCTION

Rice (*Oryza sativa*) is the most staple food crop of India and Asian continent. India has the largest rice-growing area in the world, covering an area of 44 million hectares and producing 112 million tons of rice [1]. The insect pest complex of rice crop has undergone a drastic change during the last three decades following green revolution. The losses in rice yield are due to moderate to severe incidence of stem borer, gundhi bugs, hoppers and other insect pests in India. The intensity of insect pest damage varies in different seasons, years and agro-climatic zones due to variability in weather parameters and biotic factors. Yellow Stem

Borer (YSB) *Scirpophaga incertulas* Walker has emerged as one of the most important pests of rice during post green revolution years throughout the country and damage of YSB can lead to about 20 % yield loss in early planted rice crops and 70 % in late planted crops. The YSB larva lives inside the rice stem and grows for a period of 40 days and pupates inside the stem in a white silken cocoon and later becomes adult YSB. The YSB larvae bore at the base of the plants during the vegetative stage. On older plants, they bore through the upper nodes and feed toward the base. The larva YSB, adult YSB and damage symptoms of yellow stem borer infected rice are depicted in Figure 1.



(a) (b) (c)

Figure 1. (a) Larva yellow stem borer (b) Adult yellow stem borer (c) Symptoms of yellow stem borer infected rice.

Both biotic and abiotic factors are believed to be responsible for pest population dynamics [2]. Besides inherent biotic potential of the insect to a large extent abiotic factors like temperature, rainfall, relative humidity, sunshine hours etc. determine the abundance of insect pests in a crop ecosystem. An efficient forewarning system based on robust statistical model to predict YSB population dynamics is of great importance in designing and implementation of effective location specific pest management strategies to avoid yield losses [3]. Count regression modelling is a popular approach employing in understanding the relationship between the discrete dependent count variables and continuous or discrete exogenous variables. Crop pest modelling is one of the major areas of count data regression modelling wherein daily or weekly counts of insects (pests), are considered as dependent variables and corresponding weather variables are considered as exogenous variables.

Though the count regression data modelling approach is applied in many areas; Identifying defects in manufacturing [4], In domestic violence data [5], caries research [6], spontaneous abortion [7], modelling of death due to covid-19 in Ghana [8] and zoological data [9] Contrary to count regression modelling, the continuous linear regression model was applied in many insect pest modelling and as well as in agricultural data sets; weather based regression modelling of white rust disease of Indian mustard [10], regression modelling factors influencing agricultural diversification of Karnataka[11], regression modelling of biometrical characters in Sesame [12], regression analysis of growth patterns of root and shoot morphological traits in Sesame [13], weather based YSB regression model [14], modelling of YSB population under changing climatic scenarios [15].

Crop pest modelling is one of the popular areas of discrete regression modelling wherein daily or weekly counts of insects or pests which are considered dependent variable. As the YSB population will not occur regularly on daily basis there use to be many zeroes in weekly count data under such condition the classical regression and count regression models may not yield better results alternatively zero excess count regression models can be used to model the data with excess zeroes. With this background, this study was undertaken to develop zero excess count regression models using data driven approaches. Further, the paper is arranged in different sections; the data description and statistical models used viz., stepwise regression model, Poisson regression, Negative binomial regression model and their counter parts such as zero inflated poison regression model and zero inflated negative binomial regression models are explained in methodology section. The results obtained under each section are depicted and discussed in results and discussion section and finally the outcome of the work are highlighted in conclusion section.

2. MATERIAL AND METHODS

2.1. Data description

The weekly cumulative catches of YSB population was recorded from light trap installed at All India Coordinated Rice Improvement Project (AICRIP), PJTSAU-Regional Agricultural Research Station, Warangal centre. Corresponding climatological data on maximum temperature (MAXT), minimum temperature (MINT), total rainfall (RF), morning relative humidity (RHM), evening relative humidity (RHE) and sunshine hours (SSH) were also collected from weather stations installed at Warangal centre. Standard meteorological week (SMW)-wise cumulative catches of YSB population and weekly averages of climatological parameters from 2013-2021 were considered for this study. The required data for this study were taken from AICRIP ICAR-Indian Institute of Rice Research Hyderabad. The study area is depicted in following Figure 2.

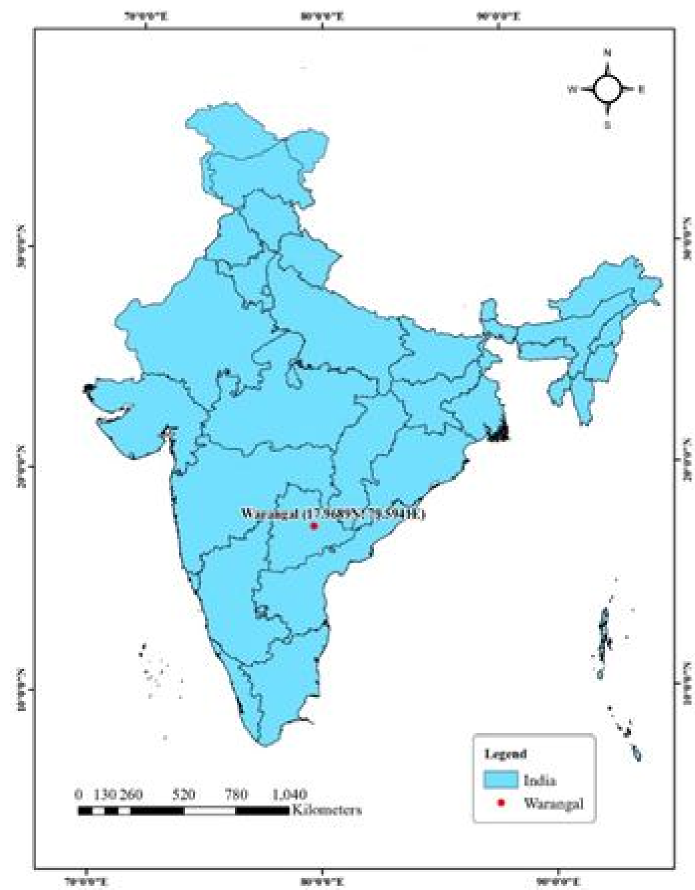


Figure 2. Location map of Warangal centre (study area)

2.2. Statistical Models

In this work statistical modelling framework begin with summary statistics where data distribution and heterogeneity among the data in terms of coefficient of variation (CV) is explained. The SMW-wise data from 2013-2021 is depicted graphically with time series plots. The correlation analysis was carried out to understand the interrelationship between the YSB population and other exogenous variables. Further, the stepwise multiple linear regression (MLR) was carried out know the cause and effect relationship between YSB population and independent weather variables.

The regression equation in terms of matrix notation can be expressed as;

$$Y = X\beta + e \qquad \text{... (1)}$$

where, Y is the dependent variable, X is the vector of exogenous variables, β is the regression coefficient vector, and e is the residuals term.

Correlation analysis and stepwise MLR analysis were carried out in SAS version 9.3 available at ICAR- Indian institute of Rice research Hyderabad [16]. The count regression models were built in R software [17].

2.2.1. Count regression models

The count data observations following generalized linear model (GLM) framework was elaborated in terms of Poisson and Negative binomial regression models as follows;

Poisson Regression Model

The Poisson regression model is derived from Poisson distribution where mean and variances are equal. A discrete random variable Y is said to follow Poisson distribution with parameter $\lambda > 0$, if its probability mass function (*pmf*) is given as follows;

$$f(Y = y) = P_r(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \qquad \dots (2)$$

where the mean and variance expression of the distribution is $E(y) = \sigma^2{}_y = \lambda$, changes in means also influence the changes variance [4]. The Poisson regression model is expressed as follows;

$$y_i = \exp(X_i{}'\beta) + \varepsilon_i \qquad \dots (3)$$

The parameters of Poisson regression models are estimated using maximum likelihood estimation method.

Negative Binomial Regression Model

The Negative binomial regression is a class of generalized linear model where the discrete dependent variable Y is over dispersed. This model is applied to over dispersed count or to the count data where conditional variance is greater than conditional mean. The negative binomial distribution has same mean structure as Poisson distribution and has additional over distribution parameter ϕ.

Let Y be a random variable follows negative binomial distribution with parameters (r, θ), where θ ∈ (0, 1) and r an integer, then its *pmf* is given as

$$\boldsymbol{P(Y = y) = \binom{y+r-1}{y}} \Theta^{y}(\boldsymbol{1} - \Theta)^{r}, \boldsymbol{y = 0, 1, 2} \quad y \sim NegBin\,(r, \theta) \qquad \dots (4)$$

$$\boldsymbol{E(Y) = \frac{r\Theta}{(1-\Theta)} \; and \; Var\,(Y) = \frac{r\Theta}{(1-\Theta)^2}}$$

If the conditional distribution of the outcome variable is over-dispersed, then confidence interval of the negative binomial distribution is shorter than the Poisson distribution [6].

2.2.2. Zero inflated count regression models

The count data observations contain excess zeroes in the data sets, then the regular count regression models unable to estimate the parameters properly, then one has to switch to the model which considers the excess zero in the data, called as zero inflated count regression models [18].

In zero inflated Poisson (ZIP) regression model, the counts Yi=0 with probability pi and 1- pi which follows Poisson distribution with mean μ_i where i=0,1,2…,n. The zero inflated Poisson regression model is a mixture of two components i.e. zero and no-zero components.

$$P(\mathbb{Y} = \mathbb{y}) = \begin{cases} \mathcal{P}_{\mathbb{i}} + (1 - \mathcal{P}_i)e^{-\mu_i} & \mathcal{Y}_{\mathrm{i}} = 0 \\ (1 - \mathcal{P}_i)\frac{e^{-\mu_i}\mu_i^{\mathbb{y}_i}}{\mathbb{y}_i} & ,\mathcal{Y}_i = 1,2,3 \end{cases} \quad \ldots(5)$$

The zero inflated negative binomial (ZINB) model is a mixture distribution which assigns p to ‘extra’ zeros and a mass of (1 − p) to a negative binomial distribution, where 0 ≤ p ≤ 1. The probability mass function for ZINB is expressed as follows;

$$P(\mathbb{Y} = \mathbb{y}) = \begin{cases} \mathcal{P} + (1 - \mathcal{P})\left(\frac{\phi}{\mu+\phi}\right)^{\phi} & y = 0 \\ (1 - \mathcal{P})\frac{\tau(\mathcal{Y}+\phi)}{\tau(\mathcal{Y}+1)\mathcal{T}(\phi)}\left(\frac{\phi}{\mu+\phi}\right)^{\phi}\left(\frac{\mu}{\mu+\phi}\right)^{\mathcal{Y}} & ,y = 1,2,3 \end{cases} \quad \ldots(6)$$

Where, ϕ^{-1} is dispersion, μ is mean and Γ(.) is gamma function respectively. The ZIP and ZINB regression models are represented in terms of logistic regression function and negative binomial regression function in following equation;

$$Logit(\wp_i) = x_i^{\mathbb{T}}\beta \ and \ \ Logit(\mu_i) = Z_i^{T}\gamma$$

where β are the vector coefficients X_i^T and γ are the vector coefficients Z_i^T.

3.RESULTS AND DISCUSSIONS

The weekly (SMW wise) counts of yellow stem borer light trap catches at Warangal centre observed during 2013–2021 period was plotted in figure 3. The yellow stem incidence was higher between 36th to 45th SMWs every year.

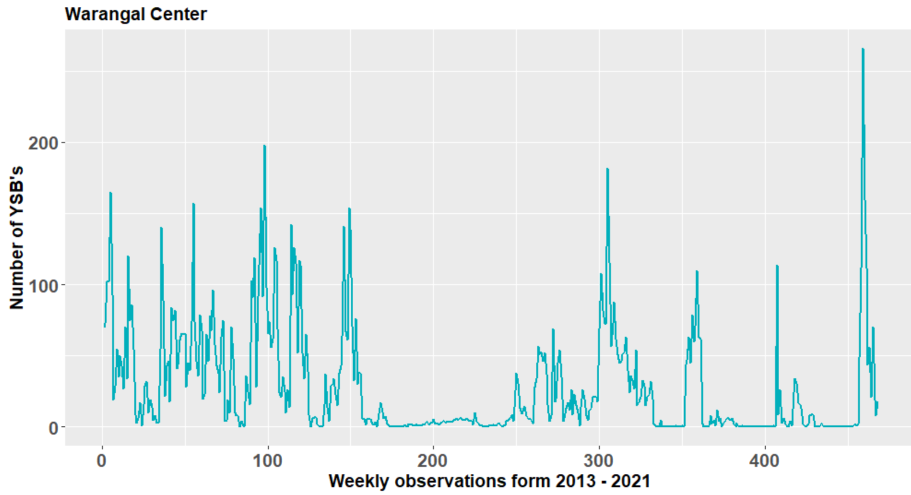


Figure 3: YSB papulation of Warangal centre

3.1. Summary statistics

Summary statistics of the dependent variable yellow stem borer population and exogenous weather variables were calculated and presented in Table 1. The YSB populations at Warangal were 468. Leading to a high percentage of CV and an abnormality of data as skewness and kurtosis are out of normal range. Summary statistics of weather variables presented in Table.1 were self-explanatory, showing that data under consideration were highly heterogeneous in nature.

Table 1: Descriptive statistics of Yellow Stem Borer of Warangal Centre

Location	Statistics	Population	MAXT	MINT	RF	RHM	RHE	SSH
Warangal	Mean	28.2	32.4	20.6	8.1	97.07	56.2	6.1
	S. E	1.7	0.20	0.20	1.05	0.2	0.52	0.12
	Skewness	2.01	1.02	-0.52	5.2	-2.33	0.22	-0.67
	Kurtosis	5.1	0.24	-0.74	32.5	11.9	-0.43	-0.49
	Minimum	0	25.7	11.2	0	53.3	28	0
	Maximum	266	45.9	31	204.7	97.7	94	11.1
	CV (%)	135.8	13.6	21.1	278.4	5.1	20.27	44.3

MAXT: maximum temperature, MINT: minimum temperature, RF: rainfall RHM: morning relative humidity, RHE: evening relative humidity, SSH: sunshine hours.

3.1. Correlation Analysis

Pearson correlation coefficients between YSB populations and considered climatological variables are depicted in Table 2. A low negative significant correlation between YSB and MAXT & MINT was observed; a low positive significant correlation was observed between YSB population and MRH & SSH. The ERH and Rainfall data had non-significant correlation with YSB population at this centre. The bivariate correlation coefficients between weather variables are given in table 1 are self-explanatory.

Table 2: Pearson correlation coefficients between YSB and weather variables.

	YSB	MAXT	MINT	RF	MRH	SSH
MAXT	-0.14348 (0.0019)					
MINT	-0.19489 (< .0001)	0.59858 (< .0001)				
RF	-0.05397 (0.2444)	-0.19653 (< .0001)	0.14864 (0.0013)			
MRH	0.11316 (0.0144)	-0.22146 (< .0001)	-0.04595 (0.3218)	0.05786 (0.2120)		
ERH	-0.00137 (0.9765)	-0.22175 (< .0001)	0.43084 (< .0001)	0.32459 (< .0001)	0.48630 (< .0001)	
SSH	0.18990 (< .0001)	0.45273 (< .0001)	-0.01842 (0.6914)	-0.39359 (< .0001)	-0.15700 (0.0007)	-0.47375 (< .0001)

Values in parentheses represent probability values.

3.3. Stepwise Regression Analysis

To identify the factors influencing the incidence of YSB population and weather variables a step-wise linear regression analysis was carried out in SAS 9.3 version available at ICAR-Indian Institute of Rice Research Hyderabad. Results of the stepwise regression analysis are depicted in Table 3. For the dependent variable YSB population, MINT, SSH and ERH are significantly contributing, further MINT have negative effect on YSB population and SSH and ERH have positive impact on YSB population for the data under consideration. Similar results were found in [2]. Though the listed variables have significant influence on the Yellow Stem Borer populations, the model R^2 value for the fitted regression in the Warangal centre is low, indicating that the model is not a strong fit, for which non-linearity and high heterogeneity in dependent variables may be responsible.

Table 3: Stepwise Regression Analysis of yellow stem borer of Warangal centre.

Parameter	Estimate	S.E.	F Value	Probability	R^2	Model R^2
Intercept	29.41	19.75	2.22	0.1371		
MINT	-1.86	0.69	18.36	<.0001	0.03	0.03
SSH	4.94	0.77	17.38	<.0001	0.03	0.07
ERH	0.75	0.21	25.30	<.0001	0.04	0.04
MAXT	-1.07	0.67	2.52	0.1128	0.004	0.12

3.4. Results of count regression models

As explained in methodology section, Poison and negative binomial regression models are fitted for the YSB population and corresponding weather variables are also considered to build the model.

The model parameters for poison regression model were given in Table 4 for the Warangal centre and all the weather parameters are significantly contributing to the YSB population incidence.

Table 4: Parameter estimation of Poison regression model

Warangal	Estimate	Std. Error	Z value	Probability
Intercept	0.22	0.25	0.875	0.382
MAXT	-0.037	0.0035	-10.390	<0.0001
MINT	-0.065	0.003	-17.625	<0.0001
RF	0.001	0.0004	4.077	<0.0001
RHM	0.032	0.002	11.080	<0.0001
RHE	0.026	0.001	18.984	<0.0001
SSH	0.202	0.004	41.556	<0.0001

Similarly, negative binomial regression model also fitted for the YSB population and weather variables where MINT, RHM and SSH showed significant influence on the dependent variable where as other variables shown non-significant relationship with the YSB population.

Table 5: Parameter estimation of negative binomial regression model

Parameter	Estimate	Std. Error	z value	Probability
Intercept	-3.00	1.74	-1.72	0.08
MAXT	-0.01	0.02	-0.58	0.55
MINT	-0.08	0.03	-2.78	<0.0001
RF	0.00	0.00	1.03	0.30
RHM	0.07	0.01	3.80	<0.001
RHE	0.01	0.01	1.40	0.15
SSH	0.18	0.03	5.40	<0.0001

3.5. Results of zero inflated count regression models

An alternative way for modelling the data contains more zeroes by using zero-inflated count regression models. In this article, we have fitted Zero-inflated Poisson regression and zero-inflated negative binomial regression models and their parameter estimates are given in Table 6 and 7 respectively. Table 6 provides parameter estimation of ZIPR model, in which most of the weather parameters are significant for nonzero outcomes as probability of significance is p<0.0001 and for zero outcomes MINT, RF, MRH and SSH are significant.

Table 6: Parameter estimation of zero inflated poison regression model

	P(Y>0)				P(Y=0)			
Parameter	Estimate	Std. Error	Z value	Prob.	Estimate	Std. Error	Z value	Prob.
Intercept	0.92	0.27	3.32	<0.0001	-1.92	3.38	-0.56	0.57
MAXT	-0.037	0.003	-9.56	<0.0001	-0.04	0.06	-0.78	0.43
MINT	-0.033	0.00	-9.80	<0.0001	0.42	0.09	4.56	<0.0001
RF	-0.00	0.00	-4.55	<0.0001	-0.03	0.01	-2.89	<0.0001
MRH	0.02	0.00	6.41	<0.0001	-0.07	0.03	-1.98	0.04
ERH	0.036	0.00	22.06	<0.0001	0.01	0.02	0.60	0.54
SSH	0.14	0.00	29.47	<0.0001	-0.29	0.06	-4.34	<0.0001

Table 7 provides parameter estimation of ZINBR model for both zero and non-zero outcomes. Parameters like ERH and SSH are significant for non-zero outcome model and RF, MRH and SSH are significant for zero outcome ZINMR models.

Table 7: Parameter estimation of zero inflated negative binomial regression model

	P(Y>0)				P(Y=0)			
Parameter	**Estimate**	**Std. Error**	**Z value**	**Probability**	**Estimate**	**Std. Error**	**Z Value**	**Probability**
Intercept	-0.090	1.96	-0.04	0.96	-5.20	5.38	-0.96	0.333
MAXT	-0.018	0.02	-0.72	0.47	-0.02	0.08	-0.25	0.80
MINT	-0.050	0.02	-1.72	0.08	0.55	0.16	3.418	0.00
RF	-0.001	0.00	-0.46	0.64	-0.04	0.01	-2.28	0.02
MRH	0.028	0.02	1.27	0.20	-0.11	0.05	-2.08	0.03
ERH	0.033	0.01	3.07	0.00	0.05	0.03	1.59	0.11
SSH	0.133	0.02	4.67	P<0.001	-0.32	0.09	-3.50	0.00

The results of modelling and predictions of the yellow stem borer population at Warangal centre obtained by applying different models were compared in terms of $R^{2,}$ MSE and RMSE and are presented in Table 8.

Table 8: comparison of performance of different models at Warangal centre

Warangal	**SRM**	**PRM**	**NBRM**	**ZIPRM**	**ZINBRM**
R^2	0.125	0.145	0.113	0.172	0.176
MSE	1320.62	1256.85	1313.18	1219.39	1275.99
RMSE	36.34	35.45	36.24	34.92	35.72

SRM: Stepwise regression model, PRM: Poisson regression model, NBRM: Negative binomial regression model, ZIPRM: Zero inflated Poisson regression model, ZINBRM: Zero inflated negative binomial regression model

In this study it is revealed that stepwise regression model was weak (low R^2) due to non-linearity and heterogeneity in the dependent variable. different models applied in this study *viz.,* Poison regression model, negative binomial regression model, zero inflated poison regression model and zero inflated negative binomial regression model. The zero inflated count regression models outperformed the classical models as their R^2 is high and MSE and RMSE is low, further ZINBR model outperformed all the models as it has highest R^2 value and lowest MSE and RMSE values. The better performance of ZINBR model could be due to its ability to capture over dispersion and heterogeneity in the data sets. Similar results were also found in [8] where zero-inflated models performed better than classical models in modelling COVID-19 deaths in Ghana country. Further, the actual vs fitted values of all the models are depicted in figure 4 which is clearly indicates, ZINBR model fitted values are closer to the actual YSB population values.

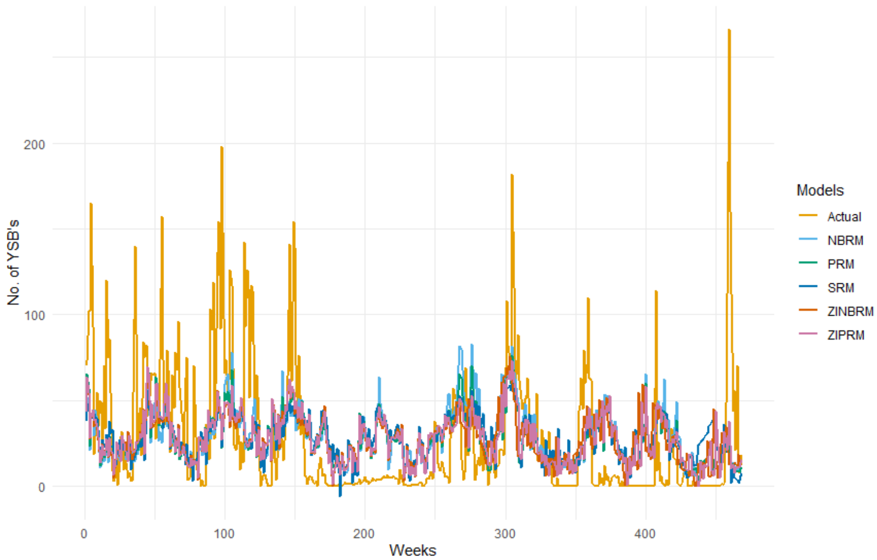


Figure 4: Actual vs fitted values of models

4. Conclusion

In the present study, different regression models were developed to model the relationship between weather variables namely maximum temperature (MAXT), minimum temperature (MINT), total rainfall (RF), morning relative humidity (RHM), evening relative humidity (RHE) and sunshine hours (SSH). The results showed that stepwise linear regression model unable to capture the pattern present in the heterogeneous count data as its yielded high RMSE values whereas count regression model are better in identifying the relationship between weather variables and YSB population. Among all the models implemented, ZINBR model performed better compared to all the models. The data under consideration was over dispersed, possibly due to two facts that are excess of zeros and heterogeneity of data. The classical regression models unable to model such data under consideration, an alternative way for modelling such type of data is by using the zero-inflated regression model which considers the excess of zeroes.

Rice yellow stem borer is most serious pest in rice cultivation, causing significant economic losses in rice ecologies across the country. The models developed in this study utilizing regression techniques will be of great assistance in identifying the relationship between weather variables and occurrence of YSB population, so that the appropriate management measures can be engaged to minimize the yield losses. In the future, it is expected that various count regression techniques will be intensively used to model the data of other crop pests.

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