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Research Paper

Prediction of peak pest population incidences in jute crop based on weather variables using statistical and machine learning models: A case study from West Bengal

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ABSTRACT

Jute crop cultivated in Cooch Behar suffers a substantial amount of physical and economical loss every year due to several major insect pest infestation such as Yellow Mite (*Polyphagotarsonemus latus* Banks) and Jute Semilooper (*Anomis sabulifera* Guen). Constructed seasonal plots reveal that for Yellow Mite pest incidence is maximum at 55 DAS, while for Jute Semi Looper it is at 45 DAS. Correlation analysis indicate that the weather parameters such as minimum temperature at current week, maximum RH at one week lag, minimum temperature, minimum and maximum RH at two-week lag are significantly correlated with the incidence of Yellow Mite, while in case of Jute Semilooper maximum temperature, minimum and maximum RH at two-week lag are significantly correlated. Different forecasting models like ARIMA, ARIMAX, SARIMA, SARIMAX and SVR have been fitted and validated using RMSE and RMdSE values. While ARIMAX and SARIMAX are found to be the best fitted model for Yellow Mite and Jute Semilooper respectively, following successful model validation, forecasting is done for the year 2022.

Key words: Jute, ARIMA, ARIMAX, SARIMA, SARIMAX, SVR.

Being one of the most important commercial crops, next to Cotton (*Gossypium spp.*) Jute (*Chorchorus spp.*) is cultivated widely in the Eastern and North Eastern states of India, which is also known as "Golden fiber" for its financial advantages. Raw jute industry has social, economic and physical importance on 33-35 lakh small and marginal farmers of West Bengal involved in jute cultivation (Sarkar *et. al.*, 2016). One of the major Raw Jute producing district in West Bengal is Cooch Behar, situated in the northern part of the state just below the Himalayas which comes under a special category of agro-ecology known as Terai zone. The primary reason behind this hefty cultivation is the presence of dominant share of small and marginal farmers within the farming community (Roy, 2016).

Jute cultivation carried out in pre-kharif season, suffers a substantial amount of physical and economical loss every year due to several major insect pest infestation such as Yellow Mite (*Polyphagotarsonemus latus* Banks) and Jute Semilooper (*Anomis sabulifera* Guen) at different stages of the crop growth. It is estimated that the avoidable loss in fibre yield was found to be around 31-34% in West Bengal (Rahman *et. al.*, 2012). Certainly, this percentage can be reduced by adopting some sustainable plant protection measures such as integrated pest management system, use of biological control, mechanical methods etc.

Various mathematical, statistical and simulation models can be used for timely and accurate forecasting of pest incidence which will eventually benefit the farmers in minimizing the losses by following proper management for the pests. Being one of the most important methods in statistical modelling, time series forecasting method predicts the future values of a variable based on the past observations. Also, now-a-days using advanced computational

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power, complex models such as Support Vector Machine (SVM) can be designed for an accurate and precise forecasting (Durgabai *et. al.*, 2018). Also, from several studies it was evident that weather parameters particularly temperature, relative humidity and rainfall played a crucial role on occurrence and survival of different insect pests on jute crop (Rahman *et. al.*, 2012; Suyal *et. al.*, 2018). Also, it was found out that incidence of insect pests was correlated with current time period as well as 1 to 4 lead times (Katke *et. al.*, 2009, Balikai *et. al.*, 2019). However, in the present investigation an attempt has been made to study the seasonal incidence and forecast the incidence of major pests of Jute crop in Cooch Behar district of West Bengal.

MATERIALS AND METHODS

Description of data

For the present study data on incidence of major pests of Jute like Yellow Mite and Jute Semi Looper recorded under All India Network Project (AINP) on Jute & Allied Fibres, Uttar Banga Krishi Viswavidyalaya (UBKV), Pundibari Centre from 2013 to 2021 have been used. During each year, incidence of pests was taken at 25, 35, 45, 55, 65 and 75 days after sowing (DAS). For Yellow Mite, incidence was measured in terms of its count per square cm of 2nd unfold leaf whereas for Jute Semilooper it is measured as percentage infestation. These pest data were taken from control fields, without spray operation.

In addition to this, daily data on weather variables *viz*., rainfall (RF in mm), maximum and minimum temperature (MaxT & MinT in ˚C), maximum and minimum relative humidity (MaxRH & MinRH in %) were collected from agromet observatory, Agrometeorological Field Unit (AMFU), Pundibari, UBKV for the year 2013 to 2021. The weather data have been considered for Standard Meteorological Weeks (SMWs) by considering the date of survey of pest incidence.

It is observed that mostly in every year pest incidence on 25 DAS and 75 DAS is zero due to the fact that these pest's life cycle in Jute crop starts around 35 DAS and it completes by 65 DAS. However, to check the actual status of pests in field condition surveys have been carried out on 25 and 75 DAS. These values may cause anomalies in model fitting and forecasting process. Further, we are mainly interested on pest incidence which is beyond economic threshold level. Therefore, the pest incidence on 25 DAS and 75 DAS are not considered and analysis has been carried out on the remaining 36 data points.

Methodology

To test the hypothesis of seasonality, the mean incidence of both the pests plotted against each season (2013-21) has been presented graphically and also Webel-Ollech (WO) test has been carried out. Also, Pearson correlation coefficients have been calculated between pest incidence and aforementioned weather parameters at current week, one- and two-week lag. Different forecasting models like Autoregressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average with Exogenous variables (ARIMAX), Seasonal ARIMA (SARIMA), Seasonal ARIMAX (SARIMAX) and Support Vector Regression (SVR) have been implemented to predict the incidence of pests using weather variables as necessitated.

Out of 36 data points, initial 32 data points are used for model building purpose and rest 4 data points are used for validation purpose. The results have been analyzed statistically by using R-Studio Version 4.1.2 and MS Excel 2019.

Autoregressive Integrated Moving Average (ARIMA) Model

Being one of the most prevalent time series model, ARIMA model gained popularity by Box and Jenkins in 1976, which is suitable for short-term forecasting dependent on past values of the variable being forecast. It can be expressed as;

$$\phi_p(B)\nabla^d y_t = \theta_q(B)\varepsilon_t$$

where, B is the backshift operator such that $(B^p)\nabla^d y_t = \nabla^d y_{t-p}$, $\nabla^d y_{t-p} = (1-B)^d y_{t-p}$, $(B^q)\varepsilon_t = \varepsilon_{t-q}$ and $\varepsilon_t \sim N(0,\sigma^2)$, known as white noise errors. $\phi_p(B)$ and $\theta_q(B)$ are the AR and MA components of order *p* and *q* respectively, where *d* denotes the order of differencing.

Autoregressive Integrated Moving Average with Exogenous variables (ARIMAX) Model

ARIMAX model (Bierens, 1987), being an extension of ARIMA model, increases the explanatory nature of the model by incorporation of exogenous independent variables which have possible influence over the predicted values. A time series process $\{(y_t, x_t)\}$ having $(k + 1)$ terms, where y_t and *k* values of x_t are real valued random variables, can be formulated as,

$$\nabla^d y_t = \phi_1\nabla^d y_{t-1} + \ldots + \phi_p\nabla^d y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \ldots - \theta_q\varepsilon_{t-q} + \beta_0 + \beta_1 x_{1t} + \ldots + \beta_k x_{kt}$$

where, ε_t 's are the errors, but here interpreting β is difficult. So, it is expressed as,

$$\nabla^d y_t = \beta_0 + \beta_1\nabla^d x_{1t} + \ldots + \beta_k\nabla^d x_{kt} + \nabla^d\eta_t$$

$$\nabla^d\eta_t = \phi_1\nabla^d\eta_{t-1} + \ldots + \phi_p\nabla^d\eta_{t-p} + z_t - \theta_1 z_{t-1} - \ldots - \theta_q z_{t-q}$$

where, η_t = eta at t and z_t = error.

Seasonal ARIMA (SARIMA) Model

In order to improve the performance of conventional ARIMA model seasonal data patterns are added to develop Seasonal ARIMA (SARIMA) model (Box and Jenkins, 1976). Let us assume a time series y_t (t = 1, 2, …, T) which follows the SARIMA can be formulated as,

Table 1: Descriptive statistics of response and regressor variables

Parameters	Response variables		Regressor variables at current week				
	Yellow Mite (no/sq cm)	Jute Semilooper (% infestation)	Rainfall (mm)	MaxT (^{0}C)	MinT (^{0}C)	MaxRH (%)	MinRH (%)
Mean	4.31	4.70	113.5	31.5	22.3	85.1	74.7
Standard deviation	5.74	5.05	126.4	2.0	2.3	10.3	9.8
CV	1.33	1.08	1.1	0.1	0.1	0.1	0.1
Minimum	0.00	0.00	0.0	28.3	13.0	46.4	37.9
Maximum	25.62	17.87	533.9	36.9	25.3	99.1	92.6
Skewness	1.81	1.12	1.8	0.7	-1.8	-1.7	-1.2
Kurtosis	3.36	0.40	2.5	-0.1	5.1	4.3	3.6

Table 2: WO test to check seasonality

	Test statistic		p-value	
Yellow Mite	0	0.111	1	0.078
Jute Semilooper	1	0.0001	0.001	0.005*

*: Significant at 5%

Table 3: Pearson's correlation coefficient of Mean incidence of Yellow Mite, Jute Semilooper with weather parameters

Weather Parameters	Yellow Mite			Jute Semilooper		
	Current week	One week lag	Two weeks lag	Current week	One week lag	Two weeks lag
Rainfall	-0.24	-0.24	-0.19	-0.07	-0.12	-0.16
MaxT	-0.15	0.21	0.34	-0.12	0.25	0.39*
MinT	-0.37*	-0.34	-0.37*	-0.01	-0.07	-0.24
MaxRH	-0.28	-0.43**	-0.61**	-0.17	-0.33	-0.49**
MinRH	-0.11	-0.3	-0.51**	-0.02	-0.23	-0.44**

**: Significant at 1%; *: Significant at 5%

Table 4: ADF and PP test for stationarity

Yellow Mite				Jute Semilooper			
ADF test		PP test		ADF test		PP test	
Test statistic	p-value	Test statistic	p-value	Test statistic	p-value	Test statistic	p-value
-3.59	0.01**	-4.86	0.01**	-4.86	0.01**	-4.76	0.01**

*: Significant at 5% ; **: Significant at 1%

$$\Phi_P(B^s)\phi_p(B)\nabla_s^D\nabla^d y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t$$

where, ε_t the residual at time *t* follows $N\left(0,\sigma^2\right)$, *B* is the backward shift operator, and *s* denotes the number of periods per season. The polynomials $\phi_p(B)$ and $\theta_q(B)$ represents the non-seasonal autoregressive and moving average terms with orders *p* and *q*, respectively. Similarly, the seasonal autoregressive and moving average terms of order *P* and *Q*, respectively are represented by $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ polynomials, and also, the seasonal and non-seasonal differencing terms are represented by ∇_s^D and ∇^d respectively.

Support Vector Regression (SVR)

The SVR method is a nonlinear modelling procedure which utilizes the principle of structured risk minimization, in which the upper bound of the generalization error is minimized (Vapnik, 2000). Let $D = \{(x_i, y_i)\}$ (i = 1 to N) be a training set, where $x_i \in R^n$ is input vector, $y_i \in R$ is scalar output and *N* is the size of the dataset. It can be expressed as

$$f(x) = w^T\varphi(x) + b$$

where $\varphi(.): R^n \rightarrow R^{n_h}$ is a nonlinear mapping function from original input space into a higher dimensional feature space, $w \in R^{n_h}$ is weight vector, *b* is bias term and the superscript *T* is transpose. The error term denoted by ε, known as tube size is also the approximation accuracy in training data.

Forecast evaluation methods

To choose the most parsimonious model, error range indexes like Root mean square error (RMSE) and Root median square error (RMdSE) have been used. RMSE measures how much a dependent series differs from its model-predicted level, while instead of RMSE, RMdSE may be applied as it is used to determine the robustness of a model against outliers. It can be expressed as;

$$RMdSE = \sqrt{Median\left(\hat{y}_{n+h} - y_{n+h}\right)^2}$$

Table 5: Parameter estimates of the ARIMA (0, 0, 1) and ARIMAX (0, 0, 1) model for Yellow Mite incidence

Model	Parameters	Estimate	S.E.	p-value
ARIMA (0, 0, 1)	C	4.55	1.43	0.002**
	MA1	0.72	0.11	0.001***
ARIMAX (0, 0, 1)	MaxRH lag1	-0.12	0.13	0.350
	MinT lag2	0.64	0.48	0.179
	MA1	0.68	0.13	0.001***

***:Significant at 0.1%

Table 6: Parameters of the SVR ($y \sim x$) model for Yellow Mite incidence

Type	Kernel	Cost (C)	Gamma	Epsilon (ε)	No. of support vectors
eps-regression	radial	1	0.5	0.1	30

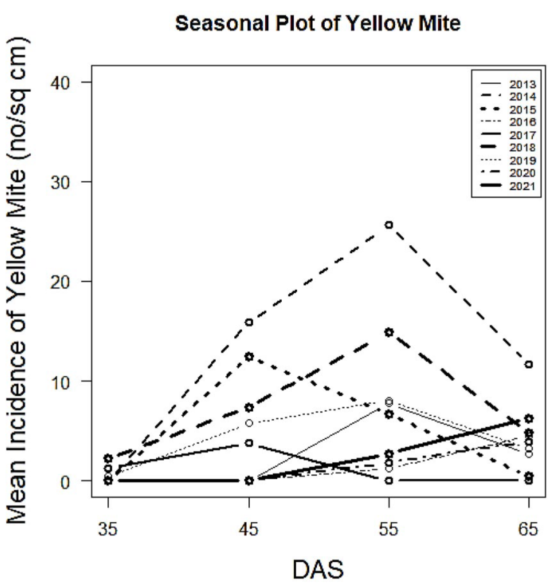

Fig. 1: Seasonal plot of Yellow Mite incidence

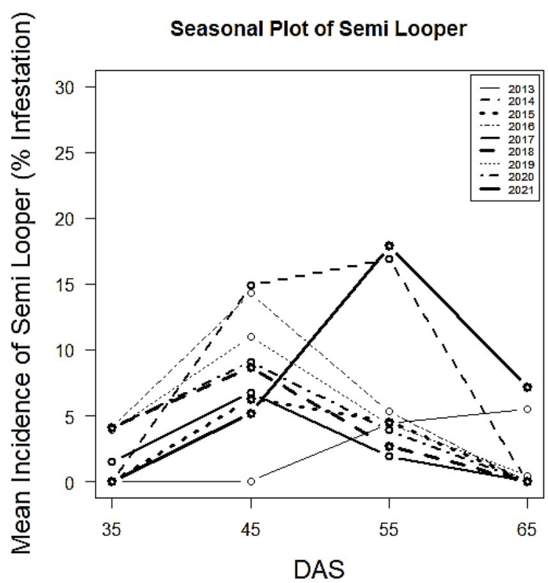

Fig. 2: Seasonal plot of Jute Semilooper incidence

Also, to ensure the adequacy of the best fitted model, the residual diagnostics have been carried out.

ARCH-LM test

The full form of this test is Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test. This test confirms whether the residuals are homoscedastic in nature or not. The null hypothesis indicates residual are homoscedastic in nature. Therefore, rejection of null hypothesis indicates the data set is non-stationary in mean and variance. The application of this test after fitting linear models like ARIMA indicates whether nonlinearity is present in the residuals. If residuals are not homoscedastic in nature in that case application of nonlinear models like ARCH, GARCH have to be considered.

RESULTS AND DISCUSSION

Descriptive statistics

Descriptive Statistics of Yellow Mite, Jute Semilooper and weather variables of current week has been carried out and highlighted in Table 1, which revealed that there is high variability in case of both pests as the coefficient of variation (CV) is found to be 133% and 108% for Yellow Mite and Jute Semilooper respectively. While for both Yellow Mite and Jute Semilooper it is found to be positively skewed, the former series is leptokurtic and later series is platykurtic in nature. Also, among weather variables rainfall shows very high CV.

Seasonal dynamics

From Fig. 1 it can be concluded that presence of seasonality is ambiguous as the peak incidence in Yellow Mite is observed mainly on 55, 45 and 65 DAS during 2013-21. From Fig. 2 it is evident that peak incidence is mostly on 45 DAS, which indicates the presence of seasonality for Jute Semilooper. The same can also be confirmed from the results obtained in WO test.

Correlation analysis

From Table 3 it can be perceived that mean incidence of Yellow Mite has a significant negative association with MinT in current week and MaxRH at lag2. While correlation between MaxRH in lag1, MaxRH and MinRH in lag 2 with mean pest incidence is highly significant in a negative direction. Also, from the same table it can be depicted that MaxT at lag 2 is significantly

Table 7: Parameter estimates of the SARIMA (0, 0, 2) (1, 1, 0)$_4$ and SARIMAX (0, 0, 0) (0, 1, 0)$_4$ model for Jute Semilooper incidence

Model	Parameters	Estimate	S.E.	p-value
SARIMA	MA1	0.38	0.20	0.064
(0, 0, 2) (1, 1, 0)$_4$	MA2	-0.45	0.21	0.033*
	SAR1	-0.78	0.13	0.001***
SARIMAX	MaxT lag2	0.34	0.26	0.186
(0, 0, 0) (0, 1, 0)$_4$	MaxRH lag2	-0.21	0.04	0.001***

Table 8: Parameters of the SVR (*ys ~ x*) model for Jute Semilooper incidence

Type	Kernel	Cost (C)	Gamma	Epsilon (ε)	No. of support vectors
eps-regression	radial	1	0.5	0.1	28

Table 9: Predictive abilities for ARIMA, ARIMAX and SVR models for Yellow Mite and Jute Semilooper

Pest	Model	Parameter	RMSE	RMdSE
Yellow Mite	ARIMA	(0,0,1)	3.41	3.39
	ARIMAX	(0,0,1)	1.86	1.61
	SVR (y ~ x)	eps-regression, radial	2.08	2.19
Jute Semilooper	SARIMA	(0,0,2) (1,1,0)$_4$	8.28	6.18
	SARIMAX	(0,0,0) (0,1,0)$_4$	6.58	6.07
	SVR (ys ~ x)	eps-regression, radial	6.83	4.88

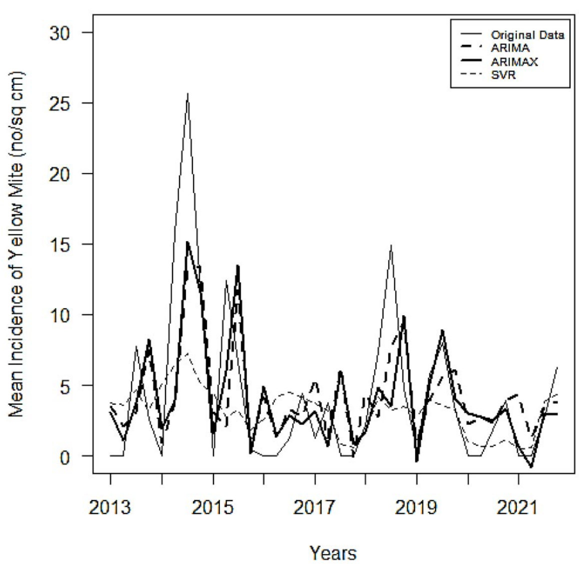

Fig. 3: Plot showing original vs fitted values by ARIMA, ARIMAX and SVR model for Yellow Mite incidence

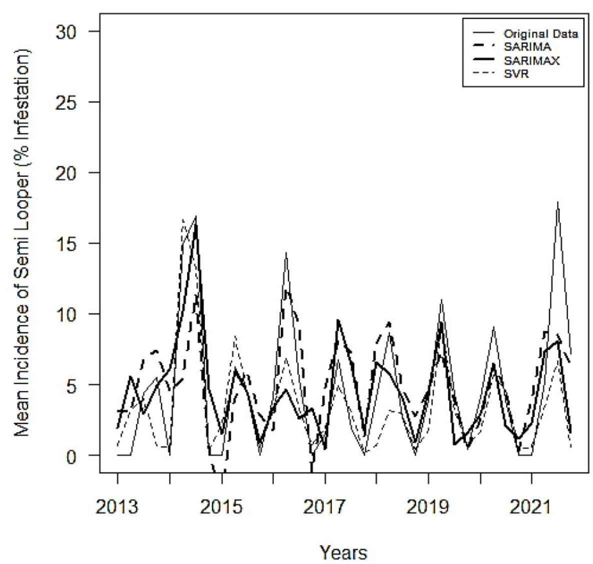

Fig. 4: Plot showing original vs fitted values by SARIMA, SARIMAX and SVR model for Jute Semilooper incidence

positively correlated with mean incidence of Jute Semilooper. But at lag 2 MaxRH and MinRH are negatively correlated with mean incidence of Jute Semilooper and the association is highly significant.

Fitting of different models of Yellow Mite

To check the presence of stationarity in the current data series Augmented-Dickey-Fuller (ADF) test and Phillips-Perron (PP) test have been applied and it is evident that p value is 0.01 and 0.05 respectively, which indicates the data series is stationary by rejecting the null hypothesis at 1% and 5% level of significance respectively. It indicates there is no requirement of regular differencing.

Accordingly, ARIMA (0, 0, 1) model is selected using "auto.arima" function in R software. The estimate of parameters, its standard error (S.E.) and respective p-values are presented in Table 5. In present study MaxRH at lag1 and MinT at lag2 are utilized in ARIMAX model building process, as proved to be the best possible pair. On the basis of minimum AIC and BIC value ARIMAX (0, 0,

Table 10: Residual diagnostics test

Diagnostic test	Yellow Mite		Jute Semilooper	
	Test statistic	p-value	Test statistic	p-value
Box-Ljung	6.75	0.56	7.30	0.50
Shapiro-Wilk	0.87	0.001**	0.93	0.03*
ARCH LM	9.62	0.29	7.70	0.46

Table 11: Out-of-sample forecast for mean incidence of Yellow Mite (no/sq cm) and Jute Semilooper (% Infestation) for 2022

DAS	Yellow Mite			Jute Semilooper		
	Mean incidence (no/sq cm)	MaxRH lag1 (%)	MinT lag2 (^{0}C)	Mean incidence (% infestation)	MaxT lag2 (^{0}C)	MaxRH lag2 (%)
35 DAS	4.12	95.51	21.07	5.05	31.49	86.44
45 DAS	2.38	94.46	21.52	3.13	31.49	84.56
55 DAS	2.89	90.56	21.52	3.27	31.49	83.52
65 DAS	3.45	92.36	21.52	4.92	31.49	82.95

1) model is selected as best fitted model using "auto.arima" function in R software and estimated parameters with S.E. and p-values are also presented in Table 5.

As it is evident from earlier sections, due to absence of seasonality and AR component in the possible ARIMA model, any seasonal adjustment or fitting regression models of pest incidence with itself is not required in the data set for application of SVR methodology. Thus, the best fitted model is selected on the basis of lowest training and testing error, which is found to be $y \sim x$ and the parameters are represented in Table 6.

Fitting of different models of jute semilooper

Similarly, the results obtained from ADF and PP tests indicate that as the p-values are 0.01, the given data set is stationary and there is no need of any regular differencing. After required seasonal differencing, on the basis of the least AIC and BIC value SARIMA (0, 0, 2) $(1, 1, 0)_4$ model is selected and the estimates of parameters, respective S.E. and p-values are depicted in Table 7.

In the present investigation MaxT and MaxRH at lag2 are considered as exogenous variables as the Variance Inflation Factor (VIF) values are below 5 indicating absence of multicollinearity. SARIMAX (0, 0, 0) $(0, 1, 0)_4$ is found to be the best fitted model using "auto.arima" function in R software and estimated parameters with S.E. and p-values are also presented in Table 7.

Evident from earlier sections, due to absence of AR component in the possible SARIMAX model pest incidence is not fitted with itself for SVR model building purpose. But because of seasonal differencing, seasonal adjustment in the data set has been carried out and $ys \sim x$ (where, ys is seasonally adjusted pest incidence values) is found to be the best fitted model on the basis of lowest training and testing error and the parameters are represented in Table 8.

Model Validation

To compare the forecast performance of different models, RMSE and RMdSE are used and results have been furnished in Table 9.

Evident from several literatures published earlier, SVR model should be the best fitted out of all the three models considered in the current investigation. But it has also been seen that SVR model performs better in non-linear data set as compared to linear data set, but results obtained from ARCH-LM test confirm that the residuals are homoscedastic in nature. Thus, the data set is stationary in mean and variance. Therefore, SVR model has not given better result as compared to the ARIMAX model.

Residual diagnostics

After getting the best fitted models, to check the appropriateness residual diagnostics has been carried out. Upon conducting the Box-Ljung test, from the results obtained it can be concluded that the residuals are independent in case of both pests. To test the normality, Shapiro-Wilk test has been applied and from the results depicted in Table 10, it can be concluded that the null hypothesis is rejected, as the p value is less than 0.05, indicating that the residuals are not normally distributed. To check the presence of ARCH effect, ARCH LM test has been carried out and from the results it is confirmed that there is no existing ARCH effect in residuals, i.e., residuals are homoscedastic in nature.

Forecasting of pest incidence

After getting ARIMAX (0, 0, 1) and SARIMAX (0, 0, 0) $(0, 1, 0)_4$ as the best fitted models for Yellow Mite and Jute Semilooper respectively on the basis of model validation, out-of-sample forecast has been carried out for the year 2022 at 35, 45, 55 and 65 DAS and the results are represented in Table 11.

CONCLUSION

Present study revealed that for Yellow Mite and Jute Semilooper, highest mean incidence is on 55 DAS and 45 DAS respectively for most of the years, while seasonality is only present in the later. Also, among years highest mean incidence is observed on 2014 and 2021 respectively. However, weather parameters such as MinT in current week, MaxRH at lag2, MaxRH in lag1, MinRH and MaxRH in lag 2 have a significant association with incidence of Yellow Mite. Similarly, mean incidence of Jute Semilooper has a significant association with MaxT, MinRH and MaxRH at lag 2. In case of Yellow Mite incidence, on the basis of least RMSE and RMdSE values, ARIMAX is found to be the best fitted model followed by SVR and ARIMA. While for Jute Semilooper incidence SARIMAX model produces the least RMSE value followed by SVR and SARIMA, but on the basis of RMdSE values SVR model is the best fitted followed by SARIMAX and SARIMA.

Some suitable techniques can also be implemented in future to lessen the effects of these outlying observations present in this time series data. These forecasting methods can also be extended to other places in Terai zone and can also be applied for some other disease data.

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